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Common Drivers of Commodity Futures?

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Abstract
We study potential drivers for a large cross section of commodity futures. Unlike previous studies, we examine the effect of monthly drivers on daily returns using mixed-frequency Granger causality tests. We find real economic activity as a main driver on a monthly basis, whereas financial variables seem to affect returns at daily frequency. The linkages are time-varying for various stages of the financialization of commodity markets with an overall dissipating impact in the recent period of de-financialization. As our results strongly differ from traditional low-frequency Granger causality tests under the 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-frequency techniques to uncover relationships between monthly-published macroeconomic variables and commodity prices.

Keywords: Commodity futures, VAR, Granger causality, Mixed data sampling

JEL classification: C58; G17; Q02

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1. Introduction

Since it is well established that prices of various "unrelated" commodities tend to co-move, researchers are trying to understand the driving forces behind joint fluctuations in commodity prices.[1] Uncovering the effects that influence the cross-section of commodity futures fosters the accuracy of market research outlooks and helps commercial traders to improve their hedging decisions. As correlations among commodities intensified during the so-called "financialization" of commodity futures markets (Tang & Xiong, 2012; Büyükşahin & Robe, 2014; Bhardwaj et al., 2016), it is also crucial for financial investors to understand the drivers shared by multiple commodities to assess the level of diversification in their portfolios properly.

The existing literature attributes the presence of commonalities in commodity prices to three major factors. Firstly, commodity prices react to changes in macroeconomic fundamentals that shift aggregate supply and demand or its expectations (Pindyck & Rotemberg, 1990). These fundamentals include real economic activity or exchange rates, for instance.[2] Secondly, a high portion of the co-movement can be attributed to the financialization of commodity markets. With financialization, commodities became a new investable asset class in the eyes of financial investors. For example, Tang & Xiong (2012) ascribe the tighter link between different commodity markets to the trading of commodity index investors as they observe stronger effects for index compared with off-index commodities.[3] Results of Adams et al. (2020) indicate a growing importance of financial variables in explaining commodity returns during financialization, which is of significant interest to our study. Lastly, various uncertainty measures have been found to affect commodity prices (e.g. Joëts et al., 2017). Effects originating from uncertainty

[1]See, e.g., Pindyck & Rotemberg (1990); Tang & Xiong (2012); Byrne et al. (2013); Chen et al. (2014); West & Wong (2014); Gao & Süss (2015); Ohashi & Okimoto (2016); Le Pen & Sévi (2018); Delle Chiaie et al. (2022), among others.

[2]The effect of real economic activity is documented in Pindyck & Rotemberg 1990; West & Wong 2014; Delle Chiaie et al. 2022, while the impact of changes in the US-Dollar exchange rate is documented in Chen et al. 2014; West & Wong 2014, amongst others. We provide a more detailed review on potential drivers of commodity prices and related empirical findings of the literature in Section 3.

[3]Academic literature on causes of financialization and the motivation of financial investors seeking, e.g., portfolio diversification is becoming increasingly ample (Tang & Xiong, 2012; Cheng & Xiong, 2014; Adams & Glück, 2015; Gao & Süss, 2015; Ohashi & Okimoto, 2016; Le Pen & Sévi, 2018).

affect commodity markets both through fundamental and financial channels.

The majority of the existing literature on the drivers of commodity prices and their co-movement uses temporally aggregated monthly, quarterly, or even annual returns for empirical analyses as most macroeconomic indicators are available at a monthly or lower frequency. This aggregation results in the loss of valuable information inherent in higher-frequency data and can distort empirical findings (Marcellino, 1999).[4] The few studies using higher-frequency data restrict themselves to a small set of potential drivers (e.g. Gao & Süss, 2015; Andreasson et al., 2016), which, in turn, leads to ignoring important variable available only at monthly data frequency.

Unlike previous studies, we seek to identify "common drivers" that jointly affect commodity futures returns by employing mixed-frequency (MF) Granger causality (Ghysels et al., 2016). The method allows to study the relation of lower-frequent, such as monthly-available fundamental, financial, and uncertainty-related variables, to variables available at a higher data frequency, such as daily or weekly commodity futures returns. Thereby, we circumvent the aforementioned difficulties caused by temporal aggregation or variable omittance. We do not aim to determine commodity-specific drivers as in Kang et al. (2020), nor do we explicitly focus on identifying drivers of a common component in commodity prices like Byrne et al. (2013), for instance. Instead, we argue that if a single factor significantly affects individual futures returns across different types of commodities, it should also constitute a cause behind their co-movement.

We find that most commodity futures returns are driven mainly by changes in real economic activity on a monthly basis, whereas financial variables affect price movements on a daily level. Many futures returns are also influenced by uncertainty, both in the short- and long-term, depending on the cause of uncertainty. We further show that the relations between commodities and drivers are time-varying throughout the distinct stages of financialization (Natoli, 2021). Our results indicate that not only linkages from financial but also from fundamental and uncertainty variables to the broad range of commodity

[4] Ghysels et al. (2016), for instance, points out that temporal aggregation can cause both spurious causality and spurious non-causality.

futures dissolved in the recent period of the so-called "de-financialization" (2014 onward). Additionally, we find that temporally aggregating commodity returns—as is done in previous work—leads to different, potentially erroneous conclusions in the Granger causality analysis underpinning Ghysels et al. (2016) and Bevilacqua et al. (2019). With an out-of-sample trading study, we demonstrate that MF models improve the economic value of directional return predictions over traditional models estimated from monthly data only.

Our contribution to the literature on commodity futures is twofold. Firstly, we add to the literature on co-movement by providing further evidence on common return drivers of commodity futures using a novel MF approach. Secondly, we show the time-variation in the relation of commodity futures to their return drivers over disparate stages of the financialization. Particularly little evidence exists for the period of de-financialization since samples of most studies end before 2014. We also contribute to the literature on Mixed Data Sampling (MIDAS) by showing the economic benefit of utilizing higher-frequency data to uncover relationships between macroeconomic indicators and commodity futures.

The remainder of the paper is organized as follows. We describe our methodology and data in Section 2 and 3. Section 4 presents our empirical results. Section 5 concludes.

2. Methodology

We build our testing framework on the recently proposed MF Granger causality test (Ghysels et al., 2016) based on MF Vector Autoregression (MF-VAR Ghysels, 2016). In contrast to traditional VAR models that can be estimated only from variables that share the same data frequency, MF-VARs combine information of multiple time series at distinct sampling frequencies. Hence, when analyzing the nexus of low-frequency (LF) and high-frequency (HF) processes, data from the HF process does not need to be temporally aggregated to the common lower frequency. While most other MIDAS models are used for predicting LF time series with HF information, MF-VARs also allow to study the opposite direction, e.g., testing for Granger causality from LF macroeconomic indicators to HF commodity futures returns. Moreover, recent findings by Foroni et al. (2018) suggest that LF information can be useful for HF variables in a MIDAS framework.

2.1. 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 low frequency (LF) processes, with $K_L < n$, and $K_H = n - K_L$ high frequency (HF) processes.[5] We focus on bivariate models and set $K_H = K_L = 1$. In what follows, we briefly introduce MF-VAR models for the case of two time series sampled at different frequencies.

Consider a univariate LF process, $x_L(\tau_L)$, with time index $\tau_L \in \{1, .., T_L\}$ representing a variable that is available monthly such as log changes in world industrial production. The log return of a commodity futures contract is described by the univariate HF process $x_H(\tau_L, k_H)$ that is sampled m times between two observations of the LF variable such that $k_H = 1, ..., m$.[6] Traditionally, the HF variable would be aggregated to match the sampling frequency of the LF variable such that $m = 1$. Instead of losing valuable information of the HF variable through temporal aggregation, Ghysels (2016) proposes to form a "stacked" vector that contains all available observations of both the LF and the HF variable. Assuming that we can observe new values for the LF series at the very end of each LF period τ_L, yields the stacked vector $\boldsymbol{X}(\tau_L) = [x_H(\tau_L, 1), ..., x_H(\tau_L, m), x_L(\tau_L)]'$.[7] If $\boldsymbol{X}$ follows a VAR(P) process, we can write the stacked vector as:

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

where $\boldsymbol{A}_j$ denotes the $K \times K$ coefficient matrix for lag $j = 1, ..., P$, with $K = K_L + m \cdot K_H$,

[5]Since the MF-VAR model proposed by Ghysels (2016) is purely observation-driven, it does not require to include latent variables as in state space models such as the Bayesian MF-VARs introduced in Eraker et al. (2015); Schorfheide & Song (2015). See also Foroni et al. (2013) for an overview of various MF-VAR models.

[6]We set $m(\tau_L) = m \ \forall \tau_L$, i.e., we assume a fixed number of HF observations during each LF period.

[7]For our analysis, it is reasonable to assume that the LF variable is observed at the end of each LF period as the figures we use always refer to the entire month (e.g., monthly world steel production). We do not consider the publication date since we are interested in the linkage between the information carried by these variables (e.g., the level of global economic activity) and price fluctuations on commodity futures markets, and not in the reaction of commodity prices to public releases of these numbers.

and (τ_L) refers to the $(K{\times}1)$-dimensional vector of errors. The bivariate MF-VAR model from Eq. (1) is a traditional finite order VAR model of dimension $K = m + 1$. Prior to fitting the MF-VAR from Eq. (1) with OLS, we demean each component of the stacked vector.

2.2. *Mixed-Frequency Granger causality*

Based on the MF-VAR, Ghysels et al. (2016) develop a methodology to test for linear MF Granger causality. Compared with traditional tests for Granger causality involving temporal aggregation of the HF variable such that it matches the lower frequency, the authors show that MF Granger causality tests have higher asymptotic power and temporal aggregation is likely to lead to either spurious causality or spurious non-causality.

For $K_H = K_L = 1$, we extract $\tilde{\boldsymbol{x}}_H(\tau_L) = [x_H(\tau_L, 1), ..., x_H(\tau_L, m)]^t$ and $x_L(\tau_L)$ separately from $\boldsymbol{X}(\tau_L)$ and define $£(\tau_L) := \boldsymbol{X}\,(-\infty, \tau_L] = \tilde{\boldsymbol{x}}_H\,(-\infty, \tau_L] + x_L\,(-\infty, \tau_L]$ as the MF reference information set in period τ_L. Our main interest is to analyze Granger causality from potential LF driver variables to HF commodity returns. Adopting the notation of Ghysels et al. (2016), we can formulate the null hypothesis of non-causality from the LF to the HF variable at the LF forecasting horizon $h \in \mathrm{N}$ as:

$H_0(h)$: x_L --I $_h$ x_H | £, if:

$$P\;\tilde{\boldsymbol{x}}_H(\tau_L + h) \mid \tilde{\boldsymbol{x}}_H\,(-\infty, \tau_L] \;\; = P\;\tilde{\boldsymbol{x}}_H(\tau_L + h) \mid £(\tau_L) \quad \forall \tau_L \in \mathrm{Z},$$

where $P\,[\tilde{\boldsymbol{x}}_H\,(\tau_L + h) \mid £(\tau_L)]$ describes the best linear h-step ahead forecast of x_H given the information £ at period τ_L. The null hypothesis states that the LF variable does not Granger-cause the HF variable at horizon h, if the h-step ahead forecast of the HF variable, x_H, based on available information on x_H up to period τ_L remains the same whether or whether not past information about the LF variable is utilized. Simply put, the prediction of the HF variable cannot be improved by looking at past values of the LF variable.

In the bivariate case, 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). We, hence, only test for non-causality at horizon $h = 1$ using the following (P, h)-autoregression based on Dufour et al. (2006):

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

given that the stacked vector follows a VAR(P) process and all elements of the stacked vector are demeaned. Then, Eq. (2) is simply the MF-VAR(P) presented in Eq. (1).[8] To circumvent parameter proliferation, we set the LF lag order to $P = 1$ resulting in

$$\boldsymbol{A}_1 \in \mathbb{R}^{K\times K} = \begin{bmatrix} a_{11} & \cdots & a_{1K} \\ \vdots & \ddots & \vdots \\ a_{K1} & \cdots & a_{KK} \end{bmatrix}$$

being the full parameter set of MF-VAR coefficients. As our primary interest to analyze Granger causality from the LF to the HF variable in a bivariate setting, we henceforth describe the testing methodology for our particular case only, which includes $K_H = K_L = 1$, $h = 1$, and $P = 1$.[9]

Recall the form of the stacked vector $\boldsymbol{X}$ with the LF variable $x_L(\tau_L)$ being observed at the very end of each LF period. The influence of the LF variable on the HF variable, represented through $x_H(\tau_L, 1), \ldots, x_H(\tau_L, m)$ in $\boldsymbol{X}$, is then given by the first $m = K - 1$ coefficients in the K-th column of $\boldsymbol{A}_1$. Therefore, from Ghysels et al. (2016) follows that we can formulate the null of non-causality from the LF to the HF variable as:[10]

$$H_0^{(1)}(h=1) : [a_{1K}, a_{2K}, \ldots, a_{mK}]^{\mathrm{t}} = \boldsymbol{0}_{m\times 1}. \tag{3}$$

Ghysels et al. (2016) propose to test the null hypothesis in Eq. (3) based on the Wald

[8] For MF Granger causality tests with multivariate MF-VARs, see Ghysels et al. (2016) together with Dufour et al. (2006).

[9] For a more general representation of MF Granger causality testing with $P, h \geq 1$ and $n \geq 2$ (non-bivariate), including MF Granger causality from LF to LF, HF to HF, all HF to all LF, and all LF to all HF variables, please refer to Ghysels et al. (2016).

[10] More general, Ghysels et al. (2016) formulates the null of non-causality (LF to HF) as H_0 : $\boldsymbol{R}\,\mathrm{vec}\,[\boldsymbol{B}(h)] = \boldsymbol{r}$ with $\boldsymbol{B}(h) = \left[\boldsymbol{A}_1^{(h)}, \ldots, \boldsymbol{A}_P^{(h)}\right]^{\mathrm{t}} \in \mathbb{R}^{PK\times K}$, where $\boldsymbol{R}$ is an $m \times PK^2$ selection matrix and $\boldsymbol{r}$ is a column-vector of zeros with length m. We obtain our formulation of the null hypothesis presented in Eq. (3) by setting $h = 1$, $P = 1$, $K_H = K_L = 1$, and using $\boldsymbol{R} = [\boldsymbol{\Lambda}(\delta_1)^{\mathrm{t}}, \ldots, \boldsymbol{\Lambda}(\delta_m)^{\mathrm{t}}]$ with $\delta_k \in \{K, 2K, \ldots, mK\}$, $k = 1, \ldots, m$, where the δ_k-th element of the $1 \times K^2$-dimensional vector $\boldsymbol{\Lambda}(\delta_k)$ is 1 and zero otherwise.

statistic $W_{T_L}[H_0(h=1)]$ with $W_{T_L}[H_0(1)] \xrightarrow{d} \chi^2_m$ under $H_0(1)$:

$$W_{T_L}[H_0(1)] = T_L \left(\boldsymbol{R} \operatorname{vec}\left[\hat{\boldsymbol{A}}_1\right] - \boldsymbol{r} \right)^{t} \left(\boldsymbol{R}\hat{\boldsymbol{\Sigma}}\boldsymbol{R}^{t} \right)^{-1} \left(\boldsymbol{R} \operatorname{vec}\left[\hat{\boldsymbol{A}}_1\right] - \boldsymbol{r} \right),$$

where $\boldsymbol{r} = \mathbf{0}_{m\times1}$. The selection matrix $\boldsymbol{R} = [\boldsymbol{\Lambda}(\delta_1)^t, \ldots, \boldsymbol{\Lambda}(\delta_m)^t]$, extracts the coefficients of interest from $\hat{\boldsymbol{A}}_1$ with $\delta_k \in \{1 \cdot K, 2 \cdot K, \ldots, m \cdot K\}$, $k = 1, \ldots, m$, where the δ_k-th element of the $(1 \times K^2)$-dimensional vector $\boldsymbol{\Lambda}(\delta_k)$ is 1 and zero otherwise. As proven by Ghysels et al. (2016), the OLS estimator $\hat{\boldsymbol{A}}_1$ for the MF-VAR parameter set is consistent and asymptotically normal with

$$\sqrt{T_L} \operatorname{vec}\left[\hat{\boldsymbol{A}}_1 - \boldsymbol{A}_1\right] \xrightarrow{d} N\left(\mathbf{0}_{K^2\times1}, \boldsymbol{\Sigma}\right),$$

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 (τ_L) are stationary and ergodic. Ghysels et al. (2016) derives an almost surely positive semi-definite (for $T_L \geq 0$) and consistent estimator $\hat{\boldsymbol{\Sigma}}$ for the covariance matrix $\boldsymbol{\Sigma}$ based on the HAC estimator of Newey & West (1987).

We calculate the p-values for Granger causality tests at horizon $h = 1$ based on the parametric bootstrap of Gonçalves & Kilian (2004) with $N = 999$ replications according to the procedure as is described in Ghysels et al. (2016).[11]

3. Data

We collect daily settlement prices of 37 front-month commodity futures traded at various exchanges via Bloomberg from January 1998 to December 2019. Motivated from theory and empirical findings of previous studies, we select 21 fundamental, financial, and uncertainty variables, that potentially affect the futures prices of many commodities. While some are readily available at daily frequency, many of the potential drivers we present below are only available on a monthly basis. A bivariate MF-VAR model with lag

[11] Ghysels et al. (2016) recommend to use bootstrapping for smaller sample sizes regarding the number of LF observations in order to avoid size distortions. The wild bootstrap of Gonçalves & Kilian (2004) allows for conditional heteroskedasticity and is implemented in the MFVAR Toolbox for Matlab kindly provided by the authors via Kaiji Motegi's Website (http://www2.kobe-u.ac.jp/~motegi/Matlab_Codes.html).

order one combining one daily and one monthly variable, however, entails more than 400 parameters. To avoid such parameter proliferation, we transform daily futures prices to weekly log-returns, when analyzing effects from monthly-available driver variables.[12] For daily-available driver variables, we use non-aggregated daily commodity returns. Thereby, we split our analysis into HF (daily) and LF (monthly) drivers to discard as few information as possible. This section presents the commodities and drivers we include in our analysis as well as data characteristics at the different sampling frequencies.

3.1. *Commodity futures*

Our data set covers a wide range of agricultural and energy commodities as well as industrial and precious metals. We build our study based on futures for two reasons. First, because they are traded on exchanges, their prices are more transparent than spot prices and may also contain more information due to their higher trading volume. Second, it enables us to test the economic significance of our results in a subsequent trading application. Table 1 presents summary statistics for daily log returns. These daily returns will serve as input for VAR models, that include daily-available driver variables. To check the robustness of our results, we also construct equally-weighted commodity portfolios and extract a common factor in the returns defined as the first principal component of standardized log returns of all 32 commodities, for which data is available over the full time period. Figure 1 depicts how the returns of different types of commodities and the common return factor evolve throughout our sample. The co-movement becomes particularly clear with simultaneous surging prices of raw materials starting from the early 2000s followed by jointly crashing prices during the Global Financial Crisis, which is also captured by the common component and found in extant literature (e.g., Ohashi & Okimoto, 2016; Le Pen & Sévi, 2018). Also in the aftermath of the Global Financial Crisis, a joint overall trend in commodity prices seems evident, however, not as obvious as before, suggesting a looser link among raw materials. Considering the full sample, the

[12]Findings of Ghysels et al. (2016) suggest that a small difference in sampling frequencies is preferable for estimating MF-VARs. Alternatively, Götz et al. (2016) propose techniques involving reduced rank regressions or Bayesian VAR estimation to reduce the number of parameter estimates in MF-VARs with a large difference in sampling frequencies (such as daily-monthly) before running Granger causality tests.

common factor grasps 20% of total commodity return variation, whereas its correlation is highest with Brent (0.73) and lowest to Feeder Cattle (0.04).[13]

Table 1: Sample statistics of commodity futures for daily log returns, 1998–2019

	BBG	Obs.	Mean	Std.Dev.	Skewn.	Ex.Kurt.	ADF	PP	KPSS
Agriculture (Softs)									
Cocoa (ICE)	CC1	5739	0.008	1.889	−0.105	2.277	−19.607***	−5865.937***	0.046
Coffee (ICE)	KC1	5739	−0.004	2.159	0.317	5.122	−19.174***	−5617.734***	0.105
Cotton (ICE)	CT1	5739	0.001	1.809	0.006	4.467	−18.776***	−5420.096***	0.041
Ethanol (CBOT)	DL1	3805	0.004	2.054	−2.440	31.640	−15.655***	−3673.614***	0.112
Lumber (CME)	LB1	5739	0.006	2.129	0.701	7.110	−18.718***	−5229.541***	0.029
Orange Juice (ICE)	JO1	5739	0.003	2.015	0.377	7.420	−19.852***	−5294.786***	0.062
Rubber (SGX)	OR1	5739	0.012	1.514	−0.441	8.437	−16.479***	−5514.569***	0.193
Sugar (ICE)	SB1	5739	0.002	2.127	−0.176	3.676	−17.064***	−5715.294***	0.075
Wool (ASX)	OL1	3913	0.010	1.234	0.001	12.036	−15.366***	−3830.093***	0.088
Portfolio (Softs)		5739	0.004	0.805	−0.163	1.930	−17.015***	−5577.602***	0.134
Agriculture (Grains)									
Corn (CBOT)	C 1	5739	0.007	1.739	−0.518	12.514	−17.235***	−5555.665***	0.064
Oats (CBOT)	O 1	5739	0.012	2.285	−1.375	17.745	−18.947***	−5212.071***	0.031
Rough Rice (CBOT)	RR1	5739	0.004	1.664	0.279	26.747	−18.940***	−5291.330***	0.103
Soybean (CBOT)	S 1	5739	0.006	1.536	−0.798	5.936	−17.517***	−5763.222***	0.071
Soybean Meal (CBOT)	SM1	5739	0.007	1.829	−1.240	12.181	−18.630***	−5659.082***	0.043
Soybean Oil (CBOT)	BO1	5739	0.006	1.427	0.125	2.490	−17.367***	−5761.564***	0.090
Wheat (CBOT)	W 1	5739	0.009	1.910	0.173	1.968	−18.448***	−5646.056***	0.044
Portfolio (Grains)		5739	0.007	1.203	−0.225	3.485	−17.119***	−5876.679***	0.099
Agriculture (Livestock)									
Feeder Cattle (CME)	FC1	5739	0.011	0.948	−0.162	11.089	−18.057***	−5282.721***	0.066
Lean Hogs (CME)	LH1	5739	0.004	2.330	−0.085	31.484	−17.710***	−5659.348***	0.013
Live Cattle (CME)	LC1	5739	0.011	1.122	−1.448	15.812	−19.372***	−5324.792***	0.028
Pork Bellies (CME)	PB1	3392	0.022	2.505	0.582	45.805	−16.294***	−3068.643***	0.019
Portfolio (Livestock)		5739	0.010	1.075	−0.120	8.346	−18.056***	−5791.765***	0.038
Energy									
Brent (ICE)	CO1	5739	0.024	2.172	−0.064	3.153	−16.238***	−6088.074***	0.159
Gasoil (NYMEX)	QS1	5739	0.025	1.979	−0.048	3.571	−16.799***	−5712.272***	0.147
Gasoline (NYMEX)	XB1	3696	0.002	2.362	−0.113	7.175	−13.585***	−3782.710***	0.068
Heating Oil (NYMEX)	HO1	5739	0.025	2.191	−0.495	6.134	−18.010***	−5927.710***	0.130
Natural Gas (NYMEX)	NG1	5739	−0.001	3.299	0.486	5.724	−17.861***	−5951.664***	0.098
WTI (NYMEX)	CL1	5739	0.022	2.348	−0.058	4.372	−17.161***	−5707.125***	0.131
Portfolio (Energy)		5739	0.020	1.830	−0.102	2.382	−16.938***	−5854.340***	0.183
Industrial Metals									
Aluminium (LME)	LA1	5739	0.003	1.344	−0.245	4.329	−18.493***	−5959.280***	0.059
Cobalt (LME)	LCO1	2567	−0.008	1.745	−0.170	11.750	−11.776***	−3297.770***	0.198
Copper (LME)	LP1	5739	0.022	1.581	−0.087	4.747	−16.454***	−6182.985***	0.180
Lead (LME)	LL1	5739	0.021	1.977	−0.164	6.656	−18.580***	−5521.674***	0.100
Nickel (LME)	LN1	5739	0.015	2.412	−0.500	17.147	−17.843***	−5876.506***	0.122
Tin (LME)	LT1	5739	0.020	1.585	−0.004	7.798	−18.317***	−5345.917***	0.133
Zinc (LME)	LX1	5739	0.013	1.988	−0.967	24.234	−18.337***	−6175.011***	0.070
Portfolio (Industrial Metals)		5739	0.015	1.339	−0.370	5.363	−17.455***	−5932.693***	0.158
Precious Metals									
Gold (COMEX)	GC1	5739	0.029	1.068	−0.090	6.841	−18.396***	−5717.254***	0.143
Palladium (NYMEX)	PA1	5739	0.039	2.065	−0.279	5.249	−16.794***	−5266.559***	0.115
Platinum (NYMEX)	PL1	5739	0.017	1.458	−1.393	24.967	−16.927***	−5394.389***	0.275
Silver (COMEX)	SI1	5739	0.019	1.853	−0.853	8.025	−18.312***	−5830.988***	0.107
Portfolio (Precious Metals)		5739	0.026	1.293	−0.602	4.591	−16.971***	−5465.160***	0.074
Common Factor									
PC1 (All Commodities)		5739	0.073	4.860	−0.282	3.734	−16.689***	−5767.638***	0.196

Notes: Summary statistics for single futures are provided for $r_t = 100 \times [\ln(p_t) - \ln(p_{t-1})]$, where $\{p_t\}_{t=1}^{T}$ is the front-month continuous futures series which contains daily settlement prices (in USD). Bloomberg tickers for the continuous series (BBG Comdty, PX_SETTLE) are given in column BBG. 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 (2005:11–2019:12), and Cobalt (2010:3–2019:12). The common factor is constructed as the first principal compoenent (PC) of standardized log returns of all commodities, for which data is available over the full sample period. The Jarque-Bera test rejects the null of normality at the 0.1% level of significance for all return series. 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.

Since our MF methodology for analyzing monthly-available potential drivers requires a fixed number of HF observations per LF observation (i.e., m is constant independent

[13] Factor loadings and correlations to all commodities and portfolios are listed in the Appendix (Table C.12).

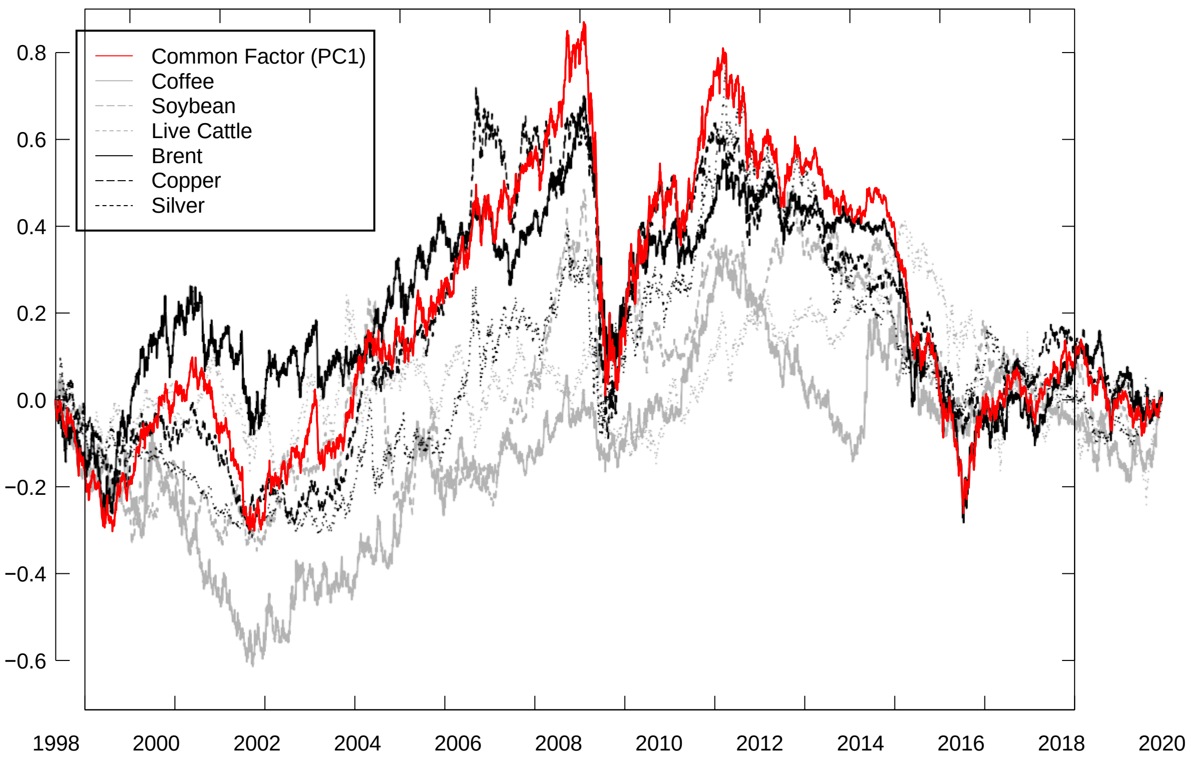

Figure 1: Cumulative standardized log returns of selected commodity futures and a common factor of commodity futures returns. The common factor is calculated as the first principal component of daily futures log returns using soft, grain, livestock, and energy commodities as well as industrial and precious metals.

of the low-frequency period τ_L), we only consider the last 20 trading days of each month for our MF-VAR models. In doing so, we drop at most the first three daily observations of a given month as 20 is the minimum number of trading days per month in our sample. Based on the 20-days-per-month futures price series, we aggregate daily prices to weekly log returns over non-overlapping 5-day intervals through $100 \times [\ln(p_t) - \ln(p_{t-5})]$. We, therefore, end up with four weekly log returns per month, such that $m = 4$.[14]

[14]Summary statistics of weekly returns for commodity futures and equally-weighted portfolios are presented in the appendix (Table C.5). 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. E.g., 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 February is the starting month of the futures series, the first weekly return is calculated from the settlement price of the first to the fifth trading day.

3.2. *Potential return drivers of commodity futures*

Our set of *fundamental* variables primarily encompasses indicators of global real economic activity. Shocks to real activity indicate changes in the aggregate demand for commodities as real physical assets. Recent work by Alquist et al. (2020) and Delle Chiaie et al. (2022) suggests that aggregate economic activity primarily drives spot price fluctuations in the cross-section of commodities. Popular indicators of global economic activity that we include in our study are the Baltic Dry Index (BDI) as published by the London Baltic Exchange, Global Crude Steel production (STEEL) published by the World Steel Association, World Industrial Production (WIP) of Baumeister & Hamilton (2019), and the Global Economic Conditions (GECON) index proposed by Baumeister et al. (2020).[15] While the BDI reflects the costs in dry bulk cargo shipping, the index of WIP measures the industrial output of countries belonging to the OECD or can be classified as major emerging markets. The GECON index aims at capturing the economic conditions globally by combining a variety of indicators related to prospective energy demand. In the recent COVID-19 pandemic, disruptions of the global supply chain had a significant impact on various commodity prices. To cover such supply side effects, we also employ a novel index for Global Supply Chain Pressure (GSCPI) published by the Federal Reserve Bank of New York (Benigno et al., 2022). We furthermore classify the following variables as potential fundamental drivers: the USD Effective Exchange Rate (USDEER) published by the Bank for International Settlements since most commodity futures are traded in USD, the three-month USD Treasury Bill Rate (TBILL) as a proxy for the risk-free rate as part of the cost of carry, the University of Michigan Consumer Sentiment index (CSENT), seasonally adjusted USD inflation (INFL) calculated as year-on-year log-differences in US CPI, and consumers' inflation expectation (INFLE) surveyed by the University of Michigan. While, for instance, Chen et al. (2010) show that exchange rates affect commodity prices, CSENT has been shown to affect long-term

[15] 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 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.

commodity volatility (Nguyen & Walther, 2020). Studies of Pindyck & Rotemberg (1990) and Gorton & Rouwenhorst (2006) show the close link of inflation to spot and futures prices of raw materials.

We expect *Financial* variables to grasp effects from the financialization of commodity futures markets as financial investors adjust their commodity trading positions based on the performance of core financial asset classes such as equities (Cheng & Xiong, 2014). The more financial investors engage in commodity markets, the stronger commodity returns should be therefore influenced by variables representing key financial asset classes (Adams et al., 2020). We use the S&P 500 (SPX) and the Cboe Volatility Index (VIX), that reflects the markets expectations of near-term SPX volatility, to capture the stock market's risk and return. Cheng et al. (2015) find that during the great recession, financial investors reduced their risk exposure in commodity futures markets in response to a soaring VIX. Links between stock markets and commodities have been also documented in numerous other studies.[16] We also include the Investor Sentiment index (ISENT) from Baker & Wurgler (2006) as Gao & Süss (2015) provide evidence that—next to fundamental and equity variables—market sentiment contributes to the co-movement of commodity returns.

Uncertainty can affect commodity futures prices through different channels. Low uncertainty indicates high confidence in the future, which ought to stimulate today's investments, whereas high uncertainty might raise the hedging demand of commercial traders and cause firms to hold back investments.[17] Through encouraging or hampering investments, declining or rising uncertainty can cause changes in the industrial demand for raw materials (Joëts et al., 2017). But uncertainty can also raise precautionary demand, which has been identified as a driver of real crude oil prices found by Alquist & Kilian (2010) and Cross et al. (2022). Results by Joëts et al. (2017) indeed suggest that macroeconomic uncertainty has an impact on commodity prices that are strongly linked to the global business cycle, such as industrial metals, energy and agricultural commodi-

[16] See Byrne et al. (2013); Büyükşahin & Robe (2014); Adams & Glück (2015); Basak & Pavlova (2016); Andreasson et al. (2016); Zhang et al. (2017); Adams et al. (2020); Dinh et al. (2022), among others.
[17] See, for example, Dixit & Pindyck (1994) for a discussion of the effects of uncertainty on firms' investment decisions.

ties. Next to this fundamental channel, other authors, for instance Adams et al. (2020), interpret effects from uncertainty variables on commodity prices in the sense of financialization. They expect uncertainty to foster informational frictions and as Singleton (2014) argues for the case of crude oil markets, informational frictions can incite speculation, leading to futures prices deviating from their fundamental values. Likewise, Cheng & Xiong (2014) identify informational frictions as the reason for surging futures prices of many commodities before they collapsed in mid-2008. As uncertainty indicators cannot be clearly assigned to either the fundamental or financial category, they form our third class of potential drivers.

Irrespective of the channel through which uncertainty may induce commodity prices to fluctuate, results of many studies support that they are related to various types of uncertainty measures (e.g., Bakas & Triantafyllou 2018; Prokopczuk et al. 2019; Adams et al. 2020; Nguyen & Walther 2020). The following measures form our set of uncertainty variables, of which many but not all are employed in related previous work as well. The indices of Macro (MUNC), Financial (FUNC) as well as Real Uncertainty (RUNC) based on the work of Jurado et al. (2015) and Ludvigson et al. (2021) aim to quantify the unpredictability of a wide range of macroeconomic (mostly real activity, price, and financial), financial, and real activity variables, respectively. We also incorporate the daily US Economic Policy Uncertainty (EPU) and the monthly Global Economic Policy Uncertainty (GEPU) indices as proposed by Baker et al. (2016), that employ a keyword-based search in newspaper articles to gauge the magnitude of policy-related economic uncertainty. As Kilian (2008) points out, the prices of energy commodities in particular are exposed to geopolitical events and military conflicts in the Middle East, or as recently observed, in other energy exporting countries like Russia. This is, however, not limited to energy commodities but can affect all raw materials of which a large portion of the world market supply originates from only one or a few exporting countries. To capture such effects, we use the recently proposed indices of Geopolitical Risk (GPR) from Caldara & Iacoviello (2022) and Geopolitical Volatility (GEOVOL) from Engle & Campos-Martins

(2020).[18] While Caldara & Iacoviello (2022) follow a newspaper-based approach, Engle & Campos-Martins (2020) associate geopolitical risk with common volatility shocks to multiple financial time series. As both indices are relatively novel, they are not covered in the literature on commodity drivers yet. Another traditional indicator of uncertainty is given by the TED spread (TED) defined as the difference of the three-month USD LIBOR rate and the three-month USD Treasury Bill rate.

Table 2 provides summary statistics for all variables in each category distinguished by their data availability, which is either daily (HF) or monthly (LF).[19] We use log-differenced data except for ISENT, TBILL, and GSCPI, for which we use differences due to the occurrence of negative values, GECON, which is stationary in levels, as well as INFL and INFL that already express the (expected) year-on-year change in US CPI. As Table 3 demonstrates, the vast majority of fundamental and uncertainty variables is available at monthly frequency. To enable a more concise presentation of results, we summarize information of monthly variables in the same category of drivers with their first principal component (PC).[20] This involves monthly fundamental (WIP, GECON, BDI, STEEL, GSCPI, INFL, INFLE, CSENT), monthly financial (SPX, VIX, ISENT), and monthly uncertainty (FUNC, MUNC, RUNC, TED, GEPU, GPR, GEOVOL) variables.[21] The first PC of fundamental variables explains around 25% of their total variation. It exhibits the highest correlation with the real activity measures GECON, WIP, BDI, and STEEL. The variation in the SPX and VIX mainly contribute to the first financial PC, which captures 53% of total variation. The first PC of uncertainty variables primarily expresses changes in macro uncertainty while grasping around 33% of total variation in the respective variables.[22]

[18]We are grateful to Susana Martins and Brian Reis for providing us with the GEOVOL time series.

[19]Descriptions and data sources of each variable can be found in the appendix (Table A.4).

[20]We also run the same analysis with individual variables and discuss outcomes in the results section.

[21]We aggregate daily data for variables that are similar to the monthly variables of the same category to also include their information in the first PC of the respective group of LF drivers. This pertains to the variables BDI, SPX, VIX, TED, and GEOVOL. Prior to monthly differencing, we temporally aggregate the levels of these variables by their monthly means except for the SPX where we use monthly closing prices as is common for financial price series.

[22]Please refer to Table C.16 and Figure C.6 in the Appendix for a more detailed description of the relation of individual variables to their first PCs.

Since only few measures can be retrieved on a daily basis, we do not employ PCs for HF fundamental and uncertainty variables. The SPX and VIX are, however, highly correlated and yield almost identical results in the Granger causality analysis. As for LF drivers, we will thus present Granger causalities only for the first PC of daily financial variables.

Table 2: Sample statistics of daily (HF) and monthly (LF) driver variables, 1998–2019

	Obs.	Mean	Std.Dev.	Min	Max	Skewn.	Ex.Kurt.	J.B.	ADF	PP	KPSS
Fundamental											
Daily (HF)											
BDI	5739	−0.002	1.949	−12.072	13.658	0.093	5.060	0.000	−14.390***	−1365.332***	0.059
TBILL	5739	−0.001	0.046	−0.810	0.740	−1.026	64.340	0.000	−17.679***	−4140.216***	0.385*
USDEER	5739	0.001	0.321	−2.279	2.020	0.063	3.483	0.000	−17.033***	−5785.464***	0.213
Monthly (LF)											
WIP	264	0.200	0.606	−3.265	1.842	−1.629	7.405	0.000	−5.130***	−264.803***	0.101
GECON	264	−0.046	0.393	−2.203	0.885	−1.997	7.795	0.000	−3.688**	−50.426***	0.097
BDI	264	0.024	19.436	−101.249	70.348	−0.657	3.889	0.000	−8.070***	−162.775***	0.048
STEEL	264	0.319	4.477	−13.723	13.456	0.581	0.904	0.000	−6.543***	−388.256***	0.034
GSCPI	264	0.004	0.318	−1.180	0.900	−0.375	0.988	0.000	−8.543***	−245.771***	0.016
INFL	264	0.021	0.012	−0.020	0.054	−0.328	0.910	0.001	−4.300***	−28.980***	0.590**
INFLE	264	0.029	0.006	0.004	0.052	0.842	4.901	0.000	−3.649**	−47.286***	0.407*
CSENT	264	−0.011	4.925	−19.925	12.762	−0.384	1.194	0.000	−7.534***	−218.613***	0.126
PC1	264	−0.000	1.412	−8.830	3.628	−1.977	9.073	0.000	−4.595***	−123.741***	0.107
Financial											
Daily (HF)											
SPX	5739	0.021	1.170	−9.470	10.957	−0.241	8.490	0.000	−18.176***	−5692.736***	0.156
VIX	5739	−0.010	6.712	−35.059	76.825	0.904	6.697	0.000	−20.292***	−5152.573***	0.007
PC1	5739	0.000	1.319	−10.635	9.142	−0.551	4.566	0.000	−18.918***	−5380.295***	0.061
Monthly (LF)											
SPX	264	0.456	4.330	−18.564	10.231	−0.863	1.706	0.000	−5.842***	−250.216***	0.160
VIX	264	−0.249	16.500	−37.925	71.918	1.198	3.161	0.000	−8.691***	−217.326***	0.022
ISENT	252	−0.004	0.178	−0.751	0.720	−0.395	3.871	0.000	−3.730**	−261.756***	0.040
PC1	264	−0.000	1.262	−2.842	6.198	1.116	2.727	0.000	−7.086***	−214.971***	0.079
Uncertainty											
Daily (HF)											
TED	5737	−0.025	8.199	−71.846	74.194	−0.209	9.813	0.000	−18.542***	−5680.713***	0.046
EPU	5739	0.017	60.209	−314.833	321.562	0.089	1.298	0.000	−27.491***	−6116.752***	0.002
GEOVOL	4748	−0.218	11.224	−113.531	101.026	−0.438	12.450	0.000	−17.792***	−4669.278***	0.007
Monthly (LF)											
FUNC	264	0.082	3.314	−9.143	9.933	0.277	0.445	0.062	−6.069***	−100.028***	0.075
MUNC	264	0.110	2.272	−5.550	8.284	0.487	1.066	0.000	−4.870***	−74.841***	0.069
RUNC	264	0.109	2.140	−5.444	7.775	0.329	0.977	0.000	−5.483***	−118.481***	0.072
TED	264	−0.212	30.849	−82.313	111.493	0.585	1.727	0.000	−6.608***	−234.362***	0.043
GEPU	264	0.402	17.721	−45.853	70.585	0.529	1.143	0.000	−8.116***	−249.979***	0.067
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
PC1	264	0.000	1.499	−6.819	3.593	−0.667	1.744	0.000	−5.428***	−109.754***	0.078

Notes: Summary statistics are provided for 100×log-differenced data except for GECON, INFL, and INFLE (in levels) as well as TBILL, GSCPI, and ISENTI (in differences). The data spans the period of 1998:1–2019:12 except for ISENTI (1998:1–2018:12) and GEOVOL (2000:7–2019:12). The first principal component (PC1) of each subset of drivers is calculated based on those drivers for which data was available over the entire period. 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.

4. Results

We start our analysis by testing for Granger non-causality from potential HF and LF drivers to commodity futures using data for the full sample period. To account for possible time-varying effects, we divide our sample into three subsamples and repeat Granger causality tests. For LF drivers, we encounter significant discrepancies in the results between our MF approach and the traditional LF approach involving the temporal aggregation of commodity returns to the common lower frequency. In the second part of our results section, we compare MF and LF approaches in an out-of-sample VAR-based trading study.

4.1. In-sample Granger causality analysis

We evaluate p-values of pairwise Granger causality tests based on bivariate VAR models. For monthly-available LF drivers, the stacked vector in the MF-VAR model (1) reads: $\boldsymbol{X}(\tau_L) = [x_H(\tau_L, 1), x_H(\tau_L, 2), x_H(\tau_L, 3), x_H(\tau_L, 4), x_L(\tau_L)]$, where the HF variable, $x_H(\tau_L, k_H)$, denotes the log return of a continuous front-month commodity futures contract for week k_H in month τ_L. The LF variable $x(\tau_L)$ represents a fundamental, financial, or uncertainty indicator that we consider ex-ante as a potential common driver of commodity returns. In case of daily-available HF drivers, the MF-VAR from (1) condenses to a standard VAR model. We call this a HF-VAR model as both variables are used at the highest available frequency (daily) and $\boldsymbol{X}(\tau_L) = [x_{H,1}(t), x_{H,2}(t)]$ with $m = 1$.

For the full sample of 1998–2019, Figure 2 depicts rejections of the null of non-causality from potential drivers to commodity futures up to the 10% level, which reads:[23]

- ✓ **HF Granger causality** in case of (daily-available) HF drivers:

$$H_0(h = 1) : \text{Driver } (x_{H,2}) \dashrightarrow_1 \text{Commodity } (x_{H,1}).$$

- ✓ **MF Granger causality** in case of (monthly-available) LF drivers:

$$H_0(h = 1) : \text{Driver } (x_L) \dashrightarrow_1 \text{Commodity } (x_H).$$

Since the forecasting horizon, h, in the HF case (1) is one-day-ahead and one-month-ahead in the MF case (2), we examine return drivers in both a short-term and longer-term perspective. We also include results of Granger causality tests for the six-equally weighted commodity portfolios and the common return factor as robustness checks.[24]

[23]The p-values of MF and HF Granger causality tests over the full sample are provided in the Appendix (Tables C.17, C.21). Next to the results for the first PCs of the drivers, Table C.21 also provides p-values of Granger causality tests for non-aggregated variables.

[24]In total, we present p-values of 430 pairwise Granger causality tests. However, we are not concerned

about accumulation of alpha errors as single significances do not draw our attention. For our key

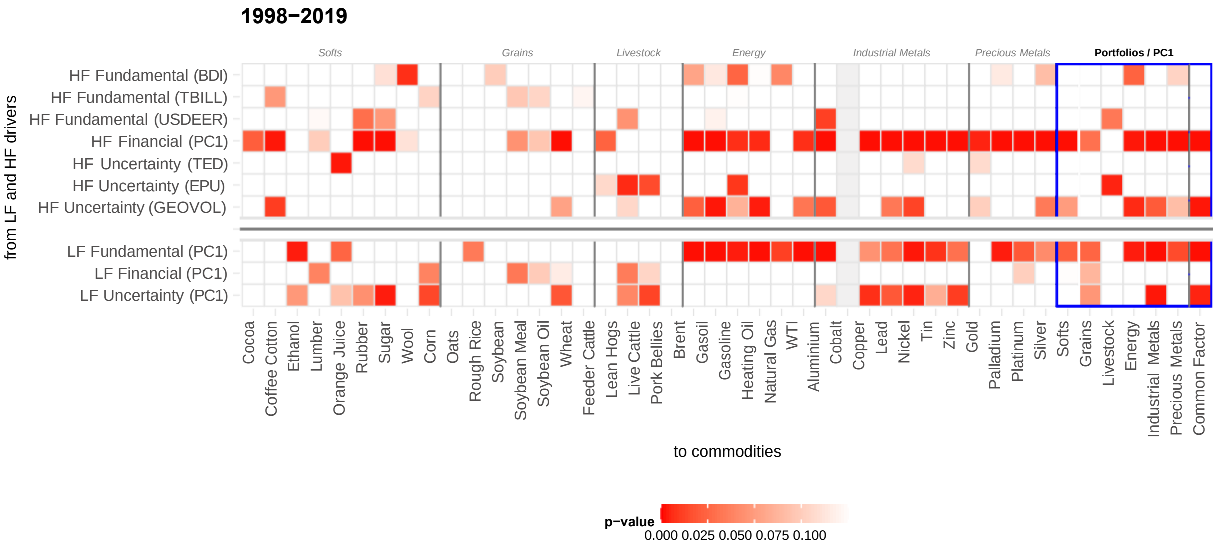

Figure 2: Bootstrapped p-values of pairwise Granger causality tests for the null of non-causality from potential HF and LF drivers to commodity futures at the prediction horizon $h = 1$, which is daily for HF and monthly for LF drivers. Granger causality tests are based on bivariate MF-VAR (HF-VAR) models using weekly (daily) commodity returns, i.e., $m = 4$ ($m = 1$) for monthly (daily) variables. The period covers the full sample from 1998–2019, provided that data of the respective driver-commodity pair is available over this period. Shadings indicate excluded pairs for which data is available for less then half of the period.

At first, we turn our attention to fundamental variables. In line with expectations, monthly measures of global economic activity, which are most represented by the LF fundamental PC1, appear to be "common" drivers of a large subset of commodity futures across different types of commodities. This corresponds to findings of Alquist et al. (2020) and Delle Chiaie et al. (2022) showing that commodity spot prices are commonly driven by aggregate demand shocks related to changes in economic activity. We can observe the most pronounced Granger causalities for energies, industrial metals, and precious metals except gold. This seems not surprising since most of the demand for these commodities stems from industrial usage and their (futures) prices should be, therefore, strongly influenced by changes in economic activity. This also includes the precious metals palladium, platinum, and—despite being classified as an investment good—also silver, which are primarily used as industrial commodities, particularly in the automotive and electrical sectors. Gold, in contrast, is predominantly considered an investment asset and is, thus, less connected to

findings, we solely focus on cases where one indicator Granger-causes at least a considerable subset of commodity futures.

the global business cycle. Agricultural commodities are only partly driven by fundamental variables, whereas we find more Granger causalities by looking at single drivers instead of PCs, particularly from GECON to the majority of grains. Granger causalities from HF fundamental variables to commodity returns are detected much less frequently. While very few Granger-causal relationships originate from T-BILL and USDEER, the latter is Granger-caused by the futures returns of nearly all commodities.[25] The null of non-causality for the BDI—as a HF indicator of real activity—is also rejected less frequently and less strongly compared to its LF counterparts. This could be due to rather noisy daily fluctuations of the BDI compared to corresponding monthly indicators, that seem to better convey the relevant information about real activity for commodity returns.

This finding reverses when we shift our focus to financial variables, which Granger-cause daily returns of the majority of softs, energies, industrial metals, precious metals, and soybean-related grains. On the contrary, we find almost no Granger causalities based on LF financial indicators. The absence of monthly Granger causality suggests that past monthly observations of financial variables do not contain any information new to the weekly commodity return series. Combined with the significant HF Granger causalities, this indicates that commodity futures prices already absorb the information from stock markets on a day-by-day basis. Our results suggest that financial variables are important drivers of daily commodity returns, presumably reflecting the influence of financial markets on commodity futures markets during their financialization. In the next section, we will zoom into different financialization phases to better control these effects.

Results for uncertainty variables depend on the group of commodities and the uncertainty measure. Many agriculturals and industrial metals are Granger-caused by the first PC of monthly uncertainty indicators. Similar patterns can be observed on a daily level from EPU to livestock futures and from GEOVOL to some industrial metals. Moreover, changes in GEOVOL appear to affect returns of energy commodities as well as gold and

[25] Likewise, Andreasson et al. (2016) find linear causation from commodity futures returns to a trade-weighted US-Dollar index. This compares with findings of Chen et al. (2010) regarding exchange rates of other commodity-exporting countries. However, they provide evidence that even though commodity prices Granger-cause exchange rates in-sample, they have only weak out-of-sample forecasting ability.

silver. TED, in contrast, exhibits almost no Granger-causal relations. As we were arguing previously, these findings reflect that changes in uncertainty can affect commodity prices through both a fundamental and a financial channel. GEOVOL links financial market reactions to geopolitical events and, thereby, encompasses both perceptions. From the perspective of financial market uncertainty, an increase in GEOVOL should entail informational frictions and, thereby, inciting the speculative behavior of financial investors in commodity markets. This is likely to affect mainly commodities that are largely held for investment purposes such as gold and silver, or those heavily weighted in popular commodity indices as is the case for energy commodities. Furthermore, based on their status as traditional safe havens (see, e.g., Baur & McDermott 2010; Klein 2017), demand for gold and silver as part of investment portfolios should increase with rising risk aversion of investors during times of higher uncertainty.[26] On the other hand, GEOVOL reflects uncertainty emanating from political and military events. That might, beyond the influence of financial players, explain observed Granger causalities to energy commodities in conjunction with tensions in the Middle East and other energy-exporting countries. Since the PC of LF uncertainty measures primarily expresses monthly changes in macroeconomic uncertainty, detected Granger causalities to softs and especially industrial metals might reflect the longer-term impact uncertainty exerts on commodity prices through a reduction in investment activity. That agricultural, energy, and industrial commodities are partly driven by uncertainty is in line with findings of, i.a., Joëts et al. (2017).

Overall, we find no single driver that affects the entire cross-section of commodity futures employed in this work. Yet, our results indicate that fundamental and financial variables in particular, but also uncertainty have significant effects on the futures returns of many different types of commodities. While monthly fundamentals seem more important than daily indicators, detected Granger causalities indicate that financial variables

[26]These findings also hold for our monthly GEOVOL measure, where we, additionally, observe Granger causality to Platinum, which can also offer safe haven properties (e.g., Klein 2017; Li & Lucey 2017). While we find no effects from our daily US-based measure of EPU to gold returns, policy-related economic uncertainty measured on a monthly and global basis (represented by GEPU) Granger-causes weekly Gold returns, which supports our argumentation regarding the linkage of uncertainty and gold. Economic policy uncertainty has been already identified numerous times as a determinant of gold prices, e.g., in Li & Lucey (2017).

drive commodity returns on a daily basis. Regarding the time horizon of Granger causality, results are not as clear-cut for uncertainty variables reflecting that uncertainty can affect commodity prices through both fundamental and financial motives. These results also hold for the common return factor, that was constructed to capture the co-movement of commodities, and is Granger-caused by HF financial, LF fundamental, and both HF and LF uncertainty variables.[27] However, we find Granger causalities slightly more often and more consistent to energies and metals in contrast to agricultural commodities. The portfolio formed of livestock commodities is the only portfolio that is neither Granger-caused by HF financial nor by LF fundamental variables. In terms of correlations, livestock commodities are also the least related to the common factor suggesting that they do not contribute significantly to the overall co-movement of commodity prices.

Although our results suggest that HF commodity futures prices entail information from daily stock prices, especially monthly indicators of real economic activity appear to contribute further valuable information on the evolution of commodity prices that might be not factored in stock prices. Our findings also hold in multivariate VAR models.

4.2. Time-variation in return drivers

Before the early 2000s, commodities used to exhibit low correlations to each other and to equity markets, which attracted financial investors through potential diversification benefits.[28] A large body of the literature claims that the increased exposure gained by financial investors resulted in the financialization of commodity futures markets and fundamentally changed their behavior (see, e.g., Cheng & Xiong, 2014). As our full sample period comprises different stages of the financialization, we now split our sample into subperiods accounting for the distinct behavior of commodity prices over time and a possible associated time-variation of the linkages to their return drivers.

According to current perceptions in the literature (Büyükşahin & Robe, 2014; Adams & Glück, 2015; Adams et al., 2020), financialization commenced around 2004 with rising open interest and net long positions in commodity futures yielding increased prices and

[27]We obtain robust results for a common factor formed of non-fuel commodities only.
[28]See, e.g., Erb & Harvey 2006; Gorton & Rouwenhorst 2006; Tang & Xiong 2012; Adams & Glück 2015.

volatility, as well as tightened correlations between individual commodities and to equity markets (Basak & Pavlova, 2016). The co-movement among commodities and with other financial asset classes exacerbated with the onset of the Global Financial Crisis in 2008 and remained particularly high over the following years (Büyükşahin & Robe, 2014; Adams & Glück, 2015; Le Pen & Sévi, 2018). However, Adams et al. (2020) argues, that commodity markets have entered a period of de-financialization around 2014 with a 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) and Bianchi et al. (2020). Based on Adams et al. (2020), Figure 3 illustrates the different stages of financialization including pre-financialization (1998–2013), emerging financialization (2004–2007), the core period of financialization beginning with the outburst of the Global Financial Crisis (2008–2013), and de-financialization (2014-2019). We summarize the emerging financialization and the following period involving the Global Financial Crisis to ensure a sufficient number of monthly observations in each subsample. Figure 4 presents p-values of HF and MF Granger causality tests over the financialization subsamples.[29]

The commodity futures market seems rather segmented during pre-financialization as we do not find any variable commonly Granger-causing the majority of futures returns. This observation matches findings of the literature on commodity co-movement, which indicate that the co-movement among different commodities only began to increase in the early years of the century (Ohashi & Okimoto, 2016; Delle Chiaie et al., 2022). HF financial variables mostly affect industrial metals as well as gold and silver. Similar causalities are detected for LF financial variables. Following our arguments from the previous section, this is a sign that HF commodity prices did not reflect all the information

[29]Subsample statistics for commodity futures and potential drivers can be found in the Appendix (Tables C.6–C.11 and C.13–C.15). Note that stationary tests show equivocal results for some drivers, i.e., we cannot unambiguously determine if the variables are stationary over the subsamples. GECON (1998–2003) and INFL (2014–2019) are non-stationary as indicated by all three tests. This might imply that supposedly causal links could be of spurious nature. One way to get around this issue might be provided by using MF Granger causality tests for processes that are possibly cointegrated as introduced by Götz & Hecq (2019). Tables C.18–C.24 provide p-values of MF and HF Granger causality tests over each of the subsamples including results for non-aggregated drivers.

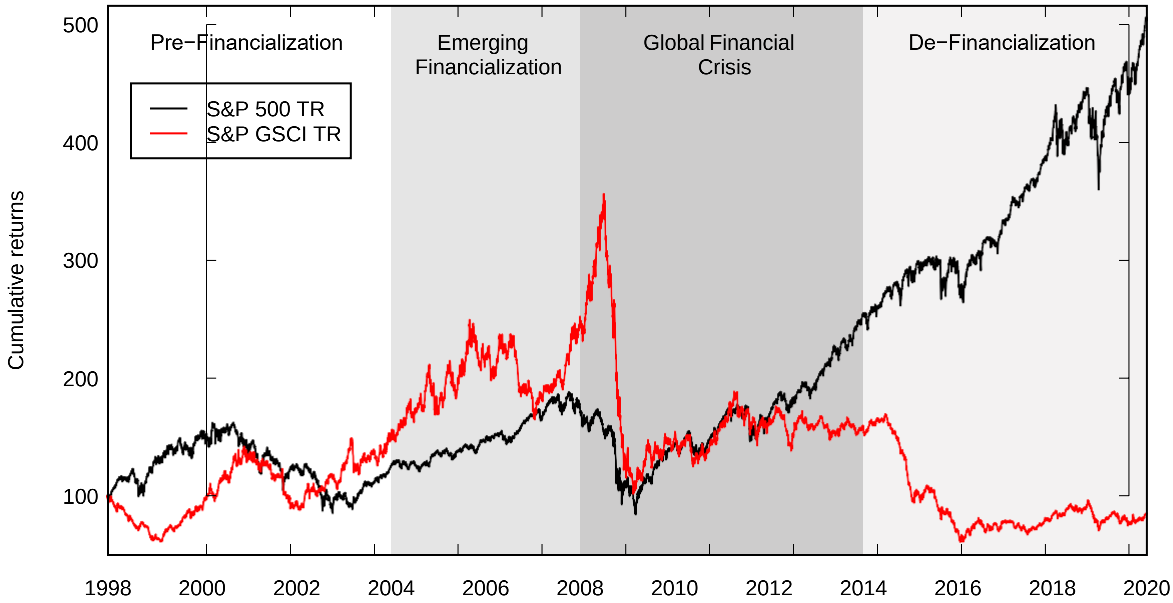

Figure 3: Different stages of the financialization of commodity futures markets illustrated by cumulative returns of the S&P 500 Total Return and the S&P GSCI Total Return indices adapted from Adams et al. (2020). Data is obtained from Refinitiv Datastream.

inherent in daily stock prices, before financial investors increasingly engaged in commodity markets. Most of the energy futures and some industrial metals as well as platinum and silver are driven by changes in real activity as indicated by our LF fundamental PC. For industrial metals, this linkage is also confirmed in the short-run perspective with linear causation from BDI. LF uncertainty measures mainly affect softs and few industrial commodities like tin, zinc, and Brent. Also GEOVOL Granger-causes Brent, gasoil, and heating oil, while other HF uncertainty measures show almost no significant causalities. That energy commodities are affected by uncertainty, especially GEOVOL, might be traced to the 9/11 terrorist attacks in 2001 and the subsequent "War on Terror" with the invasion of Iraq by the U.S. military in 2003.[30]

With increased financial investors' activity during financialization, linkages between stock markets and commodity futures intensified as indicated by strong Granger causalities from HF financial variables to the majority of commodities except for livestock contracts. Consistent with the full sample, we cannot observe most of these Granger

[30]This is supported by Granger causalities from our LF measure of geopolitical risk (GPR) to all energy commodities.The temporally aggregated LF measure of GEOVOL shows, in contrast, no Granger causalities to any of the energy commodities. This is probably due to the limited number of monthly observations of the GEOVOL time series during the first subsample as the series starts in July 2000.

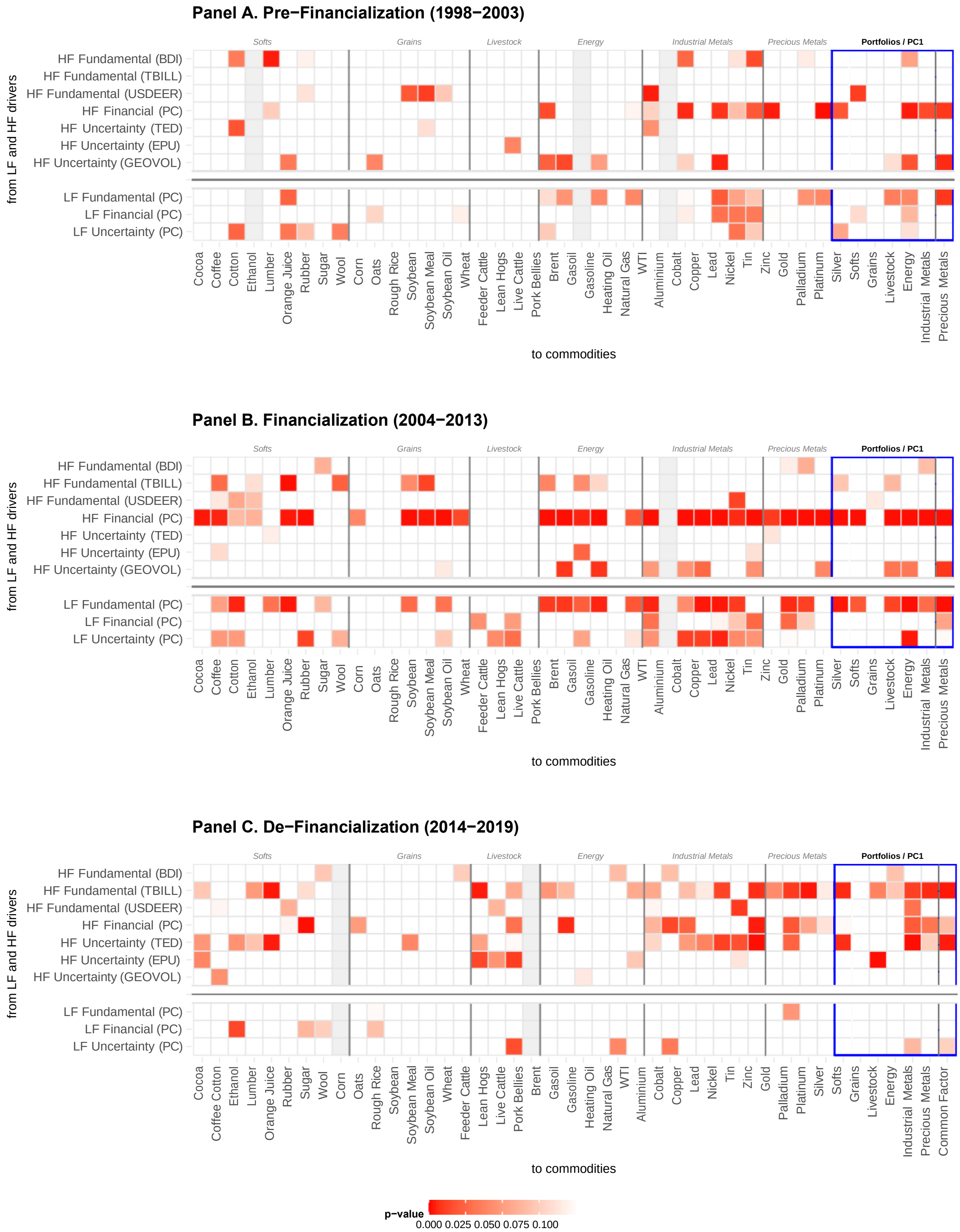

Figure 4: Bootstrapped p-values of pairwise Granger causality tests for the null of non-causality from potential HF and LF drivers to commodity futures at the prediction horizon $h = 1$, which is daily for HF and monthly for LF drivers. Granger causality tests are based on bivariate MF-VAR (HF-VAR) models using weekly (daily) commodity returns, i.e., $m = 4$ ($m = 1$) for monthly (daily) drivers. Shadings indicate excluded pairs for which data is available for less then half of the respective subsample period.

causalities from LF financial variables. Next to HF financial, also LF fundamental variables drive the major part of soft and energy commodities, industrial metals as well as soybeans, soybean oil, palladium, and platinum. This finding corresponds to Bhardwaj et al. (2016) arguing that the business cycle caused increasing commodity correlations since 2004. Likewise, Delle Chiaie et al. (2022) find that changes in global demand during the Global Financial Crisis, covered by this subsample, affected a wide range of commodity spot prices more than usual. As this period does not only entail the Global Financial Crisis but also the ensuing European sovereign debt crisis and severe economic downturns, we detect monthly Granger causalities primarily from macroeconomic uncertainty to industrial metals and some agricultural and energy commodities. Except for agricultural commodities, this finding is corroborated by the uncertainty indicator GEOVOL. Surprisingly, TED and EPU seem to were rather unimportant for daily commodity returns.

Coinciding with the idea that commodity markets entered the de-financialization around 2014, the number of daily Granger causalities from financial variables declined substantially in this period. The bulk of detected links to the HF financial PC now narrows down to industrial metals (aluminium, cobalt, copper, zinc) and precious metals with industrial usage (palladium, platinum, silver). Interestingly, we find that instead TBILL and TED influence daily returns of multiple soft and livestock commodities, industrial and precious metals, as well as Brent, gasoil and WTI over the last subsample. Astonishingly, Granger causalities from the first PCs of LF fundamental and uncertainty variables dissipated almost entirely, suggesting that commodity futures returns are much less sensitive to changes in real activity and macro uncertainty during this recent period. Results for non-aggregated fundamental and financial variables show only few linkages to certain groups of commodities. While GECON and GEPU cause some of the industrial metals, the uncertainty measures FUNC, GEPU, and GEOVOL show Granger causalities to energy commodities.[31] Compared with previous periods, we observe more Granger

[31]INFL Granger-causes the most commodities out of the LF variables during de-financialiaztion including softs, grains, livestock, industrial, and precious metals. We do not pay attention to these findings, however, since all three statistical tests indicate that the INFL series is non-stationary over the last

causalities for monthly SPX returns mainly to softs, industrial, and precious metals.

In summary, we find the following by splitting our sample into financialization subperiods. (1) Relationships between drivers and commodity futures fundamentally change over time and our previous full sample results do not hold in each of the subsamples. (2) We find less and statistically weaker Granger causalities during the periods of pre-financialization and de-financialization compared to the financialization period. (3) Most of the Granger causalities from the LF variables identified during financialization and partly pre-financialization vanished over the course of de-financialization. Our findings also hold for the common factor in commodity returns underpinning the transferability of our results to the drivers of the co-movement of commodity futures prices.

4.3. *Out-of-sample trading backtest*

Our in-sample analysis suggests that monthly-updated indicators of global economic activity and uncertainty can contain useful information for the development of commodity futures prices. Since it is common practice in the majority of published research to temporally aggregate commodity prices to the data frequency of macroeconomic variables, we also tested for Granger causalities based on monthly (LF) commodity returns. For many pairs of commodities and drivers, this would have guided us to other conclusions in the previous two sections, as we find substantial differences in LF and MF Granger causalities in accordance with Ghysels et al. (2016) and Bevilacqua et al. (2019). For instance, the variable MUNC Granger-causes 31 out of 43 commodity return series in the LF setting at a 10% level given data from 1998 to 2019.[32] This compares with only 19 rejections using our MF methodology. Results from the literature on MIDAS indicate that MF approaches generally are not only preferable to uncover true causalities (Ghysels et al., 2016) but also to gain significant forecast improvements.[33] The purpose of this section

period, which can distort empirical findings.

[32]Table C.25 shows the proportion of rejections of the null hypothesis of non-causality relative to the total number of bivariate Granger causality tests per driver.

[33]The majority of published research in the field of MIDAS deals with the forecasting of LF variables using HF information (Andreou et al., 2011) but there is also evidence that LF variables can be used to improve predictions of HF series as indicated by results of Foroni et al. (2018) or the literature on volatility modeling with MIDAS.

is to investigate whether this statistical significance is also accompanied by economic significance. To provide evidence to this question, we implement a VAR-based trading backtest and compare trading profits generated from MF-VAR and LF-VAR models.

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.[34] We compare the trading performance of an MF-VAR that uses weekly GSCI returns together with monthly observations of potential driver variables against a traditional LF-VAR estimated only from monthly data. Besides, we examine how the combination of daily GSCI returns with LF drivers, and thereby even more information at the expense of parameter proliferation, changes the performance of the MF model.[35] We repeat the trading backtest for the three types of VAR models and for different sets of monthly drivers, where variable set S either comprises all variables, only fundamental, only financial, or only uncertainty variables. The implemented trading rules are as follows:

- ✓ On the last day of a given month, we fit bivariate VAR(1) models for each variable of set S to the data of the last 50 months corresponding to a rolling window of 1,000 trading days.
- ✓ We obtain our trading signal by averaging over one-month-ahead GSCI log return forecasts that are generated by the bivariate models.
- ✓ We enter a long position if the average predicted return for the next month is positive and exit an open long position if the average 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 remain unchanged.

Profits are fully reinvested. Transaction costs are not taken into account but should merely play a minor role as trades are at most executed on a monthly basis.[36]

[34]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 allows to calculate returns that are independent of margin requirements.

[35]Sample statistics for the GSCI at the three data frequencies can be found in the Appendix (Table C.26).

[36]Note that for some drivers this strategy uses "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 and might

A popular method for evaluating the directional predictive accuracy of forecasts is given by the success ratio (see, e.g., Degiannakis et al. 2022) stating the proportion of months for which the sign of the return was correctly predicted. The success ratio on its own, however, does not allow to draw conclusions about the profitability of a trading strategy. To test the significance of trading returns, we rely on the excess profitability (EP) test of Anatolyev & Gerko (2005) that 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 r_τ denotes the actual discrete return of month τ_L and $sign(\hat{r}_\tau)$ is -1 if the predicted return averaged over the respective bivariate VAR models for month τ_L, $\hat{r}_\tau$, is negative and $+1$ otherwise.[37] In order to test the null hypothesis of conditional mean independence, i.e., $\mathbb{E}[r_{\tau+1}|\mathcal{I}(\tau)] = \text{const.}$, the authors propose the following Hausman-type test statistic:

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

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, $B_T = \left(T^{-1} \sum_{\tau=1}^{T} \text{sign}(\hat{r}_\tau)\right)\left(T^{-1} \sum_{\tau=1}^{T} r_\tau\right)$, $\widehat{\text{var}}(A_T - B_T) = 4T^{-2} p_{\hat{r}}(1 - p_{\hat{r}}) \sum_\tau (r_\tau - \overline{r})^2$, and $p_{\hat{r}} = 0.5\left(1 + T^{-1} \sum_\tau \text{sign}(\hat{r}_\tau)\right)$. 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 that is tested.

We expect the trading performance to vary over time as relationships between commodities and their drivers also change. If encountered differences in MF and LF Granger causalities are indeed due to spurious (non-)causality provoked by temporal aggregation (Ghysels et al., 2016), a trading strategy that relies on MF-VAR return predictions should outperform the same strategy based on LF-VAR forecasts. The MF-VAR using weekly GSCI returns should, moreover, produce higher (risk-adjusted) returns than the MF-VAR

adjust positions based on updated forecasts as soon as the variable is officially published.

[37] Please refer to Appendix B for a description on how we obtain return forecasts of the HF variable in an MF-VAR.

with daily returns as the latter is expected to suffer from parameter proliferation. Annualized return figures, the success ratio and its significance based on the non-parametric test of directional accuracy suggested in Pesaran & Timmermann (1992)[38], as well as results of the EP test are presented in Table 3.

Table 3: Trading results for VAR-based directional forecasts of the S&P GSCI

	Annualized return			Annualized Sharpe ratio			Success ratio			Mean monthly returns (A_T)		
	$m = 1$	$m = 4$	$m = 20$	$m = 1$	$m = 4$	$m = 20$	$m = 1$	$m = 4$	$m = 20$	$m = 1$	$m = 4$	$m = 20$
All	0.624	8.115	2.939	0.042	0.573	0.187	0.523	0.565**	0.570**	0.122	1.308***	0.526
Fundamental	0.555	8.122	3.299	0.041	0.590	0.213	0.495	0.570**	0.561*	0.076	1.301***	0.578*
Financial	1.359	7.198	3.098	0.088	0.488	0.198	0.495	0.537	0.575**	0.259	1.179***	0.550
Uncertainty	1.988	6.831	1.000	0.137	0.475	0.061	0.537	0.547	0.561*	0.339	1.113***	0.226

Notes: This table presents the results of a trading strategy based on one-month-ahead directional return forecasts of the S&P GSCI index, which is also used as the trading instrument. Monthly return forecasts used as long and short signals are obtained by averaging the monthly return forecasts of the bivariate VAR models of either all LF driver variables, only fundamental, only financial, or only uncertainty-related LF driver variables. Trading positions are opened and exited at the close. 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. Return figures (annualized return and A_T) are stated in percent. Note that A_T is not a return in the conventional sense as it also takes avoided negative and foregone positive returns into account. 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 non-parametric test of directional accuracy for the success ratio (Pesaran & Timmermann, 1992) and the excess profitability test for A_T (Anatolyev & Gerko, 2005) at the 10%*, 5%**, and 1%*** level, respectively.

From Table 3 we can deduce that both annualized returns and annualized Sharpe ratios are consistently and substantially higher for the MF-VAR estimated from weekly GSCI returns (MF-VAR$_{m=4}$) compared to the MF-VAR using daily returns (MF-VAR$_{m=20}$) and the LF-VAR (LF-VAR$_{m=1}$). Averaging return forecasts over bivariate MF-VAR$_4$ models with fundamental drivers yields an annualized return (Sharpe ratio) of 8.12% (0.59) as opposed to merely 0.56% (0.04) for the LF-VAR$_1$, and 3.30% (0.21) for the MF-VAR$_{20}$. In case of the MF-VAR$_4$, fundamental driver variables deliver the highest risk-adjusted performance, closely followed by the backtest that takes return predictions from all variables into account. Relying on uncertainty indicators results in the least risk-adjusted performance, which is, however, still remarkably superior to the benchmark VAR models. According to the EP test, mean returns are both positive and highly significant

[38] For the success ratio $SR = T^{-1}\sum_{\tau=1}^{T} I\{r_\tau \hat{r}_\tau > 0\}$, where $I\{\cdot\}$ is the indicator function that is one if the condition in curly brackets is true and zero otherwise, Pesaran & Timmermann (1992) suggest the following Hausman-type test statistic:

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

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

in case of MF-VAR_4 return predictions across all sets of driver variables. The MF-VAR_{20} yields significant returns at the 10% level merely when the model includes fundamental drivers. The LF-VAR_1 is not able to produce significant returns at all. In contrast, success ratios differ only slightly and are mostly even higher for the MF-VAR_{20} compared to the MF-VAR_4. On average, the MF-VAR_4 model variants achieve 55.49% correct directional return predictions, which is higher than 51.29% for the LF-VAR_1, but also slightly less than 56.66% in case of the MF-VAR_{20}. The far higher and significant 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, but from more accurate directional forecasts of relatively high positive and negative GSCI returns.

The upper panel of Figure 5 depicts the trading performance over time with cumulative returns of the VAR-based strategies for each set of drivers relative to a GSCI buy-and-hold benchmark. Over the full trading period, all VAR models beat the passive buy-and-hold investment, that yields a negative annualized return of -0.54%. However, at the beginning of the trading period, all VAR-models lagged behind the buy-and-hold investment when commodity prices rapidly climbed up during the first years of financialization until the GSCI reached its peak in 2008. While the index crashed with the outburst of the Global Financial Crisis, most VAR models issued sell signals after prices began to shrink and thereby avoided sharper losses. Thereafter, the MF-VAR_4-based strategy strongly outperformed the buy-and-hold strategy and the other VAR-models. The superior trading performance attained by using information from weekly instead of monthly aggregated GSCI returns is not limited to the full sample period as the lower panel of Figure 5 demonstrates by plotting the 12-month rolling excess returns of the MF-VAR_4 over the LF-VAR_1.

Whether the higher trading profits from MF-VAR_4 return forecasts are due to better capturing the nexus of GSCI returns and external return drivers, or due to better accounting for the interdependencies among lagged GSCI returns, depends on the time period. As we know from the Granger causality analysis, dependencies of commodity returns on fundamental, financial, and uncertainty indicators are not constant over time.

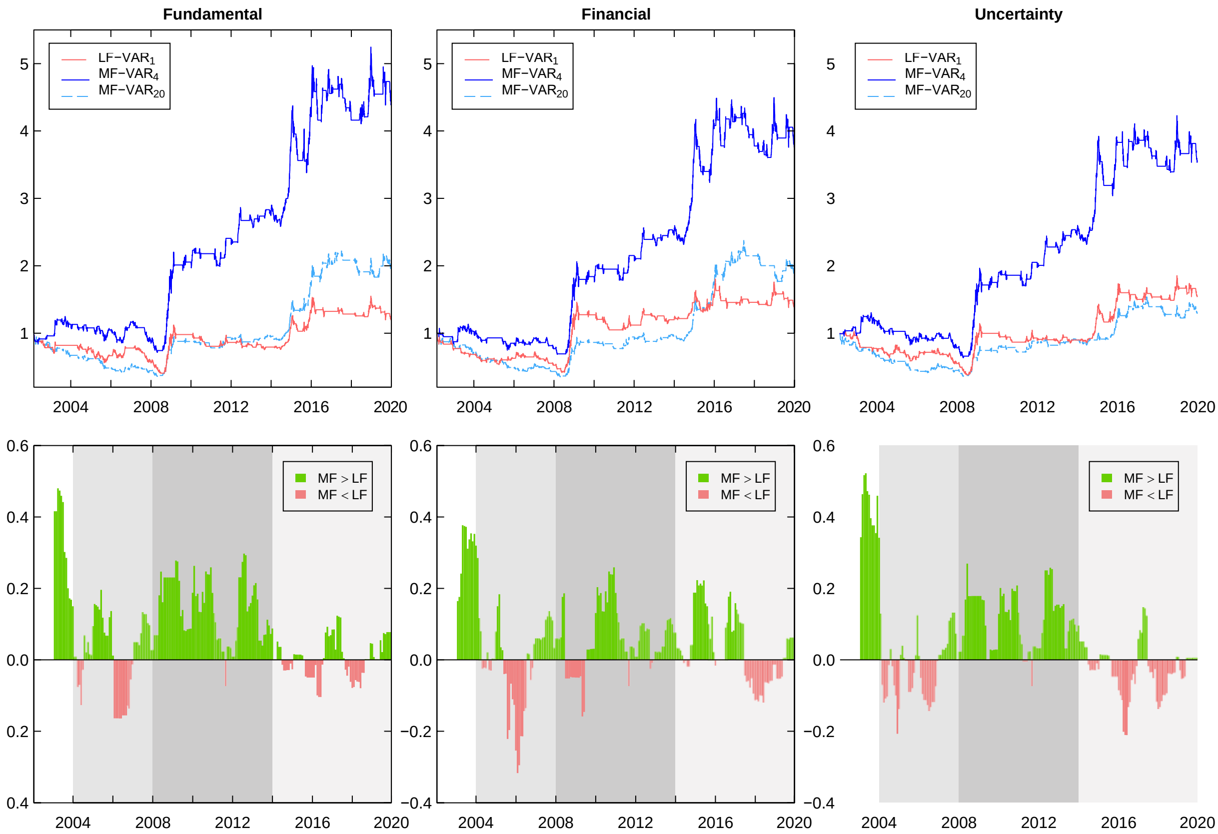

Figure 5: Cumulative returns relative to buy-and-hold (upper panel) and 12-month rolling excess returns of MF-VAR (m = 4) over LF-VAR (m = 1) on a monthly basis (lower panel) for trading the S&P GSCI based on averaged one-month-ahead directional return forecast from bivariate VAR models. Shadings in the lower panel indicate the following periods: Pre-Financialization (1998–2003), Emerging Financialization (2004–2007), Global Financial Crisis (2008–2013), and De-Financialization (2014–2019). The trading period runs from the end of 2002:2 to 2019:12.

Likewise, the drivers' contribution to the trading performance of our model are different across drivers and time. Using forecasts from an MF-VAR4 that is estimated only from GSCI returns without including any driver shows, that periods in which external variables improve returns alternate with periods in which their inclusion has a detrimental or no effect on directional GSCI return predictions.[39]

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 and disregarding HF information in an LF environment or parameter proliferation in an MF model where the frequency mismatch becomes too large. The outcome of the trading study further supports the conclusion on common commodity drivers gained from the

[39]We present relative cumulative returns and 12-month rolling excess returns of the MF-VAR4 strategy over an equivalent MF-VAR that does not encompass the LF drivers in the appendix (Figure C.7).

in-sample analysis. We cannot identify variables that drive the returns across a large cross-section of commodity futures consistently over time.

5. Conclusion

Previous studies on the return drivers of commodities or their co-movement faced either of two difficulties: (1) They needed to aggregate daily to monthly return data to match the frequency of monthly macroeconomic variables, thereby disregarding valuable information; or (2) they could only use daily or weekly drivers and therefore neglected important variables usually available at monthly frequency.

We evade these problems by using a mixed-frequency approach to study the effects of monthly drivers on higher-frequency returns. In particular, we examine potential fundamental, financial, and uncertainty indicators. We find that most commodity futures are driven by real economic activity on a monthly basis and by financial variables on a daily level. The relation, however, does not hold over time. While most of the effects are visible during the period of financialization (2004-2013), we encounter dissipating linkages in the period afterward. In an out-of-sample analysis, we show that using these insights together with mixed-frequency models results in superior trading performance.

Our study adds to the literature on commodity futures by exploring their time-varying relation to a broad range of potential fundamental, financial, and uncertainty-related variables that could cause joint price fluctuations. In addition, we contribute to the literature on MIDAS by presenting the economic benefits of utilizing mixed-frequency models in the commodity futures space.

This study uncovers new research opportunities for commodities and their co-movement. One limitation of our study is that we only use pairwise linear Granger causality tests based on bivariate VAR models. Hence, we might oversee potential non-linearities or causality chains. Also, we did not specifically focus on modeling the co-movement among commodities and its causes. It might be interesting to revisit the findings of related literature using mixed-frequency methodologies as already mentioned by Le Pen & Sévi (2018). Lastly, we expect that the economic repercussions of the COVID-19 pandemic and the

Ukraine war again led to major shifts in the linkages of commodity markets and their drivers, which is certainly worth investigating.

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Appendix A. Variable definitions

Table A.4: Variable definitions

Variable	Definition	Frequency	Data source
BDI	Baltic Dry Index published by the London Baltic Exchange. Reflects costs in dry bulk cargo shipping	Daily	Refinitiv Datastream
CSENT	Consumer sentiment index published by the University of Michigan	Monthly	http://www.sca.isr.umich.edu
EPU	US Economic Policy Uncertainty by Baker et al. (2016). Measures US policy-related economic uncertainty based on US newspaper coverage of articles related to economic policy uncertainty	Daily	https://www.policyuncertainty.com/index.html
FUNC	Financial Uncertainty by Jurado et al. (2015) and Ludvigson et al. (2021). Measures uncertainty based on the predictability of financial series	Monthly	https://www.sydneyludvigson.com/
GECON	Global Economic Conditions by Baumeister et al. (2020) measured based on 16 indicators related to energy demand such as real economic activity, uncertainty, financial indicators, transportation, expectations	Monthly	https://sites.google.com/site/cjsbaumeister/research
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	Daily	Data kindly provided by Susana Martins and Brian Reis (https://vlab.stern.nyu.edu/)
GEPU	Global Economic Policy Uncertainty by Baker et al. (2016) measures as the GDP-weighted average of 21 country-specific EPU indices that measure policy-related economic uncertainty based on national newspaper coverage of articles related to economic policy uncertainty	Monthly	https://www.policyuncertainty.com/index.html
GPR	Geopolitical risk by Caldara & Iacoviello (2022). Measures geopolitical risk based on the number of geopolitical event- or risk-related newspaper articles	Monthly	https://www.matteoiacoviello.com/gpr.htm
GSCPI	Global Supply Chain Pressure Index by the Federal Reserve Bank of New York. Indicates disruptions of global supply chains by combining information from multiple variables associated with supply chains and transportation cost	Monthly	https://libertystreeteconomics.newyorkfed.org
INFL	YoY log difference in US CPI (seasonally adjusted)	Monthly	https://www.bls.gov/
INFLE	12 months inflation expectation of consumers published by the University of Michigan	Monthly	http://www.sca.isr.umich.edu
ISENT	Investor Sentiment index by Baker & Wurgler (2006) that gauges sentiment based on six equity-related components	Monthly	http://people.stern.nyu.edu/jwurgler/
MUNC	Macro Uncertainty by Jurado et al. (2015) and Ludvigson et al. (2021). Measures uncertainty based on the predictability of real activity, price, and financial series	Monthly	https://www.sydneyludvigson.com/
RUNC	Real Uncertainty by Jurado et al. (2015) and Ludvigson et al. (2021). Measures uncertainty based on the predictability of real activity series	Monthly	https://www.sydneyludvigson.com/
SPX	S&P 500 stock market index (closing prices)	Daily	Refinitiv Datastream
STEEL	Volume of global crude steel production published by the World Steel Association	Monthly	Refinitiv Datastream
TBILL	3-month USD Treasury Bill rate	Daily	Refinitiv Datastream
TED	TED spread calculated as the difference of the 3-month USD LIBOR rate and the 3-month USD Treasury Bill rate	Daily	Refinitiv Datastream
USDEER	USD effective exchange rate calculated as the geometric weighted average of 60 bilateral exchange rates	Daily	https://www.bis.org/statistics/
VIX	Cboe Volatility Index that measures implied volatility of S&P 500 options with a maturity of more than 23 but less than 37 days (settlement values)	Daily	Refinitiv Datastream
WIP	World Industrial Production by Baumeister & Hamilton (2019). Measures production output generated by the industrial sector in OECD countries and six emerging markets	Monthly	https://sites.google.com/site/cjsbaumeister/research

Notes: Definitions and data sources for economic variables used as potential drivers of commodity futures returns in our analysis. The stated frequency refers to the original data availability.

Appendix B. Forecasting HF commodity futures returns in an MF-VAR

We obtain monthly return forecasts from an MF-VAR model by forecasting the GSCI log return for each of the m HF periods (days or weeks) during the one-step-ahead LF period (month) and then aggregating HF log return forecasts to the monthly level. We forecast the log return for the i-th HF period of the following month in a bivariate MF-VAR(1) through:

$$\begin{aligned}\hat{x}_H(T_L+1,k_H) \mid \mathcal{I}(T_L) &= E\left[x_H(T_L+1,k_H) \mid \mathcal{I}(T_L)\right] \\ &= \hat{a}_{11}x_H(T_L,1) + \ldots + \hat{a}_{1m}x_H(T_L,m) + \hat{a}_{1(m+1)}x_L(T_L,m),\end{aligned}$$

where $k_H = 1, \ldots, m$, the reference information set

$$\mathcal{I}(T_L) = \{x_H(1,1), \ldots, x_H(T_L,1), \ldots, x_H(1,m), \ldots, x_H(T_L,m), x_L(1), \ldots, x_L(T_L)\}$$

over the window size T_L, and either $m = 20$ in case of daily log returns or $m = 4$ in case of weekly log returns. Then, we predict the log return over the next month by adding the individually forecasted HF log returns:

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

We further aggregate the HF log return predictions of x_H over the bivariate VAR models with the respective group of driver variables through simple averaging, which yields the final return forecast, $\hat{r}_T$, the trading signal is based on.

Appendix C. Additional tables and figures

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

	BBG	Obs.	Mean	Std.Dev.	Skewn.	Ex.Kurt.	ADF	PP	KPSS
Agriculture (Softs)									
Cocoa (ICE)	CC1	1056	0.042	4.543	0.178	1.646	−10.290***	−925.317***	0.061
Coffee (ICE)	KC1	1056	−0.021	4.842	0.327	1.368	−9.244***	−1023.794***	0.131
Cotton (ICE)	CT1	1056	0.003	4.248	−0.378	3.995	−9.564***	−923.139***	0.045
Ethanol (CBOT)	DL1	700	0.017	5.028	−1.460	9.782	−9.443***	−665.940***	0.108
Lumber (CME)	LB1	1056	0.032	4.864	0.080	1.012	−9.910***	−1021.886***	0.034
Orange Juice (ICE)	JO1	1056	0.018	4.952	0.341	2.450	−9.456***	−997.246***	0.082
Rubber (SGX)	OR1	1056	0.065	3.959	−1.143	9.095	−9.055***	−953.870***	0.162
Sugar (ICE)	SB1	1056	0.009	4.788	0.029	1.524	−9.509***	−1081.916***	0.070
Wool (ASX)	OL1	720	0.058	2.966	0.287	2.719	−7.717***	−719.204***	0.086
Portfolio (Softs)		1056	0.020	2.037	−0.363	3.043	−8.436***	−1040.804***	0.118
Agriculture (Grains)									
Corn (CBOT)	C 1	1056	0.037	4.094	−0.220	3.547	−9.368***	−1087.932***	0.063
Oats (CBOT)	O 1	1056	0.063	5.153	−0.140	1.865	−10.918***	−1020.563***	0.041
Rough Rice (CBOT)	RR1	1056	0.020	3.985	0.213	6.579	−9.516***	−902.526***	0.119
Soybean (CBOT)	S 1	1056	0.034	3.624	−0.969	5.938	−9.388***	−1073.929***	0.069
Soybean Meal (CBOT)	SM1	1056	0.039	4.288	−0.806	5.766	−10.094***	−995.482***	0.046
Soybean Oil (CBOT)	BO1	1056	0.031	3.399	−0.120	1.921	−9.021***	−1037.910***	0.087
Wheat (CBOT)	W 1	1056	0.050	4.392	0.276	0.794	−10.620***	−1020.920***	0.051
Portfolio (Grains)		1056	0.039	2.797	−0.239	1.695	−9.305***	−1025.571***	0.094
Agriculture (Livestock)									
Feeder Cattle (CME)	FC1	1056	0.063	2.389	−0.468	4.490	−8.987***	−1194.923***	0.064
Lean Hogs (CME)	LH1	1056	0.020	5.734	−0.299	3.847	−11.019***	−1035.006***	0.014
Live Cattle (CME)	LC1	1056	0.062	2.810	−0.530	2.416	−9.835***	−1104.615***	0.032
Pork Bellies (CME)	PB1	624	0.118	6.605	0.184	8.140	−9.231***	−579.250***	0.024
Portfolio (Livestock)		1056	0.055	2.780	−0.406	1.886	−11.122***	−1032.449***	0.040
Energy									
Brent (ICE)	CO1	1056	0.132	4.968	−0.474	3.105	−9.362***	−1186.024***	0.144
Gasoil (NYMEX)	QS1	1056	0.134	4.701	−0.462	2.150	−9.121***	−1093.413***	0.134
Gasoline (NYMEX)	XB1	684	−0.016	5.652	−0.257	4.486	−7.645***	−792.766***	0.038
Heating Oil (NYMEX)	HO1	1056	0.134	5.052	−0.374	2.612	−9.303***	−1042.040***	0.133
Natural Gas (NYMEX)	NG1	1056	0.002	7.401	0.095	1.124	−10.694***	−1013.340***	0.116
WTI (NYMEX)	CL1	1056	0.119	5.316	−0.220	2.399	−9.283***	−1114.968***	0.129
Portfolio (Energy)		1056	0.108	4.432	−0.283	1.799	−9.082***	−1080.172***	0.174
Industrial Metals									
Aluminium (LME)	LA1	1056	0.014	2.977	0.096	2.210	−9.060***	−1091.361***	0.062
Cobalt (LME)	LCO1	472	−0.055	3.798	−0.341	3.502	−6.588***	−506.552***	0.147
Copper (LME)	LP1	1056	0.120	3.569	−0.814	6.186	−8.546***	−1116.661***	0.148
Lead (LME)	LL1	1056	0.116	4.500	−0.238	2.945	−9.491***	−1012.827***	0.111
Nickel (LME)	LN1	1056	0.080	5.167	−0.276	2.472	−9.439***	−1088.691***	0.117
Tin (LME)	LT1	1056	0.110	3.842	−0.558	4.242	−8.488***	−1092.765***	0.130
Zinc (LME)	LX1	1056	0.070	4.026	−0.430	2.239	−9.020***	−1077.933***	0.074
Portfolio (Industrial Metals)		1056	0.083	2.961	−0.569	3.582	−8.695***	−1053.068***	0.147
Precious Metals									
Gold (COMEX)	GC1	1056	0.157	2.440	−0.179	2.716	−10.167***	−924.486***	0.178
Palladium (NYMEX)	PA1	1056	0.212	5.020	−0.111	3.187	−9.927***	−1041.536***	0.109
Platinum (NYMEX)	PL1	1056	0.092	3.242	−0.584	3.005	−8.912***	−1001.061***	0.264
Silver (COMEX)	SI1	1056	0.104	4.252	−0.749	5.308	−10.479***	−938.532***	0.121
Portfolio (Precious Metals)		1056	0.141	2.979	−0.692	3.149	−9.591***	−1002.686***	0.072
Common Factor									
PC1 (All Commodities)		1056	0.401	11.836	−0.664	4.265	−8.048***	−1088.730***	0.176

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. Bloomberg tickers for the continuous series BBG Comdty (PX_SETTLE) are given in column BBG. Portfolio log returns are calculated as $n^{-1}\sum_{i=1}^{n} r_{i,t}$, where $i = 1, ..., n$ 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). The common factor is constructed as the first principal compoenent (PC) of standardized log returns of all commodities, for which data is available over the full sample period. The Jarque-Bera test rejects the null of normality at the 0.1% level of significance for all return series. 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 C.6: Sample statistics of commodity futures for daily log returns, 1998–2003

	BBG	Obs.	Mean	Std.Dev.	Skewn.	Ex.Kurt.	ADF	PP	KPSS
Agriculture (Softs)									
Cocoa (ICE)	CC1	1565	−0.005	2.091	0.016	2.027	−10.898***	−1679.248***	0.225
Coffee (ICE)	KC1	1565	−0.059	2.603	0.494	6.662	−13.197***	−1451.230***	0.143
Cotton (ICE)	CT1	1565	0.007	1.811	0.725	5.067	−11.743***	−1544.760***	0.269
Ethanol (CBOT)	DL1	−	−	−	−	−	−		
Lumber (CME)	LB1	1565	0.006	2.140	0.484	5.066	−11.035***	−1480.534***	0.047
Orange Juice (ICE)	JO1	1565	−0.018	1.863	1.663	23.380	−12.148***	−1530.514***	0.139
Rubber (SGX)	OR1	1565	0.034	1.315	−0.099	5.152	−10.385***	−1335.883***	0.385*
Sugar (ICE)	SB1	1565	−0.049	2.284	−0.408	4.099	−11.447***	−1592.705***	0.120
Wool (ASX)	OL1	1565	0.007	1.445	0.227	10.051	−11.066***	−1635.197***	0.215
Portfolio (Softs)		1565	−0.009	0.777	0.129	1.170	−11.508***	−1474.443***	0.392*
Agriculture (Grains)									
Corn (CBOT)	C 1	1565	−0.005	1.409	0.458	3.183	−11.574***	−1431.816***	0.103
Oats (CBOT)	O 1	1565	−0.002	2.494	−3.133	35.285	−13.491***	−1454.636***	0.089
Rough Rice (CBOT)	RR1	1565	−0.015	1.961	1.871	32.484	−11.826***	−1420.601***	0.509**
Soybean (CBOT)	S 1	1565	0.010	1.308	−0.232	3.179	−10.804***	−1605.325***	0.507**
Soybean Meal (CBOT)	SM1	1565	0.011	1.615	−0.771	9.903	−11.724***	−1465.768***	0.268
Soybean Oil (CBOT)	BO1	1565	0.007	1.337	0.282	1.599	−10.001***	−1391.926***	0.532**
Wheat (CBOT)	W 1	1565	0.009	1.593	0.275	1.513	−11.502***	−1495.470***	0.137
Portfolio (Grains)		1565	0.002	1.069	0.041	2.595	−12.191***	−1458.207***	0.546**
Agriculture (Livestock)									
Feeder Cattle (CME)	FC1	1565	0.003	0.794	−0.976	16.642	−10.674***	−1474.138***	0.093
Lean Hogs (CME)	LH1	1565	−0.005	2.663	0.687	31.750	−11.796***	−1512.976***	0.033
Live Cattle (CME)	LC1	1565	0.010	1.107	−1.204	12.836	−11.580***	−1468.708***	0.032
Pork Bellies (CME)	PB1	1565	0.035	2.673	−1.260	13.213	−11.788***	−1423.639***	0.028
Portfolio (Livestock)		1565	0.011	1.212	−0.154	4.326	−11.401***	−1521.712***	0.045
Energy									
Brent (ICE)	CO1	1565	0.038	2.376	−0.218	2.465	−11.607***	−1582.456***	0.064
Gasoil (NYMEX)	QS1	1565	0.038	2.276	−0.424	3.815	−11.659***	−1479.900***	0.068
Gasoline (NYMEX)	XB1	−	−	−	−	−	−		
Heating Oil (NYMEX)	HO1	1565	0.040	2.602	−0.910	6.673	−12.866***	−1578.027***	0.059
Natural Gas (NYMEX)	NG1	1565	0.064	3.790	0.303	5.647	−11.535***	−1612.975***	0.052
WTI (NYMEX)	CL1	1565	0.039	2.528	−0.383	3.792	−13.052***	−1455.339***	0.051
Portfolio (Energy)		1565	0.044	2.034	−0.335	2.272	−11.954***	−1522.414***	0.076
Industrial Metals									
Aluminium (LME)	LA1	1565	0.002	0.994	0.231	2.087	−11.251***	−1459.832***	0.115
Cobalt (LME)	LCO1	−	−	−	−	−	−		
Copper (LME)	LP1	1565	0.018	1.123	0.096	2.005	−11.318***	−1519.630***	0.237
Lead (LME)	LL1	1565	0.017	1.318	−0.022	3.616	−12.332***	−1448.465***	0.423*
Nickel (LME)	LN1	1565	0.065	1.984	−0.561	9.251	−11.355***	−1503.573***	0.362*
Tin (LME)	LT1	1565	0.012	1.004	−0.250	5.604	−10.189***	−1367.165***	0.452*
Zinc (LME)	LX1	1565	−0.005	1.158	0.033	3.080	−11.775***	−1631.911***	0.165
Portfolio (Industrial Metals)		1565	0.018	0.903	−0.109	2.284	−11.115***	−1504.401***	0.489**
Precious Metals									
Gold (COMEX)	GC1	1565	0.023	0.932	1.175	10.548	−12.079***	−1609.489***	0.230
Palladium (NYMEX)	PA1	1565	−0.002	2.357	0.170	6.437	−11.464***	−1338.201***	0.595**
Platinum (NYMEX)	PL1	1565	0.050	1.590	−2.996	58.532	−13.202***	−1373.143***	0.091
Silver (COMEX)	SI1	1565	−0.000	1.324	0.059	3.165	−12.450***	−1649.340***	0.182
Portfolio (Precious Metals)		1565	0.018	1.056	−0.061	3.947	−10.998***	−1376.278***	0.105
Common Factor									
PC1 (All Commodities)		5739	0.073	4.860	−0.282	3.734	−16.689***	−5767.638***	0.196

Notes: Summary statistics for single futures are provided for $r_t = 100 \times [\ln(p_t) - \ln(p_{t-1})]$, where $\{p_t\}_{t=1}^{T}$ is the front month continuous futures series which contains daily settlement prices (in USD). Bloomberg tickers for the continuous series BBG Comdty (PX_SETTLE) are given in column BBG. 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 except for Pc1 (1998:1–2019:12). The common factor is constructed as the first principal compoenent (PC) of standardized log returns of all commodities, for which data is available over the full sample period. The Jarque-Bera test rejects the null of normality at the 0.1% level of significance for all return series. 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 C.7: Sample statistics of commodity futures for daily log returns, 2004–2013

	BBG	Obs.	Mean	Std.Dev.	Skewn.	Ex.Kurt.	ADF	PP	KPSS
Agriculture (Softs)									
Cocoa (ICE)	CC1	2609	0.022	1.919	−0.231	2.511	−14.947***	−2549.365***	0.041
Coffee (ICE)	KC1	2609	0.020	1.928	0.049	2.254	−13.363***	−2723.683***	0.267
Cotton (ICE)	CT1	2609	0.005	2.026	−0.235	3.437	−13.975***	−2374.629***	0.100
Ethanol (CBOT)	DL1	2240	0.021	2.186	−2.495	32.353	−12.684***	−2328.956***	0.132
Lumber (CME)	LB1	2609	0.005	2.246	1.107	8.602	−13.281***	−2321.366***	0.088
Orange Juice (ICE)	JO1	2609	0.031	2.162	−0.049	4.002	−14.711***	−2369.012***	0.130
Rubber (SGX)	OR1	2609	0.023	1.616	−0.763	10.940	−11.746***	−2586.459***	0.187
Sugar (ICE)	SB1	2609	0.041	2.204	−0.249	3.301	−13.313***	−2567.511***	0.207
Wool (ASX)	OL1	2348	0.013	1.070	−0.365	12.369	−13.584***	−2200.645***	0.103
Portfolio (Softs)		2609	0.020	0.861	−0.333	2.553	−12.652***	−2538.068***	0.190
Agriculture (Grains)									
Corn (CBOT)	C 1	2609	0.021	2.077	−0.765	12.396	−13.924***	−2550.230***	0.126
Oats (CBOT)	O 1	2609	0.034	2.210	−0.406	5.047	−14.658***	−2378.241***	0.037
Rough Rice (CBOT)	RR1	2609	0.023	1.653	−1.224	20.223	−13.333***	−2388.159***	0.052
Soybean (CBOT)	S 1	2609	0.020	1.789	−0.872	4.945	−13.392***	−2524.597***	0.066
Soybean Meal (CBOT)	SM1	2609	0.023	2.041	−1.203	8.925	−13.687***	−2512.570***	0.055
Soybean Oil (CBOT)	BO1	2609	0.013	1.611	0.023	2.465	−13.250***	−2725.892***	0.120
Wheat (CBOT)	W 1	2609	0.018	2.176	0.114	1.835	−13.748***	−2637.253***	0.074
Portfolio (Grains)		2609	0.022	1.405	−0.329	2.985	−13.309***	−2715.620***	0.089
Agriculture (Livestock)									
Feeder Cattle (CME)	FC1	2609	0.029	0.915	0.524	13.466	−13.703***	−2520.739***	0.094
Lean Hogs (CME)	LH1	2609	0.018	1.927	−0.179	32.698	−14.088***	−2549.285***	0.024
Live Cattle (CME)	LC1	2609	0.021	1.034	−0.607	7.749	−16.346***	−2537.570***	0.041
Pork Bellies (CME)	PB1	1827	0.011	2.352	2.887	90.541	−12.277***	−1634.296***	0.027
Portfolio (Livestock)		2609	0.021	0.943	0.383	14.421	−13.989***	−2567.265***	0.047
Energy									
Brent (ICE)	CO1	2609	0.050	2.082	−0.107	3.484	−12.585***	−2770.995***	0.127
Gasoil (NYMEX)	QS1	2609	0.048	1.901	0.083	2.221	−12.759***	−2664.924***	0.133
Gasoline (NYMEX)	XB1	2131	0.027	2.374	−0.169	4.028	−11.499***	−2094.039***	0.048
Heating Oil (NYMEX)	HO1	2609	0.047	2.069	0.031	2.096	−14.039***	−2660.041***	0.102
Natural Gas (NYMEX)	NG1	2609	−0.015	3.233	0.854	5.439	−12.654***	−2766.357***	0.047
WTI (NYMEX)	CL1	2609	0.042	2.307	0.093	5.210	−13.456***	−2621.532***	0.101
Portfolio (Energy)		2609	0.036	1.800	−0.014	2.046	−12.603***	−2640.011***	0.117
Industrial Metals									
Aluminium (LME)	LA1	2609	0.004	1.618	−0.375	3.408	−13.277***	−2788.177***	0.163
Cobalt (LME)	LCO1	1002	−0.032	1.763	0.380	3.661	−9.814***	−1115.077***	0.067
Copper (LME)	LP1	2609	0.044	1.991	−0.139	3.200	−11.835***	−2800.152***	0.248
Lead (LME)	LL1	2609	0.042	2.508	−0.200	4.569	−14.023***	−2545.718***	0.108
Nickel (LME)	LN1	2609	−0.007	2.912	−0.491	15.843	−13.247***	−2745.131***	0.105
Tin (LME)	LT1	2609	0.047	2.033	−0.004	5.083	−13.958***	−2443.199***	0.087
Zinc (LME)	LX1	2609	0.027	2.567	−1.018	18.091	−13.791***	−2840.128***	0.194
Portfolio (Industrial Metals)		2609	0.025	1.729	−0.372	3.218	−13.265***	−2680.339***	0.208
Precious Metals									
Gold (COMEX)	GC1	2609	0.041	1.263	−0.458	5.104	−14.154***	−2521.314***	0.234
Palladium (NYMEX)	PA1	2609	0.049	2.114	−0.573	3.687	−13.981***	−2367.249***	0.058
Platinum (NYMEX)	PL1	2609	0.020	1.506	−0.674	4.238	−13.068***	−2433.822***	0.118
Silver (COMEX)	SI1	2609	0.045	2.312	−0.963	6.113	−13.900***	−2594.335***	0.158
Portfolio (Precious Metals)		2609	0.039	1.552	−0.729	3.700	−13.860***	−2455.169***	0.131
Common Factor									
PC1 (All Commodities)		5739	0.073	4.860	−0.282	3.734	−16.689***	−5767.638***	0.196

Notes. Summary statistics for single futures are provided for $r_t = 100 \times [\ln(p_t) - \ln(p_{t-1})]$, where $\{p_t\}_{t=1}^{T}$ is the front month continuous futures series which contains daily settlement prices (in USD). Bloomberg tickers for the continuous series BBG Comdty (PX_SETTLE) are given in column BBG. 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 2004:1–2013:12 except for Ethanol (2005:6–2013:12), Wool (2004:1–2012:12), Pork Bellies (2004:1–2010:12), Gasoline (2005:11–2013:12), Cobalt (2010:3–2013:12), and Pc1 (1998:1–2019:12). The common factor is constructed as the first principal compoenent (PC) of standardized log returns of all commodities, for which data is available over the full sample period. The Jarque-Bera test rejects the null of normality at the 0.1% level of significance for all return series. 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 C.8: Sample statistics of commodity futures for daily log returns, 2014–2019

	BBG	Obs.	Mean	Std.Dev.	Skewn.	Ex.Kurt.	ADF	PP	KPSS
Agriculture (Softs)									
Cocoa (ICE)	CC1	1565	−0.004	1.605	−0.007	0.910	−11.594***	−1638.126***	0.067
Coffee (ICE)	KC1	1565	0.010	2.030	0.346	1.970	−11.819***	−1679.712***	0.096
Cotton (ICE)	CT1	1565	−0.013	1.371	−0.389	4.252	−11.939***	−1555.754***	0.089
Ethanol (CBOT)	DL1	1565	−0.021	1.848	−2.250	26.496	−11.514***	−1275.703***	0.026
Lumber (CME)	LB1	1565	0.008	1.906	−0.120	4.614	−11.470***	−1407.993***	0.077
Orange Juice (ICE)	JO1	1565	−0.022	1.904	0.180	1.435	−11.646***	−1430.713***	0.114
Rubber (SGX)	OR1	1565	−0.028	1.522	0.004	3.977	−11.069***	−1390.369***	0.182
Sugar (ICE)	SB1	1565	−0.013	1.810	0.515	2.603	−11.820***	−1503.006***	0.056
Wool (ASX)	OL1	–	–	–	–	–	–	–	–
Portfolio (Softs)		1565	−0.010	0.735	−0.083	0.536	−10.576***	−1467.252***	0.075
Agriculture (Grains)									
Corn (CBOT)	C 1	1565	−0.005	1.385	−0.005	2.322	−10.196***	−1533.858***	0.043
Oats (CBOT)	O 1	1565	−0.012	2.189	−0.403	8.848	−12.397***	−1447.152***	0.112
Rough Rice (CBOT)	RR1	1565	−0.011	1.324	−0.070	4.894	−12.590***	−1508.702***	0.194
Soybean (CBOT)	S 1	1565	−0.021	1.265	−0.922	8.210	−10.700***	−1614.959***	0.112
Soybean Meal (CBOT)	SM1	1565	−0.024	1.649	−1.711	22.827	−10.881***	−1647.057***	0.055
Soybean Oil (CBOT)	BO1	1565	−0.008	1.164	0.291	1.083	−12.553***	−1578.197***	0.124
Wheat (CBOT)	W 1	1565	−0.005	1.718	0.248	0.765	−11.432***	−1469.930***	0.096
Portfolio (Grains)		1565	−0.012	0.937	−0.054	1.935	−10.908***	−1607.165***	0.212
Agriculture (Livestock)									
Feeder Cattle (CME)	FC1	1565	−0.009	1.128	−0.463	6.055	−11.885***	−1427.228***	0.125
Lean Hogs (CME)	LH1	1565	−0.011	2.576	−0.852	23.393	−10.768***	−1568.615***	0.038
Live Cattle (CME)	LC1	1565	−0.005	1.270	−2.308	21.977	−13.074***	−1435.459***	0.059
Pork Bellies (CME)	PB1	–	–	–	–	–	–	–	–
Portfolio (Livestock)		1565	−0.008	1.136	−0.538	7.103	−11.845***	−1641.946***	0.072
Energy									
Brent (ICE)	CO1	1565	−0.033	2.104	0.226	3.418	−11.520***	−1716.323***	0.296
Gasoil (NYMEX)	QS1	1565	−0.028	1.777	0.456	4.421	−11.400***	−1566.392***	0.320
Gasoline (NYMEX)	XB1	1565	−0.032	2.345	−0.036	11.688	−11.559***	−1688.074***	0.127
Heating Oil (NYMEX)	HO1	1565	−0.027	1.923	−0.525	9.683	−12.333***	−1767.090***	0.294
Natural Gas (NYMEX)	NG1	1565	−0.042	2.854	−0.070	4.106	−11.716***	−1602.300***	0.046
WTI (NYMEX)	CL1	1565	−0.031	2.227	0.128	3.413	−11.624***	−1720.939***	0.240
Portfolio (Energy)		1565	−0.032	1.657	0.113	2.753	−11.561***	−1681.488***	0.276
Industrial Metals									
Aluminium (LME)	LA1	1565	0.001	1.129	0.160	2.921	−12.897***	−1663.492***	0.064
Cobalt (LME)	LCO1	1565	0.007	1.734	−0.539	17.317	−9.315***	−2114.121***	0.429*
Copper (LME)	LP1	1565	−0.011	1.143	0.092	1.518	−10.764***	−1705.813***	0.192
Lead (LME)	LL1	1565	−0.009	1.451	0.068	1.911	−11.640***	−1483.653***	0.065
Nickel (LME)	LN1	1565	0.001	1.806	−0.115	1.811	−11.106***	−1534.859***	0.141
Tin (LME)	LT1	1565	−0.017	1.147	−0.088	3.439	−11.355***	−1497.921***	0.121
Zinc (LME)	LX1	1565	0.007	1.472	0.136	2.092	−11.058***	−1607.383***	0.136
Portfolio (Industrial Metals)		1565	−0.003	0.881	−0.110	1.299	−10.770***	−1750.492***	0.214
Precious Metals									
Gold (COMEX)	GC1	1565	0.015	0.811	0.251	2.811	−11.761***	−1719.053***	0.095
Palladium (NYMEX)	PA1	1565	0.062	1.626	−0.456	2.429	−11.425***	−1625.503***	0.313
Platinum (NYMEX)	PL1	1565	−0.022	1.217	−0.034	1.322	−11.864***	−1686.665***	0.129
Silver (COMEX)	SI1	1565	−0.005	1.390	−0.250	3.995	−12.217***	−1697.782***	0.073
Portfolio (Precious Metals)		1565	0.013	1.001	−0.245	1.636	−11.648***	−1666.707***	0.222
Common Factor									
PC1 (All Commodities)		5739	0.073	4.860	−0.282	3.734	−16.689***	−5767.638***	0.196

Notes. Summary statistics for single futures are provided for $r_t = 100 \times [\ln(p_t) - \ln(p_{t-1})]$, where $\{p_t\}_{t=1}^{T}$ is the front month continuous futures series which contains daily settlement prices (in USD). Bloomberg tickers for the continuous series BBG Comdty (PX_SETTLE) are given in column BBG. Portfolio log returns are calculated as $n^{-1} \sum_{i=1}^{n} r_{i,t}$, where $i = 1, \dots, n$ 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 except for Pc1 (1998:1–2019:12). The common factor is constructed as the first principal compoenent (PC) of standardized log returns of all commodities, for which data is available over the full sample period. The Jarque-Bera test rejects the null of normality at the 0.1% level of significance for all return series. 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 C.9: Sample statistics of commodity futures for weekly (5-day) log returns, 1998–2003

	BBG	Obs.	Mean	Std.Dev.	Skewn.	Ex.Kurt.	ADF	PP	KPSS
Agriculture (Softs)									
Cocoa (ICE)	CC1	288	−0.025	5.105	0.659	2.385	−6.855***	−257.401***	0.244
Coffee (ICE)	KC1	288	−0.318	5.832	0.407	1.505	−7.529***	−328.769***	0.197
Cotton (ICE)	CT1	288	0.039	4.100	0.393	0.834	−7.375***	−263.838***	0.275
Ethanol (CBOT)	DL1	–	–	–	–	–	–		
Lumber (CME)	LB1	288	0.027	4.976	0.100	−0.005	−6.683***	−271.635***	0.051
Orange Juice (ICE)	JO1	288	−0.096	4.267	0.800	4.479	−7.876***	−292.683***	0.189
Rubber (SGX)	OR1	288	0.185	3.553	0.316	1.146	−6.560***	−211.511***	0.317
Sugar (ICE)	SB1	288	−0.267	4.938	0.115	0.342	−5.399***	−249.190***	0.124
Wool (ASX)	OL1	288	0.039	3.378	0.406	1.888	−5.635***	−261.655***	0.214
Portfolio (Softs)		288	−0.052	1.940	0.251	0.661	−7.247***	−292.328***	0.404*
Agriculture (Grains)									
Corn (CBOT)	C 1	288	−0.023	3.505	0.346	3.288	−6.435***	−285.508***	0.110
Oats (CBOT)	O 1	288	−0.009	5.014	−0.612	2.787	−6.809***	−293.399***	0.132
Rough Rice (CBOT)	RR1	288	−0.076	4.608	1.380	10.065	−7.047***	−273.884***	0.580**
Soybean (CBOT)	S 1	288	0.062	3.067	0.332	1.445	−6.543***	−315.189***	0.430*
Soybean Meal (CBOT)	SM1	288	0.067	3.849	0.277	2.983	−6.824***	−319.332***	0.276
Soybean Oil (CBOT)	BO1	288	0.040	3.303	0.523	1.344	−7.426***	−325.205***	0.429*
Wheat (CBOT)	W 1	288	0.045	3.893	0.584	0.928	−7.731***	−303.609***	0.170
Portfolio (Grains)		288	0.015	2.458	0.576	1.318	−6.874***	−313.120***	0.592**
Agriculture (Livestock)									
Feeder Cattle (CME)	FC1	288	0.018	2.120	−1.692	14.998	−3.376*	−351.377***	0.082
Lean Hogs (CME)	LH1	288	−0.026	6.688	−0.225	3.354	−7.055***	−312.857***	0.033
Live Cattle (CME)	LC1	288	0.060	2.898	−0.513	3.747	−4.262***	−313.889***	0.031
Pork Bellies (CME)	PB1	288	0.183	6.574	−0.788	5.405	−7.584***	−292.296***	0.030
Portfolio (Livestock)		288	0.059	3.087	−0.469	1.390	−6.781***	−321.591***	0.042
Energy									
Brent (ICE)	CO1	288	0.211	5.283	−0.352	0.957	−7.306***	−301.422***	0.062
Gasoil (NYMEX)	QS1	288	0.207	5.439	−0.649	2.694	−6.588***	−302.088***	0.066
Gasoline (NYMEX)	XB1	–	–	–	–	–	–		
Heating Oil (NYMEX)	HO1	288	0.213	5.881	−0.454	2.005	−7.160***	−279.852***	0.065
Natural Gas (NYMEX)	NG1	288	0.367	8.210	0.120	0.948	−6.453***	−282.217***	0.054
WTI (NYMEX)	CL1	288	0.217	5.665	−0.334	1.367	−7.163***	−295.767***	0.061
Portfolio (Energy)		288	0.243	4.834	−0.140	1.172	−6.609***	−273.501***	0.077
Industrial Metals									
Aluminium (LME)	LA1	288	0.012	2.204	0.200	1.180	−6.616***	−292.664***	0.133
Cobalt (LME)	LCO1	–	–	–	–	–	–		
Copper (LME)	LP1	288	0.100	2.615	0.136	0.754	−6.519***	−230.464***	0.285
Lead (LME)	LL1	288	0.091	2.863	0.270	0.426	−6.898***	−289.457***	0.468**
Nickel (LME)	LN1	288	0.353	4.615	−0.474	1.163	−4.993***	−278.648***	0.386*
Tin (LME)	LT1	288	0.068	2.220	−0.211	1.768	−5.104***	−298.183***	0.386*
Zinc (LME)	LX1	288	−0.028	2.553	0.040	−0.103	−6.929***	−257.349***	0.195
Portfolio (Industrial Metals)		288	0.099	2.106	−0.160	0.770	−5.576***	−277.776***	0.495**
Precious Metals									
Gold (COMEX)	GC1	288	0.126	2.105	0.704	2.929	−7.210***	−265.649***	0.278
Palladium (NYMEX)	PA1	288	−0.009	5.929	0.543	3.392	−6.749***	−297.035***	0.486**
Platinum (NYMEX)	PL1	288	0.274	3.018	−0.043	1.116	−6.391***	−275.498***	0.109
Silver (COMEX)	SI1	288	0.001	3.091	0.164	2.053	−8.008***	−249.501***	0.247
Portfolio (Precious Metals)		288	0.098	2.367	0.134	0.956	−6.766***	−296.585***	0.095
Common Factor									
PC1 (All Commodities)		1056	0.401	11.836	−0.664	4.265	−8.048***	−1088.730***	0.176

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. Bloomberg tickers for the continuous series BBG Comdty (PX_SETTLE) are given in column BBG. 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 except for Pc1 (1998:1–2019:12). The common factor is constructed as the first principal compoenent (PC) of standardized log returns of all commodities, for which data is available over the full sample period. The Jarque-Bera test rejects the null of normality at the 0.1% level of significance for all return series. 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 C.10: Sample statistics of commodity futures for weekly (5-day) log returns, 2004–2013

	BBG	Obs.	Mean	Std.Dev.	Skewn.	Ex.Kurt.	ADF	PP	KPSS
Agriculture (Softs)									
Cocoa (ICE)	CC1	480	0.121	4.684	−0.183	0.906	−8.725***	−443.683***	0.056
Coffee (ICE)	KC1	480	0.111	4.245	0.158	0.480	−8.537***	−412.048***	0.324
Cotton (ICE)	CT1	480	0.025	4.835	−0.624	4.440	−7.394***	−415.124***	0.104
Ethanol (CBOT)	DL1	412	0.108	5.203	−0.959	3.541	−6.399***	−398.408***	0.117
Lumber (CME)	LB1	480	0.029	5.017	0.134	0.927	−7.625***	−496.648***	0.096
Orange Juice (ICE)	JO1	480	0.169	5.532	0.161	2.112	−8.014***	−471.883***	0.156
Rubber (SGX)	OR1	480	0.126	4.389	−1.960	12.802	−5.367***	−400.221***	0.159
Sugar (ICE)	SB1	480	0.221	5.041	−0.319	1.704	−7.035***	−544.917***	0.188
Wool (ASX)	OL1	432	0.070	2.661	0.120	3.317	−6.545***	−464.229***	0.111
Portfolio (Softs)		480	0.108	2.236	−0.761	4.260	−6.037***	−460.157***	0.164
Agriculture (Grains)									
Corn (CBOT)	C 1	480	0.112	4.813	−0.445	3.013	−6.891***	−488.092***	0.122
Oats (CBOT)	O 1	480	0.184	5.396	0.124	1.858	−8.041***	−459.310***	0.045
Rough Rice (CBOT)	RR1	480	0.124	3.967	−0.807	3.253	−6.967***	−394.804***	0.054
Soybean (CBOT)	S 1	480	0.106	4.207	−1.283	6.105	−6.592***	−452.541***	0.067
Soybean Meal (CBOT)	SM1	480	0.124	4.776	−0.946	4.279	−6.828***	−423.513***	0.060
Soybean Oil (CBOT)	BO1	480	0.069	3.755	−0.459	2.108	−6.812***	−425.313***	0.119
Wheat (CBOT)	W 1	480	0.099	4.827	0.096	0.640	−7.958***	−458.282***	0.077
Portfolio (Grains)		480	0.117	3.257	−0.530	1.383	−6.951***	−433.424***	0.082
Agriculture (Livestock)									
Feeder Cattle (CME)	FC1	480	0.156	2.299	−0.202	1.682	−6.828***	−522.854***	0.089
Lean Hogs (CME)	LH1	480	0.098	4.673	−0.293	4.085	−7.563***	−435.366***	0.030
Live Cattle (CME)	LC1	480	0.116	2.537	−0.317	0.857	−7.237***	−537.775***	0.051
Pork Bellies (CME)	PB1	336	0.062	6.642	0.992	10.448	−8.245***	−297.351***	0.037
Portfolio (Livestock)		480	0.114	2.477	−0.352	2.160	−8.319***	−422.709***	0.053
Energy									
Brent (ICE)	CO1	480	0.271	4.866	−0.870	5.106	−5.881***	−587.257***	0.112
Gasoil (NYMEX)	QS1	480	0.259	4.578	−0.479	1.306	−6.436***	−525.116***	0.124
Gasoline (NYMEX)	XB1	396	0.098	5.690	−0.611	3.670	−5.551***	−455.302***	0.034
Heating Oil (NYMEX)	HO1	480	0.253	4.900	−0.366	2.240	−6.508***	−519.624***	0.106
Natural Gas (NYMEX)	NG1	480	−0.079	7.337	0.243	0.843	−7.755***	−501.205***	0.048
WTI (NYMEX)	CL1	480	0.231	5.256	−0.356	3.331	−5.947***	−533.226***	0.094
Portfolio (Energy)		480	0.197	4.438	−0.555	2.459	−6.185***	−535.622***	0.107
Industrial Metals									
Aluminium (LME)	LA1	480	0.021	3.554	−0.028	1.590	−6.890***	−510.223***	0.160
Cobalt (LME)	LCO1	184	−0.202	3.705	0.340	1.409	−6.229***	−218.301***	0.072
Copper (LME)	LP1	480	0.242	4.463	−1.024	4.869	−6.070***	−540.618***	0.192
Lead (LME)	LL1	480	0.228	5.821	−0.313	1.416	−7.048***	−460.117***	0.116
Nickel (LME)	LN1	480	−0.038	5.996	−0.248	2.348	−6.962***	−488.189***	0.102
Tin (LME)	LT1	480	0.255	4.981	−0.596	2.318	−7.216***	−490.486***	0.088
Zinc (LME)	LX1	480	0.147	5.060	−0.517	1.285	−6.855***	−500.721***	0.203
Portfolio (Industrial Metals)		480	0.133	3.794	−0.608	2.087	−6.646***	−476.819***	0.199
Precious Metals									
Gold (COMEX)	GC1	480	0.221	2.861	−0.468	2.239	−8.708***	−430.678***	0.276
Palladium (NYMEX)	PA1	480	0.269	5.100	−0.634	2.164	−6.646***	−472.190***	0.059
Platinum (NYMEX)	PL1	480	0.109	3.586	−0.946	3.770	−6.738***	−464.966***	0.102
Silver (COMEX)	SI1	480	0.245	5.273	−0.943	4.192	−8.018***	−434.533***	0.165
Portfolio (Precious Metals)		480	0.211	3.593	−0.908	2.633	−7.204***	−454.344***	0.131
Common Factor									
PC1 (All Commodities)		1056	0.401	11.836	−0.664	4.265	−8.048***	−1088.730***	0.176

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. Bloomberg tickers for the continuous series BBG Comdty (PX_SETTLE) are given in column BBG. 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 2004:1–2013:12 except for Ethanol (2005:6–2013:12), Wool (2004:1–2012:12), Pork Bellies (2004:1–2010:12), Gasoline (2005:10–2013:12), Cobalt (2010:3–2013:12), and Pc1 (1998:1–2019:12). The common factor is constructed as the first principal compoenent (PC) of standardized log returns of all commodities, for which data is available over the full sample period. The Jarque-Bera test rejects the null of normality at the 0.1% level of significance for all return series. 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 C.11: Sample statistics of commodity futures for weekly (5-day) log returns, 2014–2019

	BBG	Obs.	Mean	Std.Dev.	Skewn.	Ex.Kurt.	ADF	PP	KPSS
Agriculture (Softs)									
Cocoa (ICE)	CC1	288	−0.022	3.629	0.090	0.029	−6.521***	−245.953***	0.088
Coffee (ICE)	KC1	288	0.055	4.687	0.475	0.725	−7.547***	−258.936***	0.110
Cotton (ICE)	CT1	288	−0.071	3.241	−0.531	1.686	−5.964***	−264.851***	0.112
Ethanol (CBOT)	DL1	288	−0.114	4.772	−2.398	22.053	−7.910***	−263.337***	0.030
Lumber (CME)	LB1	288	0.041	4.492	−0.071	2.595	−6.459***	−259.328***	0.091
Orange Juice (ICE)	JO1	288	−0.118	4.559	0.383	0.715	−6.897***	−258.608***	0.143
Rubber (SGX)	OR1	288	−0.155	3.572	−0.007	0.294	−5.882***	−332.224***	0.159
Sugar (ICE)	SB1	288	−0.070	4.160	0.882	2.895	−6.469***	−244.162***	0.060
Wool (ASX)	OL1								
Portfolio (Softs)		288	−0.057	1.768	0.066	0.428	−6.119***	−254.171***	0.066
Agriculture (Grains)									
Corn (CBOT)	C 1	288	−0.029	3.264	0.230	1.103	−6.862***	−318.181***	0.041
Oats (CBOT)	O 1	288	−0.067	4.879	−0.249	0.587	−7.992***	−287.082***	0.141
Rough Rice (CBOT)	RR1	288	−0.058	3.292	−0.021	1.311	−6.699***	−234.482***	0.265
Soybean (CBOT)	S 1	288	−0.115	3.047	−0.806	3.336	−6.307***	−329.253***	0.099
Soybean Meal (CBOT)	SM1	288	−0.131	3.827	−1.447	12.250	−7.462***	−284.195***	0.052
Soybean Oil (CBOT)	BO1	288	−0.041	2.831	0.144	0.299	−5.520***	−288.352***	0.159
Wheat (CBOT)	W 1	288	−0.028	4.105	0.462	0.533	−7.475***	−291.078***	0.117
Portfolio (Grains)		288	−0.067	2.233	0.056	0.475	−7.261***	−288.409***	0.202
Agriculture (Livestock)									
Feeder Cattle (CME)	FC1	288	−0.048	2.764	−0.124	2.379	−6.296***	−303.541***	0.130
Lean Hogs (CME)	LH1	288	−0.062	6.298	−0.331	2.651	−6.625***	−283.262***	0.033
Live Cattle (CME)	LC1	288	−0.026	3.140	−0.685	2.083	−6.185***	−257.943***	0.073
Pork Bellies (CME)	PB1	−	−	−	−	−	−	−	−
Portfolio (Livestock)		288	−0.045	2.939	−0.341	1.710	−6.789 ***	−294.267***	0.061
Energy									
Brent (ICE)	CO1	288	−0.180	4.814	0.037	2.822	−6.001***	−287.978***	0.255
Gasoil (NYMEX)	QS1	288	−0.149	4.070	−0.014	1.308	−6.258***	−241.290***	0.273
Gasoline (NYMEX)	XB1	288	−0.172	5.605	0.249	5.787	−6.102***	−324.090***	0.108
Heating Oil (NYMEX)	HO1	288	−0.145	4.367	−0.241	3.789	−6.801***	−248.443***	0.278
Natural Gas (NYMEX)	NG1	288	−0.229	6.628	−0.365	1.581	−7.833***	−247.975***	0.057
WTI (NYMEX)	CL1	288	−0.166	5.057	0.171	2.178	−5.870***	−279.832***	0.211
Portfolio (Energy)		288	−0.173	3.983	0.023	1.113	−6.097***	−261.142***	0.244
Industrial Metals									
Aluminium (LME)	LA1	288	0.005	2.577	0.529	1.223	−7.131***	−256.832***	0.099
Cobalt (LME)	LCO1	288	0.039	3.860	−0.731	4.727	−5.489***	−273.609***	0.257
Copper (LME)	LP1	288	−0.062	2.584	0.310	0.879	−6.339***	−237.359***	0.196
Lead (LME)	LL1	288	−0.047	3.107	0.111	0.487	−6.877***	−271.483***	0.085
Nickel (LME)	LN1	288	0.003	4.094	0.044	0.326	−5.661***	−314.015***	0.129
Tin (LME)	LT1	288	−0.091	2.800	−0.172	1.695	−5.931***	−292.396***	0.134
Zinc (LME)	LX1	288	0.038	3.213	0.021	−0.281	−5.500***	−281.211***	0.146
Portfolio (Industrial Metals)		288	−0.017	1.938	−0.013	−0.187	−5.572***	−266.238***	0.194
Precious Metals									
Gold (COMEX)	GC1	288	0.082	1.945	0.106	0.436	−6.439***	−265.846***	0.098
Palladium (NYMEX)	PA1	288	0.339	3.742	−0.262	1.427	−6.938***	−234.223***	0.341
Platinum (NYMEX)	PL1	288	−0.120	2.825	−0.009	0.667	−6.893***	−233.419***	0.154
Silver (COMEX)	SI1	288	−0.027	3.233	0.042	0.525	−7.107***	−260.909***	0.092
Portfolio (Precious Metals)		288	0.069	2.335	−0.105	0.693	−6.683***	−243.519***	0.233
Common Factor									
PC1 (All Commodities)		1056	0.401	11.836	−0.664	4.265	−8.048***	−1088.730***	0.176

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. Bloomberg tickers for the continuous series BBG Comdty (PX_SETTLE) are given in column BBG. 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 except for Pc1 (1998:1–2019:12). The common factor is constructed as the first principal compoenent (PC) of standardized log returns of all commodities, for which data is available over the full sample period. The Jarque-Bera test rejects the null of normality at the 0.1% level of significance for all return series. 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 C.12: Factor loadings and correlations of the first principal component of commodity returns to the original futures return series

	Common Factor (PC1)		Common Factor (PC1, non-fuel)	
	Factor loading	Correlation	Factor loading	Correlation
Softs				
Cocoa	0.096	0.247	−0.119	−0.266
Coffee	0.124	0.279	−0.167	−0.328
Cotton	0.114	0.308	−0.148	−0.345
Ethanol		0.313		−0.293
Lumber	0.053	0.122	−0.074	−0.148
Orange Juice	0.050	0.122	−0.061	−0.127
Rubber	0.070	0.226	−0.089	−0.249
Sugar	0.130	0.297	−0.164	−0.326
Wool		−0.007		−0.001
Grains				
Corn	0.152	0.425	−0.203	−0.493
Oats	0.144	0.306	−0.208	−0.385
Rough Rice	0.074	0.215	−0.101	−0.258
Soybean	0.148	0.469	−0.197	−0.542
Soybean Meal	0.137	0.364	−0.192	−0.444
Soybean Oil	0.147	0.499	−0.178	−0.529
Wheat	0.150	0.382	−0.202	−0.447
Livestock				
Feeder Cattle	0.008	0.04	−0.005	−0.02
Lean Hogs	0.037	0.077	−0.045	−0.081
Live Cattle	0.026	0.114	−0.029	−0.107
Pork Bellies		0.059		−0.057
Energy				
Brent	0.327	0.733		−0.359
Gasoil		0.579		−0.289
Gasoline	0.236	0.621		−0.386
Heating Oil	0.316	0.702		−0.313
Natural Gas	0.255	0.375		−0.119
WTI	0.352	0.728		−0.357
Industrial Metals				
Aluminium	0.144	0.520	−0.191	−0.602
Cobalt		0.032		−0.047
Copper	0.203	0.622	−0.271	−0.723
Lead	0.210	0.515	−0.292	−0.624
Nickel	0.263	0.531	−0.372	−0.653
Tin	0.143	0.438	−0.192	−0.512
Zinc	0.225	0.55	−0.321	−0.684
Precious Metals				
Gold	0.090	0.410	−0.115	−0.455
Palladium	0.191	0.449	−0.256	−0.524
Platinum	0.137	0.456	−0.176	−0.511
Silver	0.194	0.509	−0.250	−0.571
Portfolios				
Softs		0.510		−0.563
Grains		0.549		−0.644
Livestock		0.110		−0.106
Energy		0.796		−0.364
Industrial Metals		0.684		−0.824
Precious Metals		0.575		−0.652

Notes: This table displays the factor loadings of the first PC (common factor) based on standardized daily commodity futures log returns, that are available over the full sample period from 1998:01 through 2019:12. All energy commodities are excluded from the calculation of the non-fuel PC. Correlations to the first PC are calculated based on the available data for each commodity.

Table C.13: Sample statistics of daily (HF) and monthly (LF) driver variables, 1998–2003

	Obs.	Mean	Std.Dev.	Min	Max	Skewn.	Ex.Kurt.	J.B.	ADF	PP	KPSS
Fundamental											
Daily (HF)											
BDI	1565	0.086	0.849	−3.922	5.587	1.061	5.419	0.000	−9.760***	−321.680***	0.832***
TBILL	1565	−0.003	0.047	−0.510	0.480	−1.789	30.641	0.000	−9.858***	−1285.204***	0.341
USDEER	1565	−0.000	0.280	−2.122	1.382	−0.373	3.512	0.000	−10.676***	−1511.467***	0.483**
Monthly (LF)											
WIP	72	0.232	0.513	−1.354	1.112	−0.449	0.065	0.297	−2.041	−95.495***	0.132
GECON	72	−0.043	0.335	−1.108	0.636	−0.397	0.151	0.375	−1.193	−15.937	0.368*
BDI	72	1.839	9.826	−22.110	52.481	1.753	8.363	0.000	−2.429	−59.221***	0.456*
STEEL	72	0.304	4.157	−6.946	13.456	0.986	1.137	0.000	−5.590***	−108.137***	0.093
GSCPI	72	0.007	0.220	−0.580	0.470	−0.233	−0.192	0.683	−5.195***	−66.423***	0.039
INFL	72	0.023	0.008	0.011	0.037	0.355	−1.100	0.076	−1.833	−5.257	0.290
INFLE	72	0.026	0.005	0.004	0.032	−2.278	7.810	0.000	−3.020	−24.602**	0.222
CSENT	72	−0.136	3.780	−11.206	10.278	−0.029	0.382	0.800	−4.175***	−71.103***	0.073
PC1	72	0.181	1.078	−2.807	2.974	−0.312	0.573	0.341	−1.762	−42.202***	0.227
Financial											
Daily (HF)											
SPX	1565	0.009	1.303	−7.044	5.573	0.010	1.871	0.000	−12.127***	−1501.041***	0.199
VIX	1565	−0.017	5.390	−19.377	27.122	0.214	0.890	0.000	−13.108***	−1351.675***	0.023
PC1	1565	−0.007	1.282	−5.920	4.613	−0.098	1.193	0.000	−12.462***	−1417.278***	0.093
Monthly (LF)											
SPX	72	0.189	5.249	−15.759	9.232	−0.545	0.002	0.168	−3.364*	−67.762***	0.237
VIX	72	−0.629	14.208	−34.106	46.550	0.873	1.831	0.000	−4.442***	−50.220***	0.056
ISENT	72	−0.018	0.283	−0.751	0.720	−0.135	0.490	0.625	−3.021	−71.111***	0.225
PC1	72	0.008	1.313	−2.298	4.622	0.886	1.239	0.001	−3.597**	−56.652***	0.126
Uncertainty											
Daily (HF)											
TED	1563	−0.128	10.572	−71.846	74.194	−0.125	8.320	0.000	−12.841***	−1652.563***	0.074
EPU	1565	0.032	70.994	−248.131	294.635	0.161	0.692	0.000	−17.233***	−1799.909***	0.004
GEOVOL	866	−0.338	8.693	−35.662	34.057	−0.133	1.478	0.000	−7.724***	−914.949***	0.020
Monthly (LF)											
FUNC	72	−0.171	3.466	−7.872	9.035	0.431	0.029	0.327	−4.123***	−36.535***	0.374*
MUNC	72	0.107	1.998	−4.560	5.788	−0.150	0.251	0.795	−3.503**	−27.105***	0.219
RUNC	72	−0.035	1.877	−5.444	4.528	−0.183	0.557	0.513	−3.922**	−40.107***	0.120
TED	72	−1.458	32.281	−82.313	95.316	0.249	0.893	0.209	−6.423***	−59.699***	0.043
GEPU	72	−0.447	17.496	−34.496	70.585	1.079	2.717	0.000	−4.860***	−61.926***	0.054
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
PC1	72	0.093	1.523	−5.055	3.593	−0.380	1.090	0.071	−3.938**	−36.762***	0.224

Notes: Summary statistics are provided for 100×log-differenced data except for GECON, INFL, and INFLE (in levels) as well as TBILL, GSCPI, and ISENTI (in differences). The data spans the period of 1998:1–2003:12 except for GEOVOL (2000:7–2003:12). The first principal component (PC1) of each subset of drivers is calculated based on those drivers for which data was available over the entire period. 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 C.14: Sample statistics of daily (HF) and monthly (LF) driver variables, 2004–2013

	Obs.	Mean	Std.Dev.	Min	Max	Skewn.	Ex.Kurt.	J.B.	ADF	PP	KPSS
Fundamental											
Daily (HF)											
BDI	2609	−0.028	2.103	−11.953	13.658	0.029	4.402	0.000	−9.660***	−457.986***	0.076
TBILL	2609	−0.000	0.056	−0.810	0.740	−0.619	54.740	0.000	−14.622***	−1745.976***	0.554**
USDEER	2609	−0.004	0.357	−2.279	2.020	0.239	3.184	0.000	−13.359***	−2728.733***	0.074
Monthly (LF)											
WIP	120	0.214	0.742	−3.265	1.842	−1.931	6.849	0.000	−3.220*	−73.234***	0.116
GECON	120	−0.070	0.491	−2.203	0.885	−2.055	5.927	0.000	−2.486	−19.878*	0.221
BDI	120	−0.622	22.732	−101.249	70.348	−0.856	3.656	0.000	−4.811***	−66.842***	0.049
STEEL	120	0.413	4.563	−13.723	12.061	0.363	0.651	0.093	−5.478***	−170.384***	0.042
GSCPI	120	−0.001	0.405	−1.180	0.900	−0.339	0.037	0.316	−7.837***	−116.293***	0.027
INFL	120	0.024	0.014	−0.020	0.054	−0.672	0.641	0.004	−3.367*	−16.662	0.437*
INFLE	120	0.032	0.006	0.017	0.052	1.122	2.310	0.000	−3.758**	−27.891***	0.069
CSENT	120	−0.096	6.230	−19.925	12.762	−0.367	0.209	0.233	−6.201***	−96.434***	0.113
PC1	120	−0.246	1.797	−8.830	3.628	−1.780	5.774	0.000	−2.874	−37.192***	0.117
Financial											
Daily (HF)											
SPX	2609	0.019	1.265	−9.470	10.957	−0.330	11.547	0.000	−13.846***	−2725.361***	0.172
VIX	2609	−0.011	6.621	−35.059	49.601	0.684	4.596	0.000	−15.299***	−2497.305***	0.033
PC1	2609	−0.001	1.368	−8.694	9.142	−0.541	5.593	0.000	−14.311***	−2608.229***	0.104
Monthly (LF)											
SPX	120	0.424	4.295	−18.564	10.231	−1.087	2.827	0.000	−4.000**	−97.917***	0.151
VIX	120	−0.146	16.590	−25.390	71.918	1.616	4.252	0.000	−5.333***	−106.878***	0.070
ISENT	120	0.006	0.126	−0.539	0.264	−0.567	1.801	0.000	−4.236***	−101.173***	0.159
PC1	120	−0.016	1.274	−2.059	6.226	1.546	4.602	0.000	−4.654***	−95.197***	0.120
Uncertainty											
Daily (HF)											
TED	2609	−0.009	7.364	−57.093	53.011	−0.281	8.585	0.000	−13.285***	−2342.324***	0.100
EPU	2609	0.025	56.966	−314.833	267.690	−0.071	1.448	0.000	−20.789***	−2667.951***	0.004
GEOVOL	2427	−0.192	11.072	−113.531	85.858	−0.487	12.528	0.000	−13.678***	−2280.695***	0.006
Monthly (LF)											
FUNC	120	−0.023	3.382	−9.143	9.933	0.309	0.644	0.136	−4.096***	−43.304***	0.160
MUNC	120	−0.075	2.516	−5.550	8.284	0.699	1.384	0.000	−4.061***	−36.616***	0.200
RUNC	120	0.082	2.401	−5.369	7.775	0.353	0.525	0.145	−4.818***	−55.492***	0.097
TED	120	−0.268	33.018	−77.467	111.493	0.713	1.867	0.000	−5.309***	−124.392***	0.107
GEPU	120	0.447	17.377	−45.853	54.647	0.182	0.088	0.704	−6.146***	−120.909***	0.045
GPR	120	−0.294	27.184	−73.343	65.133	−0.025	0.119	0.959	−7.826***	−132.921***	0.043
GEOVOL	120	−0.284	42.678	−164.922	150.359	−0.178	1.834	0.000	−6.984***	−132.678***	0.029
PC1	120	−0.024	1.591	−3.096	6.730	0.959	2.128	0.000	−3.945**	−57.614***	0.168

Notes: Summary statistics are provided for 100*log-differenced data except for GECON, INFL, and INFLE (in levels) as well as TBILL, GSCPI, and ISENTI (in differences). The data spans the period of 2004:1–2013:12. The first principal component (PC1) of each subset of drivers is calculated based on those drivers for which data was available over the entire period. 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 C.15: Sample statistics of daily (HF) and monthly (LF) driver variables, 2014–2019

	Obs.	Mean	Std.Dev.	Min	Max	Skewn.	Ex.Kurt.	J.B.	ADF	PP	KPSS
Fundamental											
Daily (HF)											
BDI	1565	−0.047	2.416	−12.072	11.355	0.184	2.332	0.000	−9.707***	−492.548***	0.162
TBILL	1565	0.001	0.019	−0.080	0.140	0.389	4.595	0.000	−10.754***	−1515.582***	0.608**
USDEER	1565	0.013	0.296	−1.883	1.804	−0.047	3.021	0.000	−10.999***	−1462.522***	0.344
Monthly (LF)											
WIP	72	0.145	0.412	−0.973	1.079	0.023	−0.213	0.931	−3.499**	−103.032***	0.097
GECON	72	−0.009	0.229	−0.517	0.351	−0.337	−0.813	0.187	−2.004	−20.407**	0.167
BDI	72	−0.715	20.785	−53.387	46.504	−0.068	−0.251	0.885	−4.873***	−55.918***	0.136
STEEL	72	0.176	4.692	−9.691	13.061	0.635	1.081	0.015	−5.088***	−110.262***	0.038
GSCPI	72	0.008	0.225	−0.640	0.450	−0.151	−0.192	0.825	−5.541 ***	−94.620***	0.070
INFL	72	0.015	0.008	−0.002	0.029	−0.674	−0.446	0.049	−2.834	−8.516	0.815***
INFLE	72	0.027	0.002	0.022	0.033	0.542	0.035	0.171	−2.631	−18.984*	0.647**
CSENT	72	0.257	3.226	−9.146	7.296	−0.177	0.156	0.799	−5.403 ***	−79.894***	0.059
PC1	72	0.230	0.790	−1.794	2.225	−0.029	0.320	0.853	−3.231 *	−94.297***	0.158
Financial											
Daily (HF)											
SPX	1565	0.036	0.812	−4.184	4.840	−0.522	3.931	0.000	−12.134***	−1473.485***	0.047
VIX	1565	0.000	7.947	−29.983	76.825	1.270	8.184	0.000	−13.918***	−1462.970***	0.008
PC1	1565	0.008	1.271	−10.635	4.709	−1.031	5.612	0.000	−13.305***	−1468.938***	0.016
Monthly (LF)											
SPX	72	0.776	3.287	−9.627	7.972	−0.637	1.088	0.015	−4.423***	−82.020***	0.096
VIX	72	−0.041	18.578	−37.925	70.533	0.780	1.873	0.000	−4.683***	−68.863***	0.034
ISENT	60	−0.006	0.081	−0.256	0.199	−0.726	1.034	0.019	−3.988**	−62.257***	0.064
PC1	72	−0.043	1.215	−2.842	3.756	0.689	1.143	0.008	−4.600***	−69.608***	0.050
Uncertainty											
Daily (HF)											
TED	1565	0.051	6.672	−46.612	37.110	−0.227	4.286	0.000	−12.378***	−1586.254***	0.033
EPU	1565	−0.013	53.371	−185.874	321.562	0.236	1.365	0.000	−16.946***	−1718.374***	0.007
GEOVOL	1455	−0.191	12.720	−112.255	101.026	−0.427	12.144	0.000	−10.582***	−1379.116***	0.012
Monthly (LF)											
FUNC	72	0.509	3.039	−7.646	9.688	0.096	0.757	0.400	−3.132	−31.277***	0.175
MUNC	72	0.420	2.090	−4.011	6.436	0.615	0.138	0.100	−2.949	−19.383*	0.205
RUNC	72	0.298	1.930	−3.916	6.985	0.725	1.730	0.000	−3.250*	−38.447***	0.403*
TED	72	1.128	25.544	−49.039	92.127	0.846	1.705	0.000	−5.660***	−71.135***	0.046
GEPU	72	1.174	18.701	−43.731	60.568	0.532	1.290	0.015	−5.323***	−78.508***	0.046
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
PC1	72	0.240	1.293	−2.561	3.756	0.376	−0.152	0.414	−3.083	−45.708***	0.301

Notes: Summary statistics are provided for 100× log-differenced data except for GECON, INFL, and INFLE (in levels) as well as TBILL, GSCPI, and ISENTI (in differences). The data spans the period of 2014:1–2019:12 except for ISENTI (2014:1–2018:12). The first principal component (PC1) of each subset of drivers is calculated based on those drivers for which data was available over the entire period. 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 C.16: Factor loadings and correlations of first principal components to the original variables of the respective group of drivers

	LF PC1 (Fundamental)		HF PC1 (Financial)		LF PC1 (Financial)		LF PC1 (Uncertainty)	
	Factor loading	Correlation	Factor loading	Correlation	Factor loading	Correlation	Factor loading	Correlation
WIP	0.495	0.699						
GECON	0.570	0.804						
BDI	0.324	0.458						
STEEL	0.311	0.439						
GSCPI	0.041	0.058						
INFL	−0.266	−0.375						
INFLE	−0.292	−0.412						
CSENT	0.266	0.375						
SPX			0.707	0.933	−0.705	−0.888		
VIX			−0.707	−0.933	0.708	0.892		
ISENT					−0.053	−0.067		
FUNC							0.392	0.594
MUNC							0.560	0.847
RUNC							0.489	0.740
TED							0.299	0.453
GEPU							0.361	0.546
GPR							0.132	0.200
GEOVOL							0.238	0.361

Notes: This table displays factor loadings of the first PCs as well as the correlation of PCs to the original variables used for the PC analysis. The PCs contained in this table also comprise information of variables for which data is not available over the full sample. Hence, PCs were estimated from data spanning the period from 1998:1–2019:12 for LF fundamental and HF financial PCs, whereas the period used for the LF financial PC is 1998:1–2018:12, and 2000:7-2003:12 for the LF uncertainty PC. Note that for our Granger causality analysis, we exclude variables for which data is not available over the full (sub-)sample period prior to running the PC analysis, such that the respective PC always covers the full (sub-)sample period.

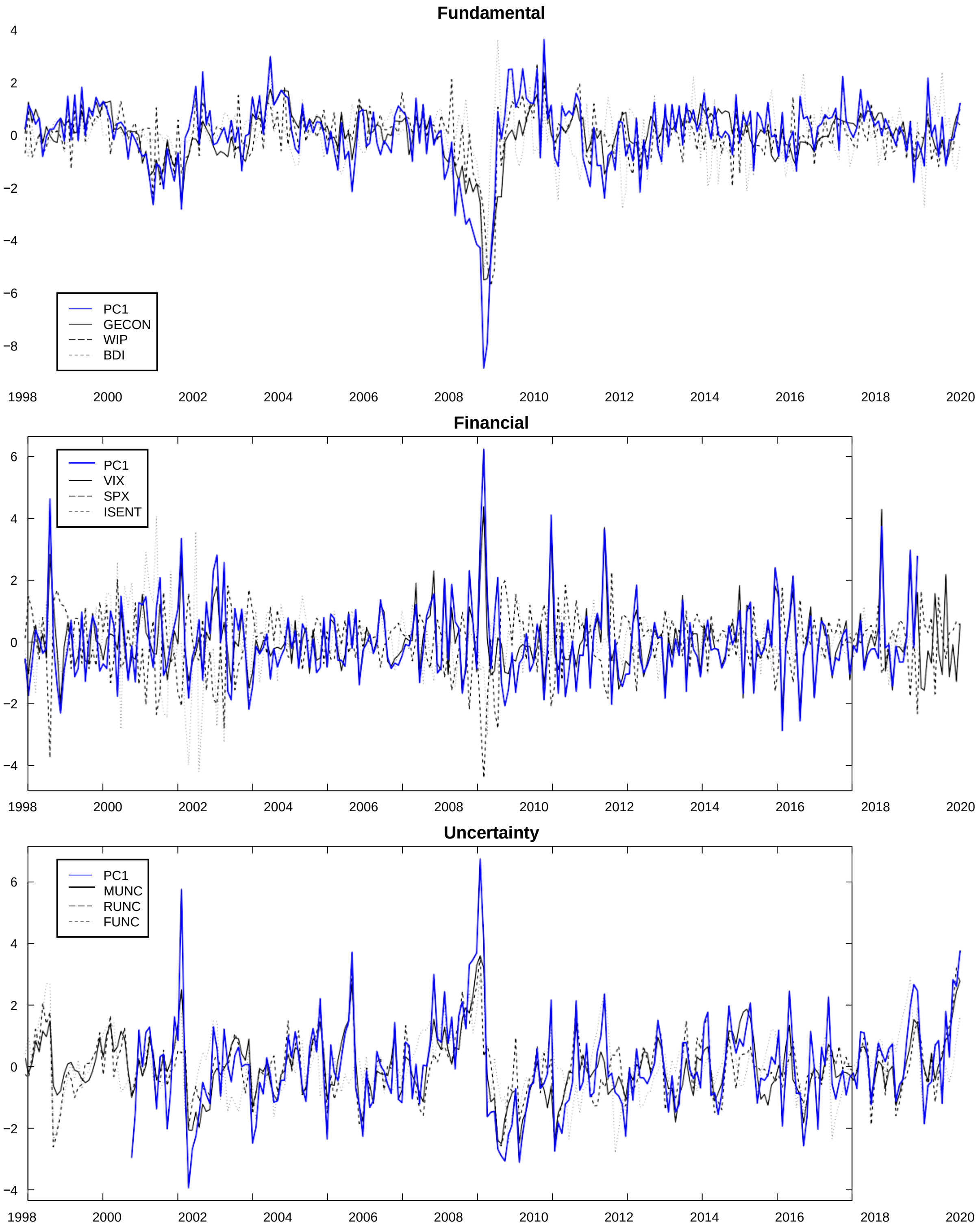

Figure C.6: First PCs of LF fundamental, financial, and uncertainty driver variables and standardized variables of the respective set of drivers that exhibit the highest correlation to the first PC. Note that for our Granger causality analysis, we exclude variables for which data is not available over the full (sub-)sample period prior to running the PC analysis, such that the respective PC always covers the full (sub-)sample period.

Table C.17: Bootstrapped p-values of pairwise Granger causality tests for the null of non-causality from potential drivers - - - commodities, 1998-2019

	HF drivers							LF drivers		
	Fundamental			Financial	Uncertainty			Fundamental	Financial	Uncertainty
	BDI	TBILL	USDEER	PC1	TED	EPU	GEOVOL	PC1	PC1	PC1
Softs										
Cocoa	0.906	0.707	0.122	0.021	0.705	0.157	0.121	0.143	0.228	0.593
Coffee	0.423	0.047	0.423	0.002	0.161	0.634	0.010	0.242	0.697	0.190
Cotton	0.414	0.737	0.287	0.179	0.134	0.326	0.185	0.003	0.681	0.047
Ethanol	0.359	0.340	0.097°	0.074°	0.328	0.498	0.997	0.378	0.037	0.296
Lumber	0.245	0.365	0.528	0.258	0.002	0.928	0.758	0.024	0.753	0.068°
Orange Juice	0.551	0.261	0.028	0.001	0.349	0.932	0.706	0.554	0.551	0.043
Rubber	0.084°	0.360	0.047	0.001	0.512	0.897	0.848	0.412	0.165	0.003
Sugar	0.006	0.228	0.674	0.085°	0.858	0.558	0.871	0.371	0.238	0.771
Wool	0.412	0.077°	0.394	0.799	0.635	0.148	0.709	0.288	0.037	0.013
Grains										
Corn	0.807	0.221	0.493	0.571	0.381	0.663	0.802	0.187	0.184	0.378
Oats	0.544	0.236	0.427	0.443	0.701	0.753	0.347	0.033	0.510	0.204
Rough Rice	0.074°	0.867	0.977	0.397	0.255	0.857	0.407	0.606	0.776	0.363
Soybean	0.954	0.071°	0.955	0.044	0.974	0.986	0.331	0.104	0.032	0.104
Soybean Meal	0.864	0.078°	0.671	0.070°	0.687	0.880	0.511	0.449	0.073°	0.128
Soybean Oil	0.328	0.224	0.976	0.001	0.990	0.474	0.052°	0.141	0.090°	0.018
Wheat	0.961	0.095°	0.517	0.201	0.863	0.355	0.343	0.746	0.250	0.866
Livestock										
Feeder Cattle	0.343	0.284	0.474	0.023	0.429	0.080°	0.755	0.854	0.562	0.312
Lean Hogs	0.807	0.790	0.044	0.804	0.255	0.005	0.079°	0.431	0.034	0.039
Live Cattle	0.988	0.965	0.210	0.138	0.541	0.014	0.401	0.587	0.078°	0.012
Pork Bellies	0.553	0.983	0.219	0.713	0.835	0.874	–	0.316	0.527	0.975
Energy										
Brent	0.053°	0.125	1.000	0.001	0.332	0.445	0.022	0.001	0.591	0.226
Gasoil	0.088°	0.628	0.093°	0.001	0.320	0.435	0.002	0.001	0.793	0.433
Gasoline	0.024	0.099°	0.720	0.006	0.499	0.008	0.060°	0.003	0.576	0.238
Heating Oil	0.099°	0.212	0.288	0.005	0.616	0.939	0.003	0.001	0.465	0.159
Natural Gas	0.039	0.374	0.149	0.457	0.719	0.810	0.253	0.011	0.776	0.915
WTI	0.188	0.268	0.348	0.006	0.219	0.267	0.031	0.001	0.407	0.210
Industrial Metals										
Aluminium	0.905	0.808	0.011	0.001	0.980	0.484	0.019	0.001	0.207	0.079°
Cobalt	–	–	–	–	–	–	–	–	–	–
Copper	0.288	0.748	0.225	0.001	0.254	0.574	0.141	0.044	0.255	0.006
Lead	0.905	0.980	0.456	0.001	0.241	0.886	0.032	0.030	0.453	0.019
Nickel	0.449	0.670	0.365	0.001	0.081°	0.569	0.012	0.002	0.743	0.004
Tin	0.555	0.889	0.117	0.001	0.229	0.832	0.167	0.007	0.478	0.058°
Zinc	0.822	0.407	0.843	0.001	0.229	0.345	0.184	0.029	0.411	0.010
Precious Metals										
Gold	0.195	0.565	0.892	0.004	0.081°	0.906	0.075°	0.596	0.601	0.803
Palladium	0.089°	0.573	0.312	0.001	0.181	0.381	0.391	0.003	0.110	0.671
Platinum	0.122	0.560	0.943	0.001	0.387	0.998	0.322	0.019	0.075°	0.511
Silver	0.066°	0.706	0.878	0.001	0.665	0.571	0.033	0.041	0.545	0.216
Portfolios / PC1										
Softs	0.635	0.446	0.670	0.001	0.289	0.529	0.049	0.022	0.099°	0.109
Grains	0.603	0.193	0.776	0.029	0.561	0.994	0.167	0.024	0.062°	0.046
Livestock	0.688	0.670	0.032	0.408	0.220	0.004	0.255	0.350	0.263	0.613
Energy	0.023	0.186	0.808	0.002	0.555	0.579	0.005	0.003	0.348	0.243
Industrial Metals	0.762	0.839	0.843	0.001	0.196	0.599	0.020	0.001	0.290	0.002
Precious Metals	0.077°	0.697	0.677	0.001	0.177	0.860	0.066°	0.014	0.166	0.433
Common Factor	0.262	0.263	0.598	0.001	0.171	0.996	0.002	0.001	0.112	0.004

Notes: This table shows bootstrapped p-values with N = 999 replications for testing the null hypothesis of non-causality from potential HF and LF drivers to commodity futures at the prediction horizon h = 1, which is daily for HF and monthly for LF drivers. Granger causality tests are based on bivariate MF-VAR (HF-VAR) models with lag order P = 1 using weekly (daily) commodity returns, and monthly (daily) (log-differenced) data for potential drivers, i.e., $m = 4$ ($m = 1$). Data was demeaned prior to VAR estimation. 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. Results are only displayed for pairs of which data is available at least over half of the sample period. The first principal component (PC1) of each subset of drivers is calculated based on drivers for which data was available over the entire period (cf. Table 2).

Table C.18: Bootstrapped p-values of pairwise Granger causality tests for the null of non-causality from potential drivers - - - commodities, 1998-2003

	HF drivers							LF drivers		
	Fundamental			Financial	Uncertainty			Fundamental	Financial	Uncertainty
	BDI	TBILL	USDEER	PC1	TED	EPU	GEOVOL	PC1	PC1	PC1
Softs										
Cocoa	0.433	0.356	0.290	0.835	0.802	0.693	0.425	0.965	0.260	0.828
Coffee	0.956	0.854	0.467	0.250	0.531	0.216	0.486	0.710	0.944	0.424
Cotton	0.034	0.255	0.170	0.705	0.017	0.380	0.975	0.257	0.813	0.024
Ethanol	–	–	–	–	–	–	–	–	–	–
Lumber	0.003	0.658	0.993	0.074°	0.288	0.249	0.338	0.131	0.234	0.120
Orange Juice	0.392	0.223	0.154	0.100	0.972	0.975	0.033	0.023	0.393	0.031
Rubber	0.093°	0.819	0.085°	0.846	0.475	0.900	0.657	0.205	0.712	0.068°
Sugar	0.170	0.573	0.637	0.167	0.545	0.281	0.666	0.693	0.565	0.789
Wool	0.710	0.992	0.507	0.567	0.908	0.144	0.671	0.629	0.228	0.035
Grains										
Corn	0.515	0.115	0.230	0.435	0.982	0.702	0.347	0.401	0.201	0.216
Oats	0.957	0.855	0.457	0.124	0.188	0.905	0.038	0.651	0.078°	0.295
Rough Rice	0.485	0.404	0.254	0.914	0.407	0.816	0.734	0.228	0.917	0.522
Soybean	0.254	0.978	0.019	0.596	0.207	0.324	0.722	0.452	0.316	0.328
Soybean Meal	0.334	0.533	0.010	0.625	0.083°	0.372	0.316	0.455	0.113	0.678
Soybean Oil	0.616	0.692	0.071°	0.948	0.669	0.978	0.559	0.279	0.148	0.192
Wheat	0.467	0.171	0.140	0.623	0.985	0.318	0.831	0.196	0.092°	0.625
Livestock										
Feeder Cattle	0.764	0.474	0.853	0.758	0.887	0.164	0.998	0.577	0.707	0.696
Lean Hogs	0.222	0.562	0.666	0.601	0.610	0.194	0.245	0.247	0.151	0.303
Live Cattle	0.458	0.529	0.466	0.672	0.765	0.038	0.342	0.772	0.252	0.190
Pork Bellies	0.868	0.871	0.804	0.448	0.701	0.875	0.224	0.887	0.267	0.553
Energy										
Brent	0.904	0.506	0.343	0.014	0.985	0.542	0.022	0.082°	0.730	0.073°
Gasoil	0.654	0.762	0.378	0.399	0.974	0.905	0.013	0.045	0.443	0.902
Gasoline	–	–	–	–	–	–	–	–	–	–
Heating Oil	0.454	0.825	0.993	0.426	0.831	0.253	0.050°	0.040	0.496	0.518
Natural Gas	0.285	0.971	0.366	0.286	0.466	0.678	0.735	0.362	0.467	0.703
WTI	0.822	0.777	0.759	0.094°	0.786	0.750	0.175	0.039	0.858	0.549
Industrial Metals										
Aluminium	0.207	0.324	0.003	0.076°	0.043	0.524	0.482	0.299	0.781	0.169
Cobalt	–	–	–	–	–	–	–	–	–	–
Copper	0.025	0.691	0.135	0.005	0.132	0.847	0.076°	0.097°	0.091°	0.115
Lead	0.728	0.912	0.428	0.198	0.205	0.102	0.119	0.854	0.332	0.701
Nickel	0.161	0.444	0.178	0.007	0.850	0.699	0.004	0.020	0.029	0.259
Tin	0.085°	0.168	0.869	0.066°	0.618	0.754	0.360	0.052°	0.031	0.030
Zinc	0.014	0.599	0.101	0.019	0.809	0.460	0.288	0.070°	0.033	0.073°
Precious Metals										
Gold	0.851	0.507	0.111	0.003	0.676	0.164	0.689	0.217	0.099°	0.951
Palladium	0.753	0.851	0.655	0.530	0.691	0.546	0.297	0.586	0.784	0.355
Platinum	0.090°	0.823	0.745	0.677	0.554	0.343	0.754	0.044	0.899	0.451
Silver	0.677	0.744	0.373	0.001	0.683	0.149	0.124	0.039	0.106	0.354
Portfolios / PC1										
Softs	0.152	0.469	0.117	0.018	0.478	0.382	0.152	0.471	0.971	0.054°
Grains	0.399	0.556	0.010	0.363	0.147	0.735	0.155	0.174	0.081°	0.336
Livestock	0.436	0.926	0.582	1.000	0.883	0.233	0.131	0.888	0.311	0.475
Energy	0.518	0.683	0.744	0.103	0.861	0.677	0.083°	0.035	0.678	0.827
Industrial Metals	0.052°	0.375	0.130	0.003	0.290	0.719	0.017	0.039	0.063°	0.084°
Precious Metals	0.830	0.764	0.874	0.014	0.669	0.477	0.660	0.134	0.348	0.133
Common Factor	0.279	0.941	0.243	0.008	0.954	0.978	0.005	0.008	0.243	0.310

Notes: This table shows bootstrapped p-values with N = 999 replications for testing the null hypothesis of non-causality from potential HF and LF drivers to commodity futures at the prediction horizon h = 1, which is daily for HF and monthly for LF drivers. Granger causality tests are based on bivariate MF-VAR (HF-VAR) models with lag order P = 1 using weekly (daily) commodity returns, and monthly (daily) (log-differenced) data for potential drivers, i.e., $m = 4$ ($m = 1$). Data was demeaned prior to VAR estimation. 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. Results are only displayed for pairs of which data is available at least over half of the sample period. The first principal component (PC1) of each subset of drivers is calculated based on drivers for which data was available over the entire period (cf. Table C.13).

Table C.19: Bootstrapped p-values of pairwise Granger causality tests for the null of non-causality from potential drivers - - - commodities, 2004-2013

	HF drivers							LF drivers		
	Fundamental			Financial	Uncertainty			Fundamental	Financial	Uncertainty
	BDI	TBILL	USDEER	PC1	TED	EPU	GEOVOL	PC1	PC1	PC1
Softs										
Cocoa	0.578	0.841	0.573	0.002	0.344	0.738	0.213	0.166	0.378	0.262
Coffee	0.597	0.027	0.088°	0.004	0.166	0.081°	0.137	0.051°	0.509	0.047
Cotton	0.767	0.245	0.055°	0.064°	0.362	0.318	0.155	0.004	0.658	0.048
Ethanol	0.618	0.083°	0.067°	0.060°	0.856	0.436	0.641	0.112	0.151	0.202
Lumber	0.919	0.242	0.631	0.884	0.091°	0.397	0.772	0.030	0.573	0.352
Orange Juice	0.746	0.001	0.434	0.002	0.146	0.562	0.976	0.002	0.712	0.101
Rubber	0.592	0.161	0.282	0.001	0.219	0.272	0.743	0.269	0.212	0.012
Sugar	0.059°	0.325	0.755	0.250	0.531	0.476	0.732	0.063°	0.419	0.363
Wool	0.311	0.022	0.525	0.829	0.346	0.540	0.910	0.618	0.221	0.059°
Grains										
Corn	0.678	0.470	0.176	0.039	0.674	0.567	0.374	0.135	0.371	0.300
Oats	0.323	0.377	0.897	0.128	0.869	0.343	0.836	0.137	0.255	0.415
Rough Rice	0.159	0.556	0.602	0.155	0.318	0.740	0.584	0.655	0.896	0.417
Soybean	0.801	0.041	0.308	0.001	0.159	0.844	0.327	0.026	0.212	0.355
Soybean Meal	0.781	0.012	0.417	0.002	0.151	0.780	0.336	0.336	0.214	0.419
Soybean Oil	0.285	0.127	0.563	0.001	0.624	0.580	0.089°	0.030	0.148	0.072°
Wheat	0.392	0.173	0.118	0.013	0.647	0.630	0.110	0.287	0.262	0.675
Livestock										
Feeder Cattle	0.520	0.906	0.542	0.180	0.709	0.519	0.853	0.585	0.043	0.536
Lean Hogs	0.585	0.606	0.234	0.420	0.357	0.122	0.502	0.788	0.778	0.041
Live Cattle	0.782	0.259	0.345	0.406	0.417	0.503	0.787	0.290	0.049	0.028
Pork Bellies	0.460	0.931	0.155	0.791	0.363	0.732	0.856	0.471	0.585	0.432
Energy										
Brent	0.129	0.038	0.896	0.001	0.632	0.415	0.171	0.009	0.644	0.145
Gasoil	0.168	0.504	0.337	0.001	0.349	0.298	0.008	0.008	0.170	0.151
Gasoline	0.135	0.042	0.932	0.004	0.164	0.024	0.423	0.021	0.910	0.053°
Heating Oil	0.257	0.079°	0.433	0.001	0.999	0.774	0.007	0.004	0.193	0.301
Natural Gas	0.394	0.152	0.249	0.355	0.836	0.856	0.195	0.128	0.637	0.986
WTI	0.462	0.107	0.238	0.018	0.514	0.477	0.131	0.018	0.449	0.087°
Industrial Metals										
Aluminium	0.836	0.285	0.358	0.001	0.777	0.463	0.048	0.004	0.029	0.044
Cobalt	–	–	–	–	–	–	–	–	–	–
Copper	0.541	0.538	0.114	0.001	0.134	0.278	0.045	0.042	0.284	0.011
Lead	0.747	0.826	0.340	0.001	0.230	0.220	0.025	0.002	0.689	0.011
Nickel	0.187	0.888	0.774	0.001	0.150	0.396	0.184	0.002	0.094°	0.004
Tin	0.991	0.862	0.012	0.005	0.389	0.548	0.412	0.009	0.070°	0.040
Zinc	0.716	0.185	0.344	0.001	0.822	0.084°	0.043	0.117	0.025	0.045
Precious Metals										
Gold	0.133	0.900	0.537	0.009	0.086°	0.495	0.223	0.907	0.785	0.732
Palladium	0.091°	0.385	0.705	0.001	0.678	0.535	0.397	0.005	0.025	0.098°
Platinum	0.058°	0.148	0.544	0.001	0.976	0.868	0.658	0.011	0.075°	0.592
Silver	0.105	0.535	0.907	0.001	0.571	0.843	0.039	0.169	0.349	0.457
Portfolios / PC1										
Softs	0.978	0.070°	0.656	0.001	0.394	0.787	0.162	0.002	0.271	0.396
Grains	0.369	0.177	0.326	0.001	0.560	0.996	0.150	0.019	0.374	0.425
Livestock	0.531	0.999	0.089°	0.491	0.574	0.523	0.595	0.154	0.860	0.146
Energy	0.117	0.063°	0.767	0.001	0.637	0.650	0.031	0.012	0.277	0.208
Industrial Metals	0.960	0.555	0.228	0.001	0.242	0.221	0.032	0.001	0.112	0.002
Precious Metals	0.066°	0.391	0.651	0.001	0.485	0.764	0.140	0.027	0.227	0.298
Common Factor	0.456	0.156	0.203	0.001	0.599	0.489	0.008	0.001	0.053°	0.097°

Notes: This table shows bootstrapped p-values with N = 999 replications for testing the null hypothesis of non-causality from potential HF and LF drivers to commodity futures at the prediction horizon h = 1, which is daily for HF and monthly for LF drivers. Granger causality tests are based on bivariate MF-VAR (HF-VAR) models with lag order P = 1 using weekly (daily) commodity returns, and monthly (daily) (log-differenced) data for potential drivers, i.e., $m = 4$ ($m = 1$). Data was demeaned prior to VAR estimation. A highlighted cell (circle) indicates the rejection of non-causality at the 5% (10%) level. The sample spans the period 2004:1–2013:12 where data is available over the full horizon. Results are only displayed for pairs of which data is available at least over half of the sample period. The first principal component (PC1) of each subset of drivers is calculated based on drivers for which data was available over the entire period (cf. Table C.14).

Table C.20: Bootstrapped p-values of pairwise Granger causality tests for the null of non-causality from potential drivers - - - commodities, 2014-2019

	HF drivers							LF drivers		
	Fundamental			Financial	Uncertainty			Fundamental	Financial	Uncertainty
	BDI	TBILL	USDEER	PC1	TED	EPU	GEOVOL	PC1	PC1	PC1
Softs										
Cocoa	0.774	0.071°	0.507	0.488	0.046	0.038	0.573	0.873	0.208	0.662
Coffee	0.574	0.762	0.095°	0.510	0.610	0.446	0.043	0.191	0.468	0.998
Cotton	0.156	0.202	0.634	0.552	0.044	0.697	0.875	0.358	0.013	0.413
Ethanol	0.542	0.048	0.820	0.924	0.069°	0.936	0.578	0.833	0.541	0.867
Lumber	0.195	0.002	0.631	0.716	0.003	0.944	0.792	0.747	0.558	0.284
Orange Juice	0.802	0.931	0.059°	0.095°	0.894	0.591	0.806	0.667	0.453	0.566
Rubber	0.120	0.082°	0.311	0.001	0.201	0.282	0.982	0.561	0.062°	0.310
Sugar	0.071°	0.929	0.190	0.312	0.566	0.461	0.924	0.553	0.075°	0.542
Wool	–	–	–	–	–	–	–	–	–	–
Grains										
Corn	0.170	0.391	0.986	0.049	0.111	0.657	0.250	0.239	0.857	0.868
Oats	0.755	0.293	0.391	0.408	0.154	0.459	0.682	0.097°	0.067°	0.575
Rough Rice	0.370	0.348	0.599	0.399	0.842	0.439	0.284	0.207	0.481	0.221
Soybean	0.285	0.142	0.945	0.447	0.039	0.353	0.973	0.354	0.300	0.620
Soybean Meal	0.844	0.262	0.889	0.258	0.103	0.177	0.373	0.207	0.554	0.944
Soybean Oil	0.785	0.406	0.824	0.242	0.632	0.272	0.413	0.697	0.537	0.657
Wheat	0.074°	0.678	0.364	0.171	0.160	0.915	0.503	0.991	0.281	0.453
Livestock										
Feeder Cattle	0.400	0.003	0.846	0.121	0.052°	0.013	0.791	0.546	0.964	0.850
Lean Hogs	0.590	0.515	0.062°	0.767	0.558	0.045	0.182	0.830	0.136	0.583
Live Cattle	0.594	0.056°	0.641	0.029	0.097°	0.010	0.190	0.785	0.457	0.015
Pork Bellies	–	–	–	–	–	–	–	–	–	–
Energy										
Brent	0.116	0.046	0.360	0.121	0.118	0.140	0.269	0.422	0.686	0.146
Gasoil	0.261	0.064°	0.210	0.005	0.192	0.983	0.199	0.286	0.675	0.189
Gasoline	0.351	0.425	0.505	0.281	0.629	0.107	0.088°	0.263	0.867	0.541
Heating Oil	0.211	0.235	0.322	0.210	0.418	0.116	0.413	0.175	0.775	0.595
Natural Gas	0.065°	0.695	0.987	0.210	0.710	0.296	0.959	0.837	0.671	0.039
WTI	0.199	0.056°	0.672	0.446	0.124	0.071°	0.276	0.962	0.645	0.203
Industrial Metals										
Aluminium	0.843	0.055°	0.095°	0.061°	0.079°	0.300	0.528	0.402	0.953	0.197
Cobalt	0.067°	0.431	0.609	0.013	0.566	0.359	0.385	0.140	0.325	0.033
Copper	0.814	0.066°	0.638	0.023	0.048	0.363	0.187	0.879	0.318	0.114
Lead	0.176	0.089°	0.326	0.125	0.037	0.562	0.870	0.390	0.346	0.496
Nickel	0.619	0.012	0.338	0.121	0.011	0.359	0.460	0.454	0.857	0.526
Tin	0.438	0.164	0.009	0.100	0.016	0.086°	0.271	0.101	0.292	0.886
Zinc	0.353	0.006	0.342	0.003	0.001	0.263	0.294	0.983	0.406	0.523
Precious Metals										
Gold	0.806	0.041	0.769	0.914	0.668	0.325	0.266	0.123	0.631	0.948
Palladium	0.328	0.009	0.369	0.018	0.023	0.955	0.810	0.046	0.117	0.433
Platinum	0.665	0.002	0.336	0.054°	0.125	0.173	0.315	0.527	0.113	0.348
Silver	0.147	0.090°	0.984	0.085°	0.650	0.482	0.208	0.758	0.392	0.892
Portfolios / PC1										
Softs	0.678	0.005	0.970	0.097°	0.006	0.487	0.514	0.122	0.150	0.991
Grains	0.290	0.581	0.637	0.476	0.248	0.630	0.969	0.363	0.195	0.951
Livestock	0.671	0.037	0.128	0.453	0.142	0.001	0.729	0.602	0.671	0.777
Energy	0.068°	0.071°	0.455	0.417	0.197	0.239	0.252	0.805	0.900	0.260
Industrial Metals	0.755	0.011	0.030	0.020	0.001	0.240	0.814	0.255	0.346	0.063°
Precious Metals	0.396	0.005	0.999	0.031	0.075°	0.409	0.357	0.168	0.286	0.787
Common Factor	0.407	0.002	0.386	0.065°	0.003	0.250	0.378	0.463	0.411	0.076°

Notes: This table shows bootstrapped p-values with N = 999 replications for testing the null hypothesis of non-causality from potential HF and LF drivers to commodity futures at the prediction horizon h = 1, which is daily for HF and monthly for LF drivers. Granger causality tests are based on bivariate MF-VAR (HF-VAR) models with lag order P = 1 using weekly (daily) commodity returns, and monthly (daily) (log-differenced) data for potential drivers, i.e., m = 4 (m = 1). Data was demeaned prior to VAR estimation. 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. Results are only displayed for pairs of which data is available at least over half of the sample period. The first principal component (PC1) of each subset of drivers is calculated based on drivers for which data was available over the entire period (cf. Table C.15).

Table C.21: Bootstrapped p-values of pairwise Granger causality tests for the null of non-causality from potential drivers - - - commodities, 1998-2019

	Fundamental (HF)			**Financial**(HF)		**Uncertainty** (HF)			**Fundamental** (LF)								**Financial**(LF)		**Uncertainty** (LF)						
	BDI	TBILL	USDEER	SPX	VIX	TED	EPU	GEOVOL	WIP	GECON	BDI	STEEL	GSCPI	INFL	INFLE	CSENT	SPX	VIX	ISENT	FUNC	MUNC	RUNC	TED	GEPU	GPR	GEOVOL
Softs																										
Cocoa	0.906	0.707	0.122	0.024	0.154	0.705	0.157	0.121	0.925	0.697	0.084°	0.281	0.130	0.319	0.585	0.334	0.037	0.958	0.819	0.166	0.714	0.792	0.306	0.940	0.185	0.643
Coffee	0.423	0.047	0.423	0.001	0.020	0.161	0.634	0.010	0.630	0.598	0.871	0.198	0.569	0.018	0.096°	0.925	0.262	0.655	0.025	0.274	0.237	0.882	0.055°	0.477	0.969	0.340
Cotton	0.414	0.737	0.287	0.205	0.235	0.134	0.326	0.185	0.032	0.036	0.569	0.644	0.801	0.019	0.017	0.607	0.822	0.565	0.162	0.132	0.022	0.121	0.395	0.514	0.609	0.580
Ethanol	0.359	0.340	0.097°	0.055°	0.409	0.328	0.498	0.997	0.097°	0.267	0.430	0.781	0.349	0.236	0.308	0.865	0.222	0.083°	0.149	0.332	0.125	0.199	0.808	0.360	0.135	0.592
Lumber	0.245	0.365	0.528	0.370	0.242	0.002	0.928	0.758	0.641	0.242	0.282	0.377	0.716	0.525	0.345	0.033	0.877	0.743	0.036	0.357	0.062°	0.329	0.384	0.509	0.906	0.286
Orange Juice	0.551	0.261	0.028	0.002	0.001	0.349	0.932	0.706	0.828	0.964	0.019	0.725	0.462	0.181	0.271	0.664	0.599	0.203	0.745	0.041	0.128	0.322	0.271	0.529	0.701	0.413
Rubber	0.084°	0.360	0.047	0.001	0.001	0.512	0.897	0.848	0.051°	0.190	0.298	0.282	0.451	0.178	0.182	0.850	0.609	0.015	0.725	0.126	0.005	0.051°	0.024	0.246	0.364	0.422
Sugar	0.006	0.228	0.674	0.016	0.176	0.858	0.558	0.871	0.512	0.032	0.934	0.419	0.611	0.480	0.946	0.802	0.128	0.693	0.349	0.541	0.858	0.128	0.713	0.543	0.936	0.749
Wool	0.412	0.077°	0.394	0.941	0.516	0.635	0.148	0.709	0.259	0.429	0.075°	0.027	0.536	0.018	0.078°	0.200	0.073°	0.095°	0.561	0.039	0.123	0.282	0.193	0.119	0.064°	0.544
Grains																										
Corn	0.807	0.221	0.493	0.472	0.750	0.381	0.663	0.802	0.098°	0.080°	0.604	0.143	0.880	0.096°	0.240	0.803	0.070°	0.521	0.024	0.527	0.143	0.248	0.461	0.644	0.772	0.307
Oats	0.544	0.236	0.427	0.251	0.777	0.701	0.753	0.347	0.013	0.012	0.572	0.842	0.322	0.793	0.699	0.516	0.646	0.407	0.021	0.953	0.055°	0.158	0.498	0.719	0.993	0.903
Rough Rice	0.074°	0.867	0.977	0.585	0.348	0.255	0.857	0.407	0.647	0.060°	0.082°	0.091°	0.700	0.670	0.945	0.069°	0.936	0.431	0.787	0.346	0.379	0.456	0.425	0.604	0.203	0.710
Soybean	0.954	0.071°	0.955	0.053°	0.064°	0.974	0.986	0.331	0.316	0.007	0.777	0.130	0.279	0.060°	0.145	0.591	0.113	0.024	0.087°	0.423	0.067°	0.028	0.913	0.399	0.279	0.088°
Soybean Meal	0.864	0.078°	0.671	0.129	0.071°	0.687	0.880	0.511	0.623	0.487	0.892	0.040	0.601	0.049	0.737	0.703	0.390	0.426	0.033	0.350	0.088°	0.236	0.895	0.954	0.284	0.518
Soybean Oil	0.328	0.224	0.976	0.004	0.002	0.990	0.474	0.052°	0.103	0.027	0.548	0.110	0.549	0.086°	0.289	0.443	0.122	0.084°	0.787	0.006	0.025	0.026	0.867	0.134	0.670	0.278
Wheat	0.961	0.095°	0.517	0.132	0.466	0.863	0.355	0.343	0.461	0.316	0.825	0.022	0.356	0.323	0.424	0.723	0.254	0.532	0.062°	0.799	0.416	0.274	0.380	0.756	0.669	0.694
Livestock																										
Feeder Cattle	0.343	0.284	0.474	0.094°	0.060°	0.429	0.080°	0.755	0.985	0.577	0.559	0.222	0.544	0.738	0.820	0.293	0.259	0.608	0.188	0.245	0.731	0.611	0.111	0.020	0.435	0.356
Lean Hogs	0.807	0.790	0.044	0.561	0.939	0.255	0.005	0.079°	0.679	0.588	0.591	0.002	0.793	0.059°	0.214	0.547	0.150	0.060°	0.779	0.011	0.174	0.128	0.350	0.343	0.983	0.356
Live Cattle	0.988	0.965	0.210	0.226	0.182	0.541	0.014	0.401	0.518	0.470	0.353	0.017	0.384	0.464	0.309	0.355	0.065°	0.185	0.049	0.100	0.074°	0.795	0.243	0.004	0.685	0.160
Pork Bellies	0.553	0.983	0.219	0.440	0.943	0.835	0.874	–	0.036	0.049	0.084°	0.059°	0.585	0.600	0.525	0.697	0.291	0.735	0.209	0.611	0.841	0.359	0.241	0.626	0.216	–
Energy																										
Brent	0.053°	0.125	1.000	0.001	0.001	0.332	0.445	0.022	0.001	0.088°	0.171	0.103	0.606	0.138	0.279	0.312	0.352	0.611	0.765	0.610	0.129	0.422	0.381	0.772	0.118	0.480
Gasoil	0.088°	0.628	0.093°	0.001	0.001	0.320	0.435	0.002	0.001	0.005	0.036	0.075°	0.487	0.346	0.609	0.375	0.604	0.833	0.256	0.706	0.265	0.922	0.338	0.806	0.172	0.309
Gasoline	0.024	0.099°	0.720	0.004	0.042	0.499	0.008	0.060°	0.006	0.031	0.002	0.011	0.669	0.012	0.015	0.751	0.638	0.823	0.619	0.056°	0.137	0.401	0.643	0.819	0.930	0.161
Heating Oil	0.099°	0.212	0.288	0.010	0.005	0.616	0.939	0.003	0.001	0.010	0.006	0.060°	0.903	0.355	0.371	0.523	0.379	0.721	0.203	0.442	0.125	0.511	0.275	0.769	0.054°	0.407
Natural Gas	0.039	0.374	0.149	0.174	0.978	0.719	0.810	0.253	0.187	0.102	0.459	0.535	0.847	0.613	0.187	0.408	0.703	0.891	0.205	0.520	0.999	0.714	0.396	0.969	0.803	0.541
WTI	0.188	0.268	0.348	0.005	0.012	0.219	0.267	0.031	0.001	0.060°	0.120	0.350	0.845	0.078°	0.416	0.074°	0.503	0.261	0.548	0.583	0.058°	0.611	0.446	0.338	0.139	0.270
Industrial Metals																										
Aluminium	0.905	0.808	0.011	0.001	0.001	0.980	0.484	0.019	0.003	0.002	0.381	0.009	0.849	0.168	0.524	0.762	0.374	0.109	0.651	0.030	0.088°	0.324	0.258	0.330	0.677	0.598
Cobalt	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Copper	0.288	0.748	0.225	0.001	0.001	0.254	0.574	0.141			0.548	0.209	0.253	0.115	0.151	0.905	0.357	0.263	0.919	0.038	0.022	0.079°	0.741	0.590	0.823	0.230
Lead	0.905	0.980	0.456	0.001	0.001	0.241	0.886	0.032	0.038	0.140	0.557	0.681	0.672	0.109	0.270	0.703	0.613	0.155	0.775	0.015	0.044	0.187	0.677	0.108	0.808	0.305
Nickel	0.449	0.670	0.365	0.001	0.001	0.081°	0.569	0.012	0.010	0.003	0.579	0.280	0.708	0.203	0.005	0.419	0.381	0.651	0.238	0.013	0.002	0.029	0.878	0.861	0.422	0.173
Tin	0.555	0.889	0.117	0.004	0.001	0.229	0.832	0.167	0.004	0.017	0.728	0.594	0.974	0.376	0.277	0.215	0.647	0.704	0.773	0.183	0.014	0.155	0.721	0.301	0.344	0.169
Zinc	0.822	0.407	0.843	0.001	0.001	0.229	0.345	0.184	0.050°	0.035	0.914	0.137	0.466	0.068°	0.018	0.195	0.406	0.393	0.877	0.028	0.004	0.192	0.909	0.603	0.256	0.037
Precious Metals																										
Gold	0.195	0.565	0.892	0.004	0.001	0.081°	0.906	0.075°	0.426	0.660	0.953	0.589	0.542	0.232	0.526	0.362	0.510	0.621	0.892	0.461	0.687	0.770	0.615	0.045	0.163	0.040
Palladium	0.089°	0.573	0.312	0.001	0.001	0.181	0.381	0.391	0.037	0.086°	0.648	0.591	0.968	0.251	0.043	0.025	0.211	0.102	0.903	0.388	0.499	0.595	0.927	0.340	0.275	0.453
Platinum	0.122	0.560	0.943	0.001	0.001	0.387	0.998	0.322	0.364	0.416	0.940	0.034	0.519	0.482	0.136	0.458	0.461	0.063°	0.605	0.180	0.371	0.826	0.949	0.346	0.425	0.047
Silver	0.066°	0.706	0.878	0.001	0.001	0.665	0.571	0.033	0.390	0.789	0.541	0.181	0.362	0.021	0.327	0.395	0.645	0.596	0.867	0.081°	0.328	0.610	0.774	0.391	0.389	0.002
Portfolios / PC1																										
Softs	0.635	0.446	0.670	0.002	0.001	0.289	0.529	0.049	0.019	0.148	0.623	0.532	0.746	0.160	0.081°	0.426	0.165	0.207	0.088°	0.055°	0.055°	0.470	0.255	0.728	0.300	0.654
Grains	0.603	0.193	0.776	0.054°	0.066°	0.561	0.994	0.167	0.023	0.002	0.670	0.320	0.427	0.128	0.548	0.772	0.157	0.179	0.046	0.190	0.033	0.057°	0.804	0.386	0.548	0.484
Livestock	0.688	0.670	0.032	0.435	0.402	0.220	0.004	0.255	0.269	0.035	0.309	0.263	0.739	0.940	0.828	0.208	0.384	0.531	0.134	0.347	0.287	0.353	0.083°	0.179	0.887	0.565
Energy	0.023	0.186	0.808	0.004	0.002	0.555	0.579	0.005	0.001	0.070°	0.025	0.111	0.767	0.180	0.285	0.519	0.177	0.792	0.771	0.540	0.219	0.392	0.406	0.662	0.193	0.317
Industrial M.	0.762	0.839	0.843	0.001	0.001	0.196	0.599	0.020	0.001	0.003	0.675	0.028	0.626	0.042	0.030	0.789	0.517	0.146	0.691	0.001	0.001	0.014	0.926	0.484	0.644	0.057°
Precious M.	0.077°	0.697	0.677	0.001	0.001	0.177	0.860	0.066°	0.719	0.456	0.998	0.257	0.286	0.175	0.195	0.144	0.478	0.194	0.735	0.366	0.369	0.621	0.767	0.332	0.419	0.036
Common F.	0.262	0.263	0.598	0.002	0.001	0.171	0.996	0.002	0.001	0.027	0.190	0.208	0.922	0.276	0.134	0.508	0.098°	0.567	0.419	0.139	0.003	0.039	0.758	0.707	0.141	0.636

Notes: This table shows bootstrapped p-values with N = 999 replications for testing the null hypothesis of non-causality from potential HF and LF drivers to commodity futures at the prediction horizon h = 1, which is daily for HF and monthly for LF drivers. Granger causality tests are based on bivariate MF-VAR (HF-VAR) models with lag order P = 1 using weekly (daily) commodity returns, and monthly (daily) (log-differenced) data for potential drivers, i.e., m = 4 (m = 1). Data was demeaned prior to VAR estimation. 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. Results are only displayed for pairs of which data is available at least over half of the sample period.

Table C.22: Bootstrapped p-values of pairwise Granger causality tests for the null of non-causality from potential drivers - - - commodities, 1998-2003

	Fundamental (HF)			**Financial**(HF)		**Uncertainty** (HF)			**Fundamental** (LF)								**Financial**(LF)		**Uncertainty** (LF)						
	BDI	TBILL	USDEER	SPX	VIX	TED	EPU	GEOVOL	WIP	GECON	BDI	STEEL	GSCPI	INFL	INFLE	CSENT	SPX	VIX	ISENT	FUNC	MUNC	RUNC	TED	GEPU	GPR	GEOVOL
Softs																										
Cocoa	0.433	0.356	0.290	0.830	0.866	0.802	0.693	0.425	0.904	0.620	0.409	0.046	0.229	0.259	0.026	0.807	0.105	0.900	0.916	0.761	0.848	0.532	0.087°	0.382	0.055°	0.940
Coffee	0.956	0.854	0.467	0.115	0.718	0.531	0.216	0.486	0.657	0.181	0.318	0.884	0.804	0.203	0.084°	0.784	0.647	0.800	0.001	0.160	0.502	0.882	0.388	0.753	0.303	0.901
Cotton	0.034	0.255	0.170	0.833	0.512	0.017	0.380	0.975	0.345	0.165	0.112	0.194	0.619	0.280	0.278	0.899	0.724	0.816	0.463	0.045	0.029	0.039	0.553	0.148	0.715	0.738
Ethanol	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Lumber	0.003	0.658	0.993	0.253	0.022	0.288	0.249	0.338	0.880	0.691	0.077°	0.469	0.490	0.201	0.002	0.561	0.308	0.665	0.269	0.144	0.199	0.118	0.293	0.080°	0.892	0.303
Orange Juice	0.392	0.223	0.154	0.309	0.077°	0.972	0.975	0.033	0.153	0.004	0.780	0.817	0.491	0.095°	0.611	0.084°	0.496	0.319	0.638	0.286	0.280	0.041	0.252	0.164	0.659	0.510
Rubber	0.093°	0.819	0.085°	0.664	0.893	0.475	0.900	0.657	0.282	0.627	0.480	0.317	0.972	0.260	0.177	0.771	0.638	0.757	0.774	0.463	0.003	0.178	0.842	0.164	0.826	0.514
Sugar	0.170	0.573	0.637	0.174	0.233	0.545	0.281	0.666	0.789	0.324	0.609	0.412	0.487	0.068°	0.361	0.333	0.915	0.138	0.244	0.179	0.539	0.883	0.769	0.079°	0.038	0.785
Wool	0.710	0.992	0.507	0.576	0.565	0.908	0.144	0.671	0.342	0.217	0.224	0.594	0.102	0.129	0.104	0.094°	0.320	0.289	0.258	0.309	0.229	0.138	0.244	0.221	0.199	0.525
Grains																										
Corn	0.515	0.115	0.230	0.310	0.648	0.982	0.702	0.347	0.713	0.229	0.586	0.049	0.545	0.423	0.492	0.798	0.225	0.481	0.347	0.318	0.159	0.261	0.065°	0.676	0.356	0.878
Oats	0.957	0.855	0.457	0.207	0.052°	0.188	0.905	0.038	0.624	0.086°	0.315	0.126	0.153	0.054°	0.723	0.974	0.023	0.530	0.274	0.803	0.161	0.335	0.753	0.685	0.511	0.387
Rough Rice	0.485	0.404	0.254	0.778	0.511	0.407	0.816	0.734	0.165	0.492	0.061°	0.280	0.832	0.509	0.861	0.771	0.791	0.899	0.833	0.247	0.294	0.757	0.758	0.230	0.576	0.851
Soybean	0.254	0.978	0.019	0.403	0.909	0.207	0.324	0.722	0.480	0.289	0.142	0.540	0.708	0.275	0.629	0.781	0.508	0.191	0.263	0.424	0.199	0.108	0.757	0.484	0.958	0.359
Soybean Meal	0.334	0.533	0.010	0.322	0.871	0.083°	0.372	0.316	0.719	0.590	0.373	0.304	0.744	0.175	0.096°	0.791	0.469	0.172	0.039	0.771	0.788	0.333	0.638	0.598	0.885	0.855
Soybean Oil	0.616	0.692	0.071°	0.706	0.674	0.669	0.978	0.559	0.285	0.544	0.050°	0.537	0.939	0.632	0.194	0.035	0.248	0.128	0.997	0.067°	0.060°	0.496	0.982	0.833	0.414	0.415
Wheat	0.467	0.171	0.140	0.591	0.667	0.985	0.318	0.831	0.107	0.270	0.068°	0.694	0.537	0.611	0.506	0.498	0.205	0.097°	0.289	0.339	0.674	0.273	0.475	0.367	0.875	0.565
Livestock																										
Feeder Cattle	0.764	0.474	0.853	0.841	0.615	0.887	0.164	0.998	0.456	0.720	0.034	0.015	0.866	0.519	0.349	0.593	0.566	0.115	0.408	0.823	0.940	0.327	0.340	0.093°	0.296	0.863
Lean Hogs	0.222	0.562	0.666	0.371	0.936	0.610	0.194	0.245	0.661	0.421	0.696	0.155	0.471	0.430	0.624	0.414	0.075°	0.299	0.661	0.456	0.727	0.568	0.404	0.283	0.192	0.065°
Live Cattle	0.458	0.529	0.466	0.530	0.962	0.765	0.038	0.342	0.248	0.908	0.067°	0.163	0.290	0.324	0.081°	0.788	0.501	0.206	0.244	0.117	0.491	0.036	0.760	0.398	0.606	0.297
Pork Bellies	0.868	0.871	0.804	0.297	0.785	0.701	0.875	0.224	0.940	0.491	0.431	0.349	0.412	0.359	0.898	0.177	0.621	0.552	0.761	0.348	0.563	0.303	0.814	0.658	0.481	0.805
Energy																										
Brent	0.904	0.506	0.343	0.065°	0.007	0.985	0.542	0.022	0.036	0.257	0.428	0.893	0.926	0.018	0.012	0.302	0.601	0.918	0.944	0.179	0.250	0.253	0.275	0.457	0.014	0.623
Gasoil	0.654	0.762	0.378	0.655	0.205	0.974	0.905	0.013	0.230	0.260	0.360	0.713	0.764	0.238	0.466	0.552	0.315	0.574	0.681	0.748	0.663	0.956	0.657	0.598	0.039	0.224
Gasoline	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Heating Oil	0.454	0.825	0.993	0.657	0.259	0.831	0.253	0.050°	0.043	0.027	0.058°	0.696	0.907	0.441	0.165	0.437	0.785	0.539	0.795	0.445	0.393	0.962	0.379	0.438	0.062°	0.943
Natural Gas	0.285	0.971	0.366	0.251	0.312	0.466	0.678	0.735	0.360	0.249	0.170	0.892	0.759	0.138	0.035	0.208	0.368	0.825	0.439	0.374	0.848	0.822	0.497	0.461	0.092°	0.886
WTI	0.822	0.777	0.759	0.355	0.027	0.786	0.750	0.175	0.038	0.078°	0.331	0.840	0.916	0.002	0.004	0.039	0.775	0.945	0.773	0.246	0.704	0.719	0.639	0.314	0.059°	0.669
Industrial Metals																										
Aluminium	0.207	0.324	0.003	0.037	0.365	0.043	0.524	0.482	0.124	0.397	0.045	0.026	0.631	0.889	0.567	0.850	0.870	0.629	0.855	0.500	0.190	0.665	0.918	0.232	0.316	0.879
Cobalt	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Copper	0.025	0.691	0.135	0.006	0.032	0.132	0.847	0.076°	0.131	0.301	0.035	0.369	0.031	0.258	0.460	0.929	0.226	0.047	0.460	0.581	0.021	0.383	0.885	0.040	0.565	0.589
Lead	0.728	0.912	0.428	0.165	0.253	0.205	0.102	0.119	0.980	0.561	0.049	0.680	0.926	0.107	0.412	0.198	0.269	0.716	0.962	0.220	0.421	0.922	0.834	0.121	0.751	0.854
Nickel	0.161	0.444	0.178	0.005	0.047	0.850	0.699	0.004	0.440	0.069°	0.060°	0.229	0.923	0.305	0.132	0.403	0.244	0.045	0.080°	0.666	0.162	0.843	0.044	0.286	0.539	0.586
Tin	0.085°	0.168	0.869	0.046	0.228	0.618	0.754	0.360	0.334	0.555	0.089°	0.092°	0.769	0.041	0.043	0.106	0.116	0.169	0.539	0.051°	0.069°	0.368	0.207	0.049	0.120	0.047
Zinc	0.014	0.599	0.101	0.027	0.049	0.809	0.460	0.288	0.423	0.168	0.077°	0.257	0.488	0.150	0.665	0.884	0.123	0.268	0.773	0.170	0.049	0.597	0.885	0.214	0.174	0.820
Precious Metals																										
Gold	0.851	0.507	0.111	0.013	0.007	0.676	0.164	0.689	0.832	0.670	0.652	0.563	0.410	0.537	0.536	0.092°	0.031	0.568	0.798	0.937	0.741	0.685	0.591	0.437	0.049	0.165
Palladium	0.753	0.851	0.655	0.585	0.458	0.691	0.546	0.297	0.488	0.339	0.263	0.071°	0.244	0.155	0.215	0.215	0.514	0.896	0.680	0.216	0.580	0.370	0.877	0.997	0.497	0.545
Platinum	0.090°	0.823	0.745	0.879	0.358	0.554	0.343	0.754	0.125	0.277	0.262	0.763	0.524	0.709	0.322	0.441	0.620	0.989	0.581	0.444	0.621	0.552	0.258	0.675	0.124	0.480
Silver	0.677	0.744	0.373	0.001	0.001	0.683	0.149	0.124	0.080°	0.333	0.143	0.664	0.443	0.170	0.263	0.335	0.567	0.482	0.982	0.265	0.157	0.194	0.653	0.635	0.187	0.147
Portfolios / PC1																										
Softs	0.152	0.469	0.117	0.034	0.015	0.478	0.382	0.152	0.716	0.544	0.650	0.339	0.955	0.053°	0.043	0.243	0.921	0.739	0.032	0.037	0.018	0.375	0.880	0.465	0.015	0.622
Grains	0.399	0.556	0.010	0.282	0.507	0.147	0.735	0.155	0.255	0.144	0.219	0.571	0.694	0.906	0.873	0.545	0.260	0.133	0.299	0.301	0.190	0.046	0.650	0.906	0.414	0.601
Livestock	0.436	0.926	0.582	0.887	0.882	0.883	0.233	0.131	0.639	0.476	0.137	0.820	0.644	0.276	0.349	0.286	0.325	0.620	0.465	0.526	0.814	0.350	0.340	0.227	0.646	0.098°
Energy	0.518	0.683	0.744	0.229	0.041	0.861	0.677	0.083°	0.050°	0.062°	0.036	0.824	0.816	0.164	0.042	0.240	0.416	0.983	0.916	0.252	0.892	0.980	0.386	0.396	0.050°	0.882
Industrial M.	0.052°	0.375	0.130	0.002	0.038	0.290	0.719	0.017	0.279	0.134	0.057°	0.195	0.789	0.119	0.240	0.944	0.140	0.053°	0.395	0.270	0.020	0.761	0.701	0.053°	0.149	0.951
Precious M.	0.830	0.764	0.874	0.019	0.004	0.669	0.477	0.660	0.186	0.048	0.212	0.644	0.567	0.359	0.097°	0.160	0.121	0.597	0.368	0.245	0.407	0.054°	0.581	0.787	0.675	0.688
Common F.	0.279	0.941	0.243	0.029	0.007	0.954	0.978	0.005	0.110	0.047	0.189	0.886	0.781	0.140	0.065°	0.144	0.228	0.535	0.733	0.201	0.168	0.211	0.936	0.377	0.409	0.775

Notes: This table shows bootstrapped p-values with N = 999 replications for testing the null hypothesis of non-causality from potential HF and LF drivers to commodity futures at the prediction horizon h = 1, which is daily for HF and monthly for LF drivers. Granger causality tests are based on bivariate MF-VAR (HF-VAR) models with lag order P = 1 using weekly (daily) commodity returns, and monthly (daily) (log-differenced) data for potential drivers, i.e., m = 4 (m = 1). Data was demeaned prior to VAR estimation. 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. Results are only displayed for pairs of which data is available at least over half of the sample period.

Table C.23: Bootstrapped p-values of pairwise Granger causality tests for the null of non-causality from potential drivers - - - commodities, 2004-2013

	Fundamental (HF)			Financial(HF)		Uncertainty (HF)			Fundamental (LF)								Financial(LF)			Uncertainty (LF)						
	BDI	TBILL	USDEER	SPX	VIX	TED	EPU	GEOVOL	WIP	GECON	BDI	STEEL	GSCPI	INFL	INFLE	CSENT	SPX	VIX	ISENT	FUNC	MUNC	RUNC	TED	GEPU	GPR	GEOVOL
Softs																										
Cocoa	0.578	0.841	0.573	0.003	0.006	0.344	0.738	0.213	0.726	0.795	0.685	0.651	0.263	0.090°	0.376	0.503	0.062°	0.760	0.289	0.404	0.261	0.553	0.260	0.615	0.702	0.299
Coffee	0.597	0.027	0.088°	0.001	0.002	0.166	0.081°	0.137	0.161	0.269	0.200	0.260	0.576	0.205	0.278	0.844	0.463	0.779	0.976	0.476	0.179	0.319	0.190	0.237	0.371	0.735
Cotton	0.767	0.245	0.055°	0.156	0.125	0.362	0.318	0.155	0.242	0.148	0.562	0.630	0.737	0.014	0.001	0.702	0.647	0.878	0.252	0.547	0.209	0.021	0.397	0.944	0.485	0.593
Ethanol	0.618	0.083°	0.067°	0.020	0.276	0.856	0.436	0.641	0.059°	0.156	0.069°	0.688	0.670	0.341	0.187	0.735	0.321	0.019	0.237	0.024	0.142	0.021	0.716	0.420	0.186	0.442
Lumber	0.919	0.242	0.631	0.762	0.964	0.091°	0.397	0.772	0.161	0.104	0.231	0.122	0.847	0.096°	0.653	0.048	0.967	0.415	0.181	0.860	0.356	0.788	0.676	0.449	0.879	0.200
Orange Juice	0.746	0.001	0.434	0.012	0.007	0.146	0.562	0.976	0.083°	0.467	0.023	0.478	0.433	0.076°	0.211	0.433	0.379	0.772	0.076°	0.279	0.202	0.225	0.282	0.069°	0.875	0.308
Rubber	0.592	0.161	0.282	0.001	0.001	0.219	0.272	0.743	0.031	0.034	0.647	0.072°	0.370	0.052°	0.202	0.548	0.633	0.104	0.327	0.106	0.040	0.049	0.200	0.947	0.007	0.729
Sugar	0.059°	0.325	0.755	0.176	0.455	0.531	0.476	0.732	0.252	0.008	0.331	0.660	0.878	0.243	0.542	0.439	0.405	0.715	0.417	0.569	0.287	0.077°	0.209	0.872	0.656	0.942
Wool	0.311	0.022	0.525	0.461	0.742	0.346	0.540	0.910	0.215	0.387	0.555	0.157	0.456	0.005	0.088°	0.475	0.457	0.210	0.627	0.261	0.232	0.519	0.574	0.054°	0.471	0.373
Grains																										
Corn	0.678	0.470	0.176	0.132	0.079°	0.674	0.567	0.374	0.136	0.484	0.214	0.123	0.729	0.309	0.139	0.464	0.392	0.677	0.286	0.177	0.267	0.258	0.501	0.533	0.255	0.295
Oats	0.323	0.377	0.897	0.162	0.254	0.869	0.343	0.836	0.051°	0.040	0.761	0.770	0.726	0.430	0.854	0.725	0.157	0.651	0.306	0.716	0.242	0.221	0.670	0.474	0.421	0.604
Rough Rice	0.159	0.556	0.602	0.293	0.121	0.318	0.740	0.584	0.555	0.223	0.074°	0.174	0.584	0.241	0.318	0.331	0.928	0.586	0.815	0.535	0.554	0.145	0.308	0.894	0.134	0.408
Soybean	0.801	0.041	0.308	0.004	0.002	0.159	0.844	0.327	0.851	0.250	0.715	0.291	0.245	0.006	0.266	0.153	0.205	0.579	0.197	0.311	0.445	0.333	0.907	0.517	0.084°	0.505
Soybean Meal	0.781	0.012	0.417	0.008	0.004	0.151	0.780	0.336	0.986	0.839	0.851	0.171	0.776	0.001	0.284	0.525	0.140	0.664	0.074°	0.239	0.191	0.820	0.582	0.778	0.025	0.638
Soybean Oil	0.285	0.127	0.563	0.001	0.001	0.624	0.580	0.089°	0.030	0.087°	0.551	0.485	0.696	0.031	0.178	0.435	0.166	0.164	0.053°	0.105	0.110	0.049	0.926	0.151	0.016	0.921
Wheat	0.392	0.173	0.118	0.016	0.021	0.647	0.630	0.110	0.454	0.250	0.856	0.043	0.631	0.812	0.324	0.534	0.371	0.549	0.114	0.563	0.494	0.269	0.759	0.637	0.196	0.348
Livestock																										
Feeder Cattle	0.520	0.906	0.542	0.123	0.509	0.709	0.519	0.853	0.425	0.328	0.788	0.837	0.948	0.923	0.225	0.812	0.119	0.178	0.245	0.474	0.662	0.681	0.278	0.133	0.204	0.682
Lean Hogs	0.585	0.606	0.234	0.364	0.516	0.357	0.122	0.502	0.454	0.480	0.386	0.119	0.936	0.303	0.388	0.544	0.897	0.589	0.103	0.156	0.024	0.062°	0.997	0.510	0.757	0.664
Live Cattle	0.782	0.259	0.345	0.216	0.751	0.417	0.503	0.787	0.210	0.241	0.181	0.175	0.455	0.356	0.376	0.103	0.263	0.048	0.071°	0.104	0.016	0.167	0.387	0.563	1.000	0.616
Pork Bellies	0.460	0.931	0.155	0.912	0.704	0.363	0.732	0.856	0.007	0.049	0.144	0.229	0.834	0.570	0.812	0.628	0.570	0.887	0.083°	0.918	0.248	0.155	0.466	0.995	0.591	0.387
Energy																										
Brent	0.129	0.038	0.896	0.004	0.002	0.632	0.415	0.171	0.001	0.391	0.090°	0.414	0.951	0.054°	0.005	0.718	0.295	0.680	0.843	0.290	0.052°	0.260	0.319	0.196	0.023	0.760
Gasoil	0.168	0.504	0.337	0.001	0.001	0.349	0.298	0.008	0.001	0.159	0.193	0.625	0.446	0.076°	0.001	0.788	0.333	0.583	0.621	0.281	0.410	0.583	0.630	0.289	0.016	0.812
Gasoline	0.135	0.042	0.932	0.023	0.022	0.164	0.024	0.423	0.001	0.307	0.011	0.177	0.114	0.005	0.049	0.892	0.594	0.939	0.563	0.108	0.011	0.048	0.587	0.310	0.600	0.698
Heating Oil	0.257	0.079°	0.433	0.007	0.006	0.999	0.774	0.007	0.001	0.212	0.092°	0.385	0.871	0.043	0.005	0.748	0.413	0.520	0.757	0.323	0.419	0.474	0.563	0.438	0.018	0.553
Natural Gas	0.394	0.152	0.249	0.168	0.722	0.836	0.856	0.195	0.311	0.050°	0.890	0.923	0.922	0.352	0.691	0.728	0.684	0.669	0.119	0.454	0.694	0.835	0.727	0.872	0.302	0.998
WTI	0.462	0.107	0.238	0.005	0.011	0.514	0.477	0.131	0.003	0.255	0.052°	0.729	0.951	0.144	0.011	0.466	0.711	0.529	0.880	0.507	0.082°	0.522	0.273	0.216	0.066°	0.829
Industrial Metals																										
Aluminium	0.836	0.285	0.358	0.001	0.001	0.777	0.463	0.048	0.001	0.026	0.008	0.052°	0.739	0.056°	0.249	0.714	0.521	0.031	0.311	0.115	0.081°	0.356	0.388	0.851	0.764	0.647
Cobalt	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Copper	0.541	0.538	0.114	0.001	0.001	0.134	0.278	0.045	0.002	0.010	0.675	0.652	0.556	0.040	0.090°	0.896	0.284	0.085°	0.811	0.083°	0.011	0.040	0.784	0.965	0.724	0.001
Lead	0.747	0.826	0.340	0.001	0.001	0.230	0.220	0.025	0.006	0.030	0.345	0.486	0.558	0.111	0.043	0.292	0.847	0.236	0.573	0.053°	0.038	0.066°	0.571	0.984	0.776	0.029
Nickel	0.187	0.888	0.774	0.001	0.001	0.150	0.396	0.184	0.010	0.007	0.280	0.445	0.809	0.186	0.036	0.277	0.080°	0.128	0.286	0.001	0.007	0.023	0.405	0.646	0.729	0.155
Tin	0.991	0.862	0.012	0.004	0.014	0.389	0.548	0.412	0.004	0.011	0.227	0.813	0.996	0.067°	0.051°	0.298	0.140	0.108	0.245	0.132	0.046	0.187	0.839	0.522	0.986	0.212
Zinc	0.716	0.185	0.344	0.001	0.001	0.822	0.084°	0.043	0.176	0.151	0.745	0.103	0.730	0.035	0.101	0.217	0.179	0.053°	0.594	0.064°	0.017	0.028	0.674	0.888	0.701	0.009
Precious Metals																										
Gold	0.133	0.900	0.537	0.043	0.005	0.086°	0.495	0.223	0.705	0.753	0.717	0.422	0.694	0.347	0.289	0.281	0.955	0.725	0.512	0.510	0.933	0.765	0.504	0.450	0.403	0.045
Palladium	0.091°	0.385	0.705	0.001	0.001	0.678	0.535	0.397	0.123	0.201	0.179	0.042	0.659	0.013	0.051°	0.002	0.394	0.044	0.849	0.018	0.183	0.391	0.727	0.595	0.223	0.485
Platinum	0.058°	0.148	0.544	0.001	0.001	0.976	0.868	0.658	0.102	0.282	0.330	0.043	0.921	0.131	0.080°	0.639	0.007	0.295	0.777	0.792	0.294	0.565	0.996	0.885	0.527	0.636
Silver	0.105	0.535	0.907	0.001	0.001	0.571	0.843	0.039	0.764	0.823	0.383	0.262	0.279	0.103	0.243	0.571	0.619	0.542	0.411	0.260	0.612	0.717	0.364	0.703	0.236	0.049
Portfolios / PC1																										
Softs	0.978	0.070°	0.656	0.001	0.001	0.394	0.787	0.162	0.021	0.030	0.834	0.541	0.921	0.013	0.054°	0.335	0.176	0.493	0.165	0.085°	0.386	0.143	0.163	0.470	0.669	0.325
Grains	0.369	0.177	0.326	0.003	0.001	0.560	0.996	0.150	0.210	0.063°	0.675	0.092°	0.735	0.034	0.519	0.144	0.211	0.662	0.030	0.295	0.248	0.255	0.915	0.381	0.039	0.919
Livestock	0.531	0.999	0.089°	0.253	0.847	0.574	0.523	0.595	0.010	0.020	0.698	0.480	0.948	0.740	0.968	0.145	0.983	0.511	0.025	0.404	0.100	0.052°	0.699	0.707	0.711	0.853
Energy	0.117	0.063°	0.767	0.008	0.003	0.637	0.650	0.031	0.003	0.096°	0.373	0.815	0.844	0.048	0.028	0.929	0.311	0.431	0.960	0.219	0.326	0.425	0.382	0.229	0.023	0.729
Industrial M.	0.960	0.555	0.228	0.001	0.001	0.242	0.221	0.032	0.001	0.002	0.304	0.156	0.800	0.023	0.032	0.702	0.387	0.040	0.370	0.027	0.056°	0.039	0.677	0.767	0.739	0.024
Precious M.	0.066°	0.391	0.651	0.001	0.001	0.485	0.764	0.140	0.769	0.442	0.456	0.138	0.225	0.050°	0.077°	0.024	0.354	0.272	0.794	0.333	0.312	0.496	0.511	0.829	0.257	0.256
Common F.	0.456	0.156	0.203	0.001	0.001	0.599	0.489	0.008	0.005	0.004	0.174	0.351	0.970	0.013	0.003	0.386	0.082°	0.182	0.332	0.078°	0.059°	0.127	0.856	0.812	0.062°	0.327

Notes: This table shows bootstrapped p-values with N = 999 replications for testing the null hypothesis of non-causality from potential HF and LF drivers to commodity futures at the prediction horizon h = 1, which is daily for HF and monthly for LF drivers. Granger causality tests are based on bivariate MF-VAR (HF-VAR) models with lag order P = 1 using weekly (daily) commodity returns, and monthly (daily) (log-differenced) data for potential drivers, i.e., m = 4 (m = 1). Data was demeaned prior to VAR estimation. A highlighted cell (circle) indicates the rejection of non-causality at the 5% (10%) level. The sample spans the period 2004:1–2013:12 where data is available over the full horizon. Results are only displayed for pairs of which data is available at least over half of the sample period.

Table C.24: Bootstrapped p-values of pairwise Granger causality tests for the null of non-causality from potential drivers - - - commodities, 2014-2019

	Fundamental (HF)			**Financial**(HF)		**Uncertainty** (HF)			**Fundamental** (LF)								**Financial**(LF)		**Uncertainty** (LF)							
	BDI	TBILL	USDEER	SPX	VIX	TED	EPU	GEOVOL	WIP	GECON	BDI	STEEL	GSCPI	INFL	INFLE	CSENT	SPX	VIX	ISENT	FUNC	MUNC	RUNC	TED	GEPU	GPR	GEOVOL
Softs																										
Cocoa	0.774	0.071°	0.507	0.772	0.202	0.046	0.038	0.573	0.382	0.325	0.077°	0.934	0.563	0.414	0.378	0.339	0.243	0.320	0.793	0.374	0.765	0.434	0.615	0.977	0.059°	0.645
Coffee	0.574	0.762	0.095°	0.654	0.462	0.610	0.446	0.043	0.776	0.976	0.633	0.234	0.419	0.016	0.285	0.958	0.707	0.254	0.442	0.904	0.955	0.730	0.228	0.316	0.908	0.016
Cotton	0.156	0.202	0.634	0.632	0.558	0.044	0.697	0.875	0.156	0.315	0.379	0.219	0.635	0.462	0.071°	0.302	0.035	0.110	0.129	0.020	0.039	0.223	0.552	0.480	0.836	0.894
Ethanol	0.542	0.048	0.820	0.979	0.889	0.069°	0.936	0.578	0.830	0.699	0.528	0.594	0.101	0.066°	0.138	0.038	0.583	0.573	0.817	0.949	0.544	0.999	0.771	0.150	0.236	0.873
Lumber	0.195	0.002	0.631	0.896	0.598	0.003	0.944	0.792	0.781	0.310	0.936	0.699	0.474	0.225	0.237	0.187	0.100	0.846	0.685	0.959	0.593	0.223	0.324	0.765	0.701	0.151
Orange Juice	0.802	0.931	0.059°	0.355	0.052°	0.894	0.591	0.806	0.245	0.633	0.118	0.860	0.501	0.302	0.521	0.048	0.612	0.432	0.844	0.732	0.230	0.873	0.632	0.794	0.474	0.729
Rubber	0.120	0.082°	0.311	0.002	0.001	0.201	0.282	0.982	0.896	0.428	0.083°	0.174	0.163	0.747	0.043	0.311	0.092°	0.106	0.489	0.334	0.258	0.499	0.266	0.709	0.917	0.326
Sugar	0.071°	0.929	0.190	0.128	0.533	0.566	0.461	0.924	0.966	0.160	0.324	0.966	0.674	0.007	0.661	0.212	0.069°	0.419	0.886	0.076°	0.284	0.745	0.377	0.103	0.700	0.604
Wool	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Grains																										
Corn	0.170	0.391	0.986	0.081°	0.057°	0.111	0.657	0.250	0.842	0.009	0.212	0.579	0.172	0.039	0.063°	0.106	0.859	0.709	0.540	0.273	0.310	0.897	0.738	0.497	0.864	0.683
Oats	0.755	0.293	0.391	0.192	0.608	0.154	0.459	0.682	0.444	0.068°	0.657	0.385	0.782	0.307	0.097°	0.366	0.150	0.178	0.887	0.220	0.623	0.768	0.643	0.419	0.953	0.510
Rough Rice	0.370	0.348	0.599	0.755	0.320	0.842	0.439	0.284	0.453	0.882	0.102	0.983	0.542	0.132	0.565	0.712	0.353	0.601	0.912	0.084°	0.151	0.945	0.618	0.050°	0.308	0.559
Soybean	0.285	0.142	0.945	0.416	0.452	0.039	0.353	0.973	0.803	0.234	0.330	0.799	0.134	0.119	0.006	0.514	0.098°	0.260	0.645	0.795	0.021	0.010	0.823	0.175	0.620	0.942
Soybean Meal	0.844	0.262	0.889	0.169	0.257	0.103	0.177	0.373	0.503	0.287	0.419	0.051°	0.133	0.811	0.043	0.682	0.253	0.708	0.326	0.742	0.130	0.064°	0.375	0.171	0.335	0.717
Soybean Oil	0.785	0.406	0.824	0.186	0.259	0.632	0.272	0.413	0.784	0.186	0.750	0.059°	0.926	0.003	0.288	0.341	0.319	0.530	0.407	0.079°	0.528	0.510	0.188	0.342	0.577	0.737
Wheat	0.074°	0.678	0.364	0.227	0.177	0.160	0.915	0.503	0.238	0.643	0.948	0.091°	0.866	0.013	0.354	0.482	0.674	0.693	0.663	0.092°	0.395	0.502	0.816	0.138	0.413	0.677
Livestock																										
Feeder Cattle	0.400	0.003	0.846	0.242	0.092°	0.052°	0.013	0.791	0.174	0.175	0.861	0.704	0.054°	0.200	0.071°	0.113	0.632	0.972	0.536	0.153	0.632	0.710	0.425	0.320	0.972	0.135
Lean Hogs	0.590	0.515	0.062°	0.605	0.890	0.558	0.045	0.182	0.756	0.426	0.312	0.023	0.037	0.010	0.843	0.642	0.490	0.016	0.773	0.279	0.647	0.341	0.539	0.695	0.768	0.539
Live Cattle	0.594	0.056°	0.641	0.065°	0.040	0.097°	0.010	0.190	0.951	0.939	0.940	0.560	0.612	0.042	0.216	0.647	0.756	0.604	0.496	0.599	0.002	0.173	0.574	0.004	0.319	0.486
Pork Bellies	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Energy																										
Brent	0.116	0.046	0.360	0.101	0.209	0.118	0.140	0.269	0.845	0.664	0.933	0.443	0.498	0.265	0.667	0.316	0.977	0.480	0.132	0.030	0.598	0.427	0.576	0.068°	0.983	0.012
Gasoil	0.261	0.064°	0.210	0.011	0.014	0.192	0.983	0.199	0.525	0.666	0.426	0.230	0.820	0.860	0.732	0.257	0.941	0.630	0.162	0.008	0.260	0.473	0.682	0.273	0.825	0.023
Gasoline	0.351	0.425	0.505	0.166	0.468	0.629	0.107	0.088°	0.723	0.495	0.060°	0.437	0.579	0.564	0.983	0.331	0.648	0.902	0.103	0.016	0.471	0.378	0.888	0.554	0.922	0.137
Heating Oil	0.211	0.235	0.322	0.157	0.497	0.418	0.116	0.413	0.373	0.240	0.581	0.391	0.819	0.291	0.179	0.272	0.996	0.555	0.138	0.046	0.725	0.442	0.537	0.059°	0.899	0.104
Natural Gas	0.065°	0.695	0.987	0.345	0.170	0.710	0.296	0.959	0.607	0.851	0.019	0.653	0.896	0.609	0.890	0.927	0.494	0.376	0.342	0.341	0.056°	0.019	0.677	0.248	0.747	0.154
WTI	0.199	0.056°	0.672	0.362	0.598	0.124	0.071°	0.276	0.726	0.919	0.980	0.609	0.638	0.564	0.568	0.259	0.913	0.415	0.776	0.003	0.194	0.579	0.791	0.182	0.982	0.042
Industrial Metals																										
Aluminium	0.843	0.055°	0.095°	0.124	0.060°	0.079°	0.300	0.528	0.112	0.058°	0.981	0.083°	0.992	0.019	0.744	0.834	0.758	0.836	0.710	0.060°	0.904	0.882	0.206	0.055°	0.475	0.145
Cobalt	0.067°	0.431	0.609	0.022	0.015	0.566	0.359	0.385	0.617	0.023	0.541	0.873	0.655	0.098°	0.464	0.686	0.257	0.456	0.221	0.041	0.007	0.315	0.125	0.276	0.127	0.513
Copper	0.814	0.066°	0.638	0.050°	0.009	0.048	0.363	0.187	0.264	0.365	0.866	0.694	0.769	0.008	0.318	0.423	0.067°	0.396	0.893	0.301	0.097°	0.032	0.720	0.394	0.480	0.146
Lead	0.176	0.089°	0.326	0.325	0.077°	0.037	0.562	0.870	0.643	0.119	0.880	0.404	0.480	0.002	0.346	0.014	0.325	0.137	0.952	0.562	0.289	0.563	0.409	0.056°	0.887	0.918
Nickel	0.619	0.012	0.338	0.431	0.048	0.011	0.359	0.460	0.347	0.963	0.428	0.661	0.537	0.070°	0.764	0.171	0.677	0.860	0.567	0.732	0.415	0.599	0.837	0.053°	0.180	0.161
Tin	0.438	0.164	0.009	0.219	0.072°	0.016	0.086°	0.271	0.388	0.069°	0.092°	0.462	0.614	0.676	0.394	0.218	0.053°	0.626	0.504	0.889	0.732	0.280	0.105	0.254	0.259	0.979
Zinc	0.353	0.006	0.342	0.006	0.003	0.001	0.263	0.294	0.549	0.029	0.504	0.416	0.435	0.001	0.380	0.428	0.032	0.405	0.327	0.432	0.961	0.693	0.960	0.043	0.634	0.620
Precious Metals																										
Gold	0.806	0.041	0.769	0.987	0.897	0.668	0.325	0.266	0.784	0.452	0.606	0.053°	0.351	0.124	0.049	0.661	0.402	0.456	0.554	0.710	0.815	0.767	0.464	0.223	0.970	0.291
Palladium	0.328	0.009	0.369	0.006	0.025	0.023	0.955	0.810	0.128	0.721	0.126	0.279	0.465	0.161	0.613	0.047	0.001	0.435	0.703	0.434	0.940	0.445	0.226	0.248	0.821	0.910
Platinum	0.665	0.002	0.336	0.068°	0.131	0.125	0.173	0.315	0.957	0.394	0.031	0.346	0.049	0.010	0.278	0.538	0.089°	0.135	0.432	0.059°	0.516	0.408	0.499	0.068°	0.984	0.276
Silver	0.147	0.090°	0.984	0.053°	0.094°	0.650	0.482	0.208	0.698	0.124	0.207	0.450	0.297	0.087°	0.145	0.444	0.170	0.395	0.332	0.533	0.483	0.839	0.306	0.055°	0.997	0.613
Portfolios / PC1																										
Softs	0.678	0.005	0.970	0.102	0.084°	0.006	0.487	0.514	0.551	0.481	0.027	0.989	0.950	0.308	0.618	0.166	0.061°	0.130	0.333	0.398	0.622	0.093°	0.337	0.497	0.414	0.521
Grains	0.290	0.581	0.637	0.677	0.393	0.248	0.630	0.969	0.897	0.252	0.064°	0.214	0.443	0.116	0.002	0.402	0.241	0.235	0.845	0.281	0.351	0.263	0.645	0.126	0.487	0.744
Livestock	0.671	0.037	0.128	0.631	0.360	0.142	0.001	0.729	0.203	0.255	0.300	0.310	0.903	0.080°	0.681	0.996	0.770	0.718	0.804	0.452	0.379	0.331	0.117	0.330	0.893	0.493
Energy	0.068°	0.071°	0.455	0.202	0.595	0.197	0.239	0.252	0.531	0.733	0.714	0.501	0.600	0.288	0.750	0.367	0.589	0.733	0.036	0.035	0.227	0.128	0.918	0.017	0.715	0.020
Industrial M.	0.755	0.011	0.030	0.098°	0.015	0.001	0.240	0.814	0.058°	0.262	0.694	0.188	0.863	0.002	0.373	0.527	0.768	0.299	0.919	0.440	0.359	0.353	0.727	0.014	0.751	0.408
Precious M.	0.396	0.005	0.999	0.030	0.042	0.075°	0.409	0.357	0.476	0.459	0.015	0.319	0.249	0.092°	0.225	0.649	0.124	0.844	0.447	0.763	0.739	0.525	0.706	0.310	0.990	0.499
Common F.	0.407	0.002	0.386	0.124	0.164	0.003	0.250	0.378	0.341	0.376	0.414	0.255	0.997	0.532	0.413	0.254	0.038	0.687	0.313	0.092°	0.136	0.083°	0.938	0.003	0.941	0.206

Notes: This table shows bootstrapped p-values with $N = 999$ replications for testing the null hypothesis of non-causality from potential HF and LF drivers to commodity futures at the prediction horizon $h = 1$, which is daily for HF and monthly for LF drivers. Granger causality tests are based on bivariate MF-VAR (HF-VAR) models with lag order $P = 1$ using weekly (daily) commodity returns, and monthly (daily) (log-differenced) data for potential drivers, i.e., $m = 4$ ($m = 1$). Data was demeaned prior to VAR estimation. 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. Results are only displayed for pairs of which data is available at least over half of the sample period.

Table C.25: Share of rejections of the null of non-causality per driver

		1998–2019			**1998–2003**			**2004–2013**			**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
1st Principal Components													
Fundamental PC	m = 4	**0.3023**	**0.5581**	**0.5581**	0.0244	**0.2439**	0.3415	**0.3023**	**0.5349**	**0.5814**	0.0000	0.0238	0.0476
	m = 1	**0.3721**	**0.5581**	0.6512	**0.3415**	**0.4146**	**0.4146**	**0.3721**	**0.6047**	**0.7209**	0.0238	0.0714	0.0952
Financial PC	m = 4	0.0000	0.0930	0.2326	0.0000	0.0732	0.2195	0.0000	0.1163	0.2093	0.0000	0.0238	0.0952
	m = 1	0.0000	0.0465	0.1163	0.0488	0.1220	0.1951	0.0000	0.0465	0.1628	0.0000	0.0238	0.0714
Uncertainty PC	m = 4	0.1163	0.3256	0.3953	0.0000	0.0976	0.2195	0.0465	0.2791	0.4186	0.0000	0.0714	0.1190
	m = 1	0.1395	0.4186	0.5814	0.0732	0.1707	0.2439	0.1395	0.5349	0.6744	0.0238	0.0238	0.0714
Fundamental													
WIP	m = 4	0.2558	0.4419	0.5349	0.0000	0.0732	0.1220	**0.3023**	0.4186	0.4884	0.0000	0.0000	0.0238
	m = 1	0.2093	**0.5581**	0.5814	0.0000	0.0732	0.2683	0.1860	0.3953	0.6744	0.0238	0.1190	0.2143
GECON	m = 4	0.1395	0.4186	**0.5581**	0.0244	0.0976	0.1951	0.0930	0.3023	0.3953	0.0238	0.0714	0.1429
	m = 1	0.1628	0.2326	0.2558	0.1220	0.2683	0.3659	0.0233	0.1395	0.3488	0.0000	0.0476	0.0714
BDI	m = 4	0.0465	0.1163	0.2093	0.0000	0.1220	**0.3659**	0.0233	0.0698	0.1860	0.0000	0.0952	0.2143
	m = 1	0.0000	0.0930	0.1860	0.0244	0.1951	0.2439	0.0698	0.0930	0.1395	0.0238	0.0952	0.1190
STEEL	m = 4	0.0465	0.2093	0.3023	0.0000	0.0976	0.1463	0.0000	0.0698	0.1395	0.0000	0.0238	0.1429
	m = 1	0.0233	0.2791	0.4186	0.0000	0.1463	0.2195	0.0000	0.0465	0.0930	0.0000	**0.1667**	**0.2619**
GSCPI	m = 4	0.0000	0.0000	0.0000	0.0000	0.0244	0.0244	0.0000	0.0000	0.0000	0.0000	0.0476	0.0714
	m = 1	0.0000	0.0000	0.0465	0.0000	0.0000	0.0244	0.0000	0.0000	0.0000	0.0000	0.0238	0.0714
INFL	m = 4	0.0000	0.1628	0.3023	0.0244	0.0732	0.1707	0.0930	0.3488	0.5581	**0.1429**	**0.3095**	**0.4524**
	m = 1	0.0698	0.1860	0.4884	0.0000	0.0244	0.1463	0.2326	0.4884	0.6512	**0.0476**	0.0952	0.1190
INFLE	m = 4	0.0233	0.1395	0.2093	**0.0488**	0.1951	0.3171	0.1163	0.2558	0.4186	0.0476	0.1190	0.2143
	m = 1	0.1163	0.3488	0.4419	0.0488	0.1463	0.2439	0.1395	0.5581	0.6279	0.0238	0.1190	0.2381
CSENT	m = 4	0.0000	0.0465	0.0930	0.0000	0.0488	0.1220	0.0233	0.0698	0.0698	0.0000	0.0952	0.0952
	m = 1	0.0000	0.0930	0.1628	0.0976	0.2195	0.2683	0.0000	0.0698	0.0930	0.0238	0.1190	0.1905
Financial													
SPX	m = 4	0.0000	0.0233	0.1163	0.0000	0.0488	0.0732	0.0233	0.0233	0.0930	0.0238	0.0952	0.2619
	m = 1	0.0000	0.0000	0.0698	0.0244	0.1463	0.2195	0.0000	0.0233	0.1395	0.0000	0.0952	0.1905
VIX	m = 4	0.0000	0.0465	0.1628	0.0000	0.0488	0.0976	0.0000	0.1163	0.1628	0.0000	0.0238	0.0238
	m = 1	0.0465	0.0698	0.1628	0.0488	0.0732	0.1220	0.0233	0.1163	0.2326	0.0000	0.0238	0.0476
ISENT	m = 4	0.0000	0.1628	0.2326	0.0244	0.0732	0.0976	0.0000	0.0465	0.1628	0.0000	0.0238	0.0238
	m = 1	0.0000	0.0698	0.1628	0.0244	0.0488	0.0732	0.0233	0.0233	0.1163	0.0000	0.0238	0.0952
Uncertainty													
FUNC	m = 4	0.0465	0.2326	0.3023	0.0000	0.0488	0.0976	0.0233	0.0930	0.2093	0.0476	0.1905	0.3571
	m = 1	0.2558	0.3953	0.4419	0.0244	0.1463	0.2439	0.1860	0.3721	0.5116	**0.0476**	0.0952	0.0952
MUNC	m = 4	0.1163	0.2558	0.4419	0.0244	0.1463	0.1951	0.0233	0.2093	0.3256	0.0476	0.0952	0.1429
	m = 1	0.0698	0.5116	**0.7209**	0.0732	0.2683	0.2683	0.1163	0.3953	0.5814	0.0000	0.0476	0.0476
RUNC	m = 4	0.0000	0.1163	0.1860	0.0000	0.0976	0.1220	0.0000	0.2093	0.3023	0.0000	0.0714	0.1429
	m = 1	0.0000	0.1395	0.2791	0.0244	0.0976	0.1707	0.0000	0.1860	0.3721	0.0000	0.0476	0.0952
TED	m = 4	0.0000	0.0233	0.0698	0.0000	0.0244	0.0732	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	m = 1	0.0000	0.0000	0.0233	0.0000	0.0976	0.1220	0.0000	0.0000	0.0698	0.0000	0.0476	0.0952
GEPU	m = 4	0.0233	0.0698	0.0698	0.0000	0.0488	0.1463	0.0000	0.0000	0.0465	0.0476	0.1190	0.3095
	m = 1	0.0000	0.0465	0.0930	0.0000	0.1463	0.2927	0.0000	0.0233	0.0233	0.0000	0.0476	0.0714
GPR	m = 4	0.0000	0.0000	0.0465	0.0000	0.1220	0.2439	0.0233	0.1860	0.2558	0.0000	0.0000	0.0238
	m = 1	0.0000	0.0465	0.0698	0.0000	0.0732	0.2195	0.0930	0.2093	0.2093	0.0000	0.0238	0.0238
GEOVOL	m = 4	0.0238	0.1190	0.1667	0.0000	0.0244	0.0732	0.0465	0.1395	0.1395	0.0000	0.1190	0.1190
	m = 1	0.0238	0.0476	0.2143	0.0000	0.0732	0.1463	0.0000	0.0233	0.0930	0.0000	0.0000	0.0476
total	m = 4	0.0543	0.1696	0.2472	0.0081	0.0871	0.1649	0.0543	0.1661	0.2458	0.0181	0.0771	0.1440
	m = 1	0.0710	0.1973	0.2938	0.0465	0.1405	0.2149	0.0764	0.2071	0.3112	0.0113	0.0646	0.1111

Notes: This table shows the proportion of all bivariate Granger causality tests for a given LF variable in which the null hypothesis of non-causality from the LF variable to the commodity futures is rejected at the 1%, 5%, and 10% level, respectively. Including commodity portfolios and the common factor, we conduct 43 Granger causality tests per driver for the full sample (1998–2019), 41 for the first (1998–2003), 43 for the second (2004–2013), and 42 for the third subsample (2014–2019). Granger causality tests are based on bivariate MF-VAR (LF-VAR) models using weekly (monthly) commodity returns, i.e., m = 4 (m = 1).

Table C.26: 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.

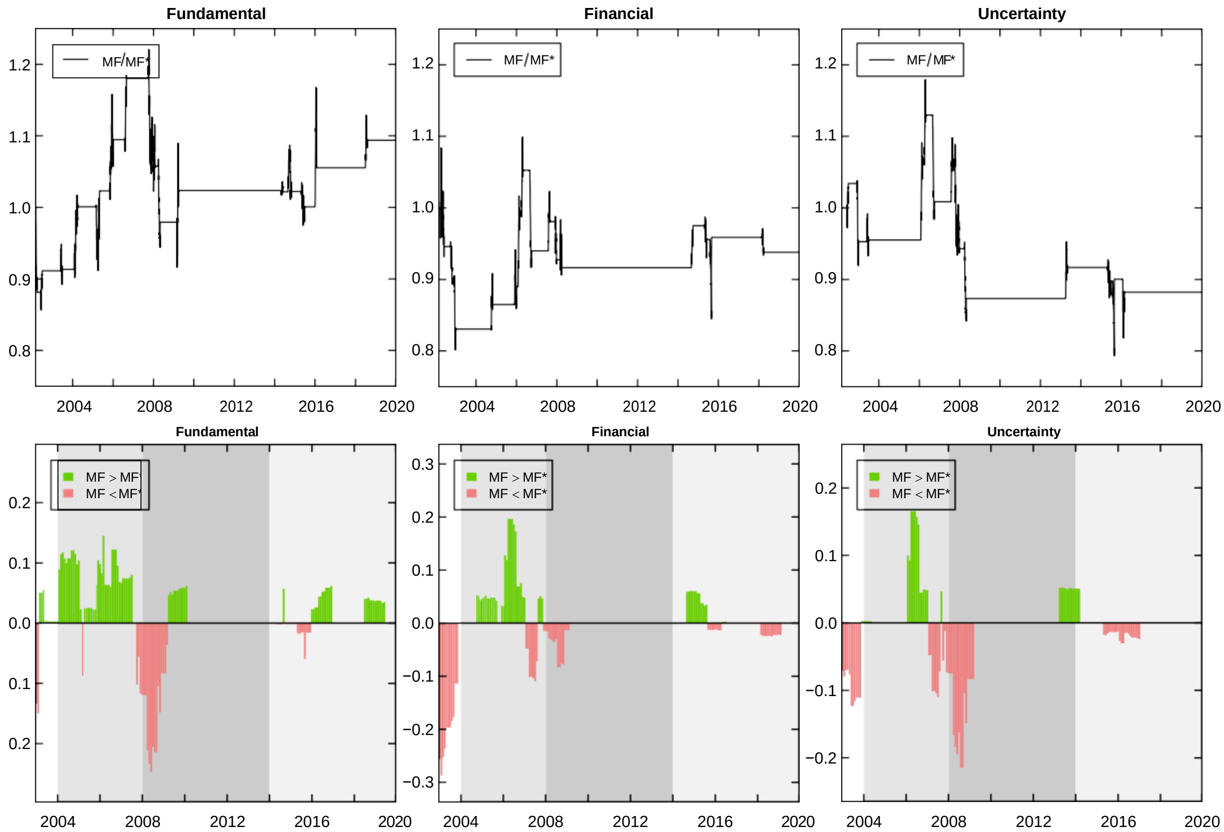

Figure C.7: Cumulative returns of MF-VARs ($m = 4$) relative to MF-VARs ($m = 4$) without including a driver variable (MF-VAR*) for trading the S&P GSCI based on averaged one-month-ahead directional return forecast from bivariate VAR models (upper panel) and 12-month rolling excess returns of MF-VARs ($m = 4$) over MF-VAR ($m = 4$) without including a driver (MF-VAR*) on a monthly basis (lower panel). The trading period runs from the end of 2002:2 to 2019:12. Shadings indicate the following periods: Pre-Financialization (1998–2003), Emerging Financialization (2004–2007), Global Financial Crisis (2008–2013), and De-Financialization (2014–2019).