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Long-memory and volatility spillovers across petroleum futures☆

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ABSTRACT

Return volatility usually presents a degree of persistence, which, although still consistent with an essential stationary process, cannot be adequately captured by standard autoregressive specifications. In this study, we examine the transmission mechanism across petroleum volatilities accounting for this stylized fact. To do so, we compute both time and frequency domain measures of connectedness based on variance decompositions from a fractionally integrated VAR (FIVAR). Our main findings summarize: (1) there is strong evidence of long-memory in petroleum volatilities, but no evidence of infinite variances; (2) an adequate quantification of spillovers must consider long-memory persistence explicitly; (3) spillovers are relatively high, but considerably lower than predicted in the traditional short-memory framework, especially at low frequencies. Thus, accounting for long-memory has asymmetric implications for different market participants.

1. Introduction

Researchers have investigated the volatility of petroleum commodities, finding significant cross-market spillover effects [1–10]. However, existing studies implicitly restrict volatilities to have short-memory, imposing shocks to vanish at a fast, exponential rate. A fast degree of mean-reversion is at odds with the observed persistence, as there is overwhelming evidence that petroleum markets take much time to forget volatility shocks.

For example, Choi and Hammoudeh [11] find strong evidence of long-memory in the volatilities of oil, natural gas, and gasoline futures. Support for long-memory is consistently found in many other petroleum volatility studies [12–21]. The solid evidence of long-memory questions the accuracy of spillover assessment in earlier studies, all confined to short memory in their econometric specifications.

This paper investigates volatility spillovers across petroleum markets, making two significant contributions to the literature. First, we relax the questionable assumptions on the persistence of petroleum volatilities in previous spillover studies by accounting for the long-memory possibility. To do so, we rely on the connectedness methodology of Diebold and Yilmaz [22,23] (henceforth DY), like many other spillover studies in the literature. However, instead of computing the connectedness indices from a vector autoregression (VAR), as typically in DY, we employ a fractionally integrated VAR (FIVAR).

The objective is twofold. First, we do not assume the persistence of petroleum volatilities but estimate it from the data. Second, unlike the VAR, which imposes short-memory, the FIVAR accommodates short-and long-term memory. The proposed model generates a realistic pattern for the responses of volatilities to shocks, imparting substantial persistence without imposing explosive trends, which is consistent with the empirical evidence.

The second contribution extends the frequency-domain approach proposed in Barunik and Krehlik [24] (BK, henceforth) to long-memory specifications. This extension, never considered before, allows us to compare connectedness measures based on short- and long-memory specifications across frequency ranges. Assessing connectedness by frequency ranges is essential for studying volatility spillovers because agents have preferences over different trading horizons, as stressed in recent financial literature [24–27]. Consider, for instance, that spillovers were significant at high frequencies but negligible at low frequencies. In such a situation, shocks transmitted across markets would have short-term effects only, not much of an issue for an agent looking for long-run investment but critical for a short-term trader.

Our findings can be summarized as follows:

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1. Consistent with univariate studies, we find strong evidence of long-memory in the weekly volatilities of petroleum futures, with short-memory decisively rejected by the data. The estimated long-memory orders lie within the stationary region.
2. Accounting for long-memory is essential to quantify spillovers. The traditional (short memory) VAR largely understates the contribution of own shocks to the variances, magnifying spillover effects, especially at low frequencies. Thus, although contagion risk is relatively high, it is significantly smaller than the traditional VAR stipulates. This result indicates that although hedge holdings (a long position) in one market with a short sell in another is possible, the hedge is considerably more costly. This finding is particularly relevant for long-term traders, as most of the discrepancies between the short- and long-memory specifications are concentrated within medium and low frequencies.
3. These findings are robust across rolling windows, accounting for both (possible) spillover variation and structural changes.

Many other energy studies rely on the DY framework to assess spillovers. However, none of these works have accounted for long-memory persistence. Minimal attention has been paid to how relaxing persistence assumptions impacts spillover indices, even outside the energy literature. This is *a priori* surprising, given the popularity of both the DY methodology and long-memory specifications in finance. GARCH-type studies have already stressed the importance of long-memory in analyzing co-movement (e.g., Refs. [28–30]).

To our knowledge, only Cipollini et al. [31]; studying transmission across country risk premia, have attempted to address this issue. Their results suggest that the long-memory specifications may lead to substantial spillover assessment differences when persistence is strong. Our results also indicate that the degree of persistence must be explicitly considered while computing connectedness indices. However, connectedness measures in the frequency domain, which Cipollini et al. [31] do not consider, show that the differences between short- and long-memory specifications concentrate at specific frequencies, impacting asymmetrically on different agents.

We organize the remainder of the paper as follows. Section 2 makes a concise review of the literature, placing this work in the context of existing studies. Section 3 discusses the econometric framework. Section 4 contains the empirical analysis and discusses the implications of our findings, while Section 5 offers some concluding remarks. Additional results and robustness tests are furnished in a separate Supplement.

2. Literature review

Literature assessing volatility spillovers in energy markets focuses on the linkages between oil and the financial market (e.g., Refs. [32–44]. However, the volatility linkages across energy commodities have recently become an active field of research. For critical markets, such as petroleum, this knowledge also concerns policymakers, as petroleum futures play a fundamental role in transferring the risk from energy producers and consumers to speculators. Consequently, regulators must rigorously monitor these volatilities to control excessive price variation, which may otherwise jeopardize supply security.

Given the importance of oil in the economy, most of the existing studies examining spillovers across energy markets concentrate on petroleum (e.g., Refs. [1–10]. The general conclusion is that there are strong volatility linkages across different petroleum commodities and oil markets at various locations.

Researchers have examined volatility spillovers in other energy markets as well, also finding significant linkages. For example, Ewing et al. [45]; Karali and Ramirez [5]; Lin and Li [46]; Perifanis and Dagoumas [47], or Lovcha and Perez-Laborda [48] study the nexus between oil and gas volatilities. Volatility linkages across electricity markets are considered, e.g., in Le Pen and Sevi [49] or Apergis et al. [50]. Batten et al. [51] and Li et al. [52] have recently analyzed the volatility connections in coal markets. Also, Liu and Chen [29]; Reboredo [53]; Ji et al. [54]; Chang et al. [38]; Chulia et al. [55]; Lin and Chen [56]; or Wang and Guo [57]; study volatility spillovers between the carbon and other energy markets. The existence of volatility linkages across energy markets has also been stressed in more general studies analyzing volatility spillovers across a broad set of commodities (e.g., Refs. [58,59].

From the methodological perspective, the literature on volatility spillovers traditionally relied on GARCH-type specifications, such as Haigh and Holt [2]. However, the framework of DY is becoming the standard nowadays, as it is particularly suited to analyze systems of interrelated variables.[1] The approach of BK is gaining favor fast among researchers, as one obtains measures of connectedness by frequency ranges in addition to standard (time-domain) DY indices (e.g., Ref. [7,40,41,44,48,51,60,61]).

The most closely related works are Barunik et al. [6] and Krehlik and Barunik [7]; which rely on DY to assess volatility spillovers across petroleum commodities. Specifically, Barunik et al. [6] employ realized semi-variances combined with DY indices, finding strong spillover effects. Krehlik and Barunik [7] assess the linkages across frequency ranges relying on the frequency-domain approach of BK. We complement these two interesting studies by focusing on another stylized fact of petroleum volatilities, long-range dependence.

3. Econometric framework

3.1. The FIVAR model and its estimation procedure

The FIVAR model is a linear model for vector time series, which is the multivariate extension of the well-known autoregressive ARFIMA [62,63]. As in Abbritti et al. [64] or Lovcha and Perez-Laborda [65]; we employ an unrestricted FIVAR specification that allows volatilities to have different integration orders, consistent with the results in univariate studies (e.g., Ref. [11].[2]

Let $Y_t = [y_{1t}, \ldots, y_{Nt}]'$ contain all the volatility series. An unrestricted FIVAR model for Y_t can be written as:

$$D(L)Y_t = u_t$$

$$u_t = F(L)u_{t-1} + \xi_t, \tag{1}$$

where $D(L)$ is a diagonal matrix with elements given by $(1-L)^{d_j}$, and $d_j \in [0,1]$ is the order of fractional integration $I(d_j)$ of the n-th series of the vector Y_t. Finally, $F(L)$ is a polynomial matrix of order p of autoregressive coefficients governing the short-run dynamics and ξ_t is a vector of zero-mean errors with $\sum$ variance-covariance matrix.

The fundamental properties of the series y_j in Y_t can be described in terms of its long-memory parameter d_j. The larger this

[1] The literature relying on DY to assess volatility spillovers is too long to be reviewed here. Energy studies within this framework include, among many others, Zhang and Wang [4]; Barunik et al. [6]; Apergis et al. [50], Magonkis and Tsukindis [8], Zhang [91], Antonakakis et al. [37], Ji et al. [54]; Krehlik and Barunik [7], Chulia et al. [55]; Batten et al. [51,57]; Li et al. [52]; or Lovcha and Perez-Laborda [48].

[2] Fractional co-integrated models, like the ones considered in Johansen [85] or Johansen and Nielsen [86]; impose equal coefficients of fractional integration for all variables and do not nest the FIVAR specification.

parameter, the more persistent the series is. If $d_j = 0$ or $d_j = 1$, y_j exhibits standard $I(0)$ or $I(1)$ properties. If $0 < d_j < 1$, the series has long-memory, with the effect of a shock fading away considerably slower than in the $I(0)$ case. In the particular case that $0 < d_j < 0.5$, y_j is still covariance stationary. However, if $0.5 \le d_j < 1$, the series is not stationary anymore, although still mean-reverting.

To estimate the model, we maximize the approximate frequency-domain likelihood ('Whittle'), as proposed by Hosoya [66]. Following this methodology, the orders of integration of the volatility series are not assumed from the outset but estimated jointly with the other parameters, representing an efficiency gain over two-step procedures, such as in Lobato [67].[3] Lovcha and Perez-Laborda [68] and Abbriti et al. [64] contain details on the estimation procedure.

3.2. Connectedness indices from the FIVAR model

3.2.1. Time-domain connectedness

DY indices are based on forecast error decomposition of autoregressive specifications and measure the contribution that a shock to one entity in the system has on the future uncertainty of the others. These indices can be computed from the estimated FIVAR accounting for the diagonal matrix containing fractional differences. Like in Diebold and Yilmaz [22,23]; we rely on generalized impulse-response [69] to deal with possible correlated innovations.

Let the M.A. (∞) representation of the FIVAR model in (1) be:

$$Y_t = D(L)^{-1}[I - F(L)]^{-1}\xi_t = \Lambda(L)\xi_t, \tag{2}$$

The matrix elements $\Lambda(L)$ are infinite polynomials whose coefficients are the impulse responses (IRF) of the variables to innovations. IRFs in the FIVAR are computed by expanding the diagonal elements of $D(L)$ with the gamma function $\Gamma(\bullet)$:

$$(1 - L)^{d_j} = \sum_{k=0}^{\infty} D_{j,k} L^k, \tag{3}$$

where $D_{j,k} = \Gamma(k - d_j) / \Gamma(k + 1)\Gamma(-d_j)$.

From Eq. (3), we can calculate the percentage contribution of innovations to y_k on the h-step-ahead forecast error variance of the variable y_j:

$$s^H_{jk} = \sigma^{-1}_{kk} \sum_{h=0}^{H-1} \left(e_j{}'\Lambda_h \Sigma e_k\right)^2 \Bigg/ \sum_{h=0}^{H-1} \left(e_j{}'\Lambda_h \Sigma \Lambda_h{}' e_j\right)^2. \tag{4}$$

The contributions are normalized by the row-sums yielding a matrix of normalized inputs $\tilde{s}^H_{jk} = s^H_{jk} / \sum_{k=1}^{N} s^H_{jk}$ known as the *connectedness table*. Each entry of this table is the *pairwise directional connectedness* measuring the uncertainty transferred from the y_k to y_j [4]:

$$C^H_{j\leftarrow k} \equiv \tilde{s}^H_{jk}, \tag{5}$$

The *directional connectedness from others* to y_j is defined from the off-diagonal row sum as:

$$C^H_{j\leftarrow \bullet} \equiv \sum_{k=1;k\neq j}^{N} C^H_{j\leftarrow k}, \tag{6}$$

and measures the total uncertainty received by the variable y_j from the other variables in the system. Likewise, the off-diagonal column sum is the *directional connectedness to*:

$$C^H_{\bullet\leftarrow j} \equiv \sum_{k=1;k\neq j}^{N} C^H_{k\leftarrow j}, \tag{7}$$

measuring the uncertainty transmitted from y_j to the others. Finally, the *total connectedness* index:

$$C^H = \frac{1}{N} \sum_{k,j,k\neq j}^{N} C^H_{jk}, \tag{8}$$

provides a quantitative measure of the uncertainty transmitted (or emitted) on average in the system. Thus, if $C^H = 0$ there are no spillover effects. Conversely, if $C^H = 1$, the system is perfectly connected and cross-market shocks explain all the system's uncertainty.

3.2.2. Connectedness in the frequency domain

BK proposed connectedness measures in the frequency domain based on the spectral decomposition of the VAR variance. This decomposition measures the contribution that shocks in one entity have on the fluctuations of another entity of the system at a given frequency or range of frequencies.

This paper extends the BK methodology to the long-memory framework computing the connectedness indices from the spectral decomposition of the FIVAR variance. This extension allows us to compare the FIVAR and VAR specifications over time and across frequency ranges.

Let i be the imaginary unit. The generalized causation spectrum of the FIVAR at the frequency ω i:

$$f_{j,k}(\omega) = \frac{\left(\sigma^2_{kk}\right)^{-1} \left| \left\{ D\left(e^{i\omega}\right)^{-1} \left[I - F\left(e^{i\omega}\right)\right]^{-1} \Omega \right\}_{j,k} \right|^2}{\left\{ D\left(e^{i\omega}\right)^{-1} \left[I - F\left(e^{i\omega}\right)\right]^{-1} \Omega \left[I - F'\left(e^{-i\omega}\right)\right]^{-1} D'\left(e^{-i\omega}\right)^{-1} \right\}_{j,j}}, \tag{9}$$

where $D(e^{i\omega}) = I + D_1 e^{i\omega} + D_2 e^{2i\omega} + D_3 e^{3i\omega} + \ldots$; $F(e^{i\omega}) = Fe^{i\omega} + Fe^{2i\omega} + \ldots + Fe^{pi\omega}$ and $D'(e^{i\omega})$, $F'(e^{-i\omega})$ are their complex-conjugate transpose.

As in BK, we aggregate the causation spectrum over different frequency bands. Consider a band of frequencies $b = (\omega_1, \omega_2) : \omega_i \in (-\pi, \pi)$, $\omega_1 < \omega_2$, and let the weighting function represents the power of variable j at the frequency ω:

$$P_j(\omega) = \frac{\left[\Lambda\left(e^{i\omega}\right)\Omega \Lambda'\left(e^{-i\omega}\right)\right]_{j,j}}{\frac{1}{2\pi}\int_{-\pi}^{\pi} \left[\Lambda\left(e^{i\lambda}\right)\Omega \Lambda'\left(e^{-i\lambda}\right)\right]_{j,j} d\lambda}$$

The following expression gives the share of a shock to y_k in the fluctuations of y_j at the band b:

$$\Theta^b_{j,k} = \frac{1}{2\pi} \int_{\omega_1}^{\omega_2} P_j(\omega) f_{j,k}(\omega) d\omega, \tag{10}$$

[3] Other method to quantify the long-memory dynamics of time series that was extensively applied in empirical finance is fractal analysis (see e.g., Refs. [87–89]).
[4] In general, $C^H_{i\leftarrow j} \neq C^H_{j\leftarrow i}$ and, $\sum_{j=1}^{N} d^H_{ij} = 1$ and $\sum_{i,j=1}^{N} d^H_{ij} = N$ by construction.

where summations for Fourier frequencies $\omega_j = 2\pi j/T, j = 1,...T/2$ belonging to the band can approximate integrals in the previous two equations [70].

The shares $\Theta^b_{j,k}$ in (10) are normalized as $\tilde{\Theta}^b_{j,k} = \Theta^b_{j,k}/\sum_k \Theta^\infty_{j,k}$, where $\Theta^\infty_{j,k}$ denotes the contribution over all frequencies. *Within connectedness* at the band b is defined from these normalized contributions as:

$$WC^b \equiv 1 - \frac{Tr\left\{\tilde{\Theta}^b\right\}}{\sum \tilde{\Theta}^b}. \tag{11}$$

Within connectedness quantifies the contribution of shock transmission on the system's fluctuations at the frequency band. However, *within connectedness* does not account for the relative importance of these fluctuations on total fluctuations.

As in BK, we account for the relative importance of the band defining the *frequency connectedness*:

$$FC^b \equiv WC^b \frac{\sum \tilde{\Theta}^b}{\sum \tilde{\Theta}^\infty}, \tag{12}$$

where *within connectedness* is weighted by the relative importance of the band. The authors show that *frequency connectedness* decomposes *total connectedness* in components at different ranges. Specifically, let $H \rightarrow \infty$, and consider a set of frequency bands $b_s \in B$ that form a partition of the space $(-\pi, \pi)$. Then:

$$C = \sum_{b_s \in B} FC^{b_s}, \tag{13}$$

where C is the *total connectedness* index defined in Eq. (8). Notice that the horizon H plays no role in the previous formula because the equality holds for $H \rightarrow \infty$. However, variance decompositions usually converge fast, and Eq. (13) generally delivers good approximations for finite horizons as well, provided those are not too short.

A caveat is necessary for the context of long-memory models, as the decomposition in (13) requires the total variance to be finite. As noted earlier, this condition is achieved in the FIVAR if the estimated orders of integration lie inside the stationary region $0 \le d_j < 0.5$. As shown in the empirical section (Section 4), stationarity holds for the three petroleum volatilities. Nevertheless, the decomposition approximates *total connectedness* indices computed at finite horizons even if this condition is not met.

4. Empirical analysis

4.1. Data description and model specification

We study volatility spillovers across three petroleum futures contracts traded at the NYMEX: WTI crude oil, reformulated RBOB gasoline, and heating oil. We use nearby futures, as these contracts tend to be more liquid.[5]

As in Haigh and Holt [2]; we base our analysis on weekly volatilities. It is to be expected that short- and long-memory models differ at relative medium and long horizons. The use of weekly volatility inside the models helps to capture long-term interactions, attenuating some high-frequency noises, such as the bid-ask effect [71]. However, our main results are robust to the use of daily frequency (see Supplement).

As volatility is latent, it must be estimated. To do so, we employ a Garman and Klass [72] range-based weekly volatility based on high, low, opening, and closing prices from Monday open to Friday close, as in Diebold and Yilmaz [73]:

$$\begin{aligned}\tilde{\sigma}^2_t &= 0.511(H_t - L_t)^2 - 0.019[(C_t - O_t)(H_t + L_t - 2O_t) \\ &-2(H_t - O_t)(L_t - O_t)] - 0.383(C_t - O_t)^2;\end{aligned} \tag{14}$$

where H_t and L_t are the natural logarithms of Monday to Friday high and low prices, O_t is the Monday open, and C_t is the Friday close (also in natural logs). Our underlying daily quotes have been extracted from Thomson-Reuters Eikon through Datastream and run from April 2006 to March 2020, resulting in 732 weekly volatility observations.[6]

Although the ideal estimator is realized volatility computed from high-frequency intra-day data (e.g., [74]), Alizadeh et al. [75] and Brandt and Diebold [76] show that range-based volatility is nearly as efficient and robust to microstructure noise. As a practical advantage, range-based volatility is more easily obtained, as it only requires four readily available inputs per day. Also, range-based is the standard volatility employed in DY studies (including the own authors of the framework), which facilitates comparison with existent studies.

Realized volatilities are right-skewed but approximately Gaussian after taking logs (see, e.g., Refs. [28,75]. Following a long tradition before us, we consider logarithmically transformed volatilities as time series to estimate spillovers (e.g., Refs. [22,23,77,78]. Fig. 1 provides plots of the log-realized volatility series used for estimation. The descriptive statistics and the results of the unit root test for the full sample can be found in the separate Supplement.

We assess volatility spillovers estimating a FIVAR model of the (log)volatility series over a rolling window. To help in the interpretation, we also estimate a traditional VAR. As Diebold and Yilmaz [22] argued, the dynamic assessment is important because it is unlikely that any fixed-parameter model would apply over the entire sample. Nevertheless, the Supplement contains static connectedness results.

Concerning the model specifications, we select one lag for the autoregressive part according to the Bayesian Information Criteria (BIC). For the VAR, we choose two lags according to the same criteria, giving this model more flexibility to capture persistence than just imposing the same lag structure of the FIVAR. However, the results are robust to using the same number of lags in the two models.

We evaluate connectedness in the frequency domain at high, medium, and low frequencies. The high-frequency band includes frequencies with a period smaller than one month. The medium-frequency band contains the frequencies between one- and three-month period, and the low-frequency band the frequencies with a period longer than three months.[7] As in Barunik and Krehlik [24]; *total connectedness* is computed aggregating *frequency connectedness* over the three bands. However, we also calculate DY indices using the finite-horizon formulas finding that the aggre-

[5] We use the "first day of month" as our roll date rule. This method attenuates liquidity issues of rolling on the last trading date. However, our results are robust to rolling over when the second month's future volume exceeds the first future month volume.

[6] The RBOB gasoline-type contract started in October 2005, but the volume of trade was very low before April 2006 because the past gasoline-type contract (based on Regular Reformulated Gasoline) stop trading in December 2006.

[7] As standard practice, the zero frequency is excluded as the FIVAR spectrum is infinite at this frequency.

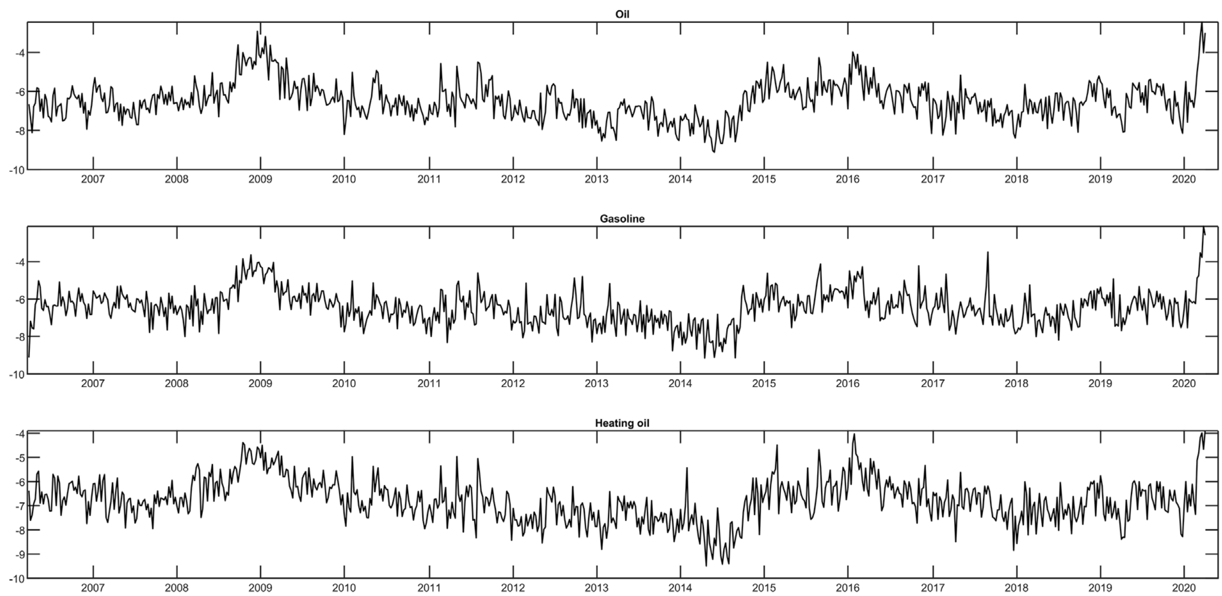

Fig. 1. Log realized volatilities.

gation by bands approximates well the indices computed at finite horizons.[8]

We estimate the models over a rolling window to obtain dynamic indices of connectedness. The objective here is twofold. The rolling estimations allow us to study the extent of spillover variation, assessing whether differences between the FIVAR and VAR specifications remain across subsamples. Rolling estimates also make our results robust to the possible existence of breaks in the data. It has been argued that long-memory may sometimes appear as a spurious phenomenon caused by a break [79]. However, the opposite effect is also documented [80].[9] Univariate studies suggest that long-memory in petroleum volatilities is robust to breaks [11,20]. The rolling windows analysis makes the importance of this possible critique irrelevant in practice, as it accounts for possible breaks (as well as smoother parameter drifting).

The length of the window corresponds to T = 260 observations. We consider this length a reasonable compromise between efficiency in estimating the long-memory parameters and the flexibility to track time variation. Nevertheless, we also repeat the analysis with a broader window as a robustness check (see Supplement), with no significant difference, except the well-known higher smoothness of dynamic estimates. The main results of the paper remain unchanged: the traditional VAR vastly overstates connectedness, especially at high frequencies.

4.2. Empirical results

In this section, we present selected results from our FIVAR and VAR estimations over the rolling windows. We discuss the implications of these results in the next section (Section 4.3).

Fig. 2 plots the estimated orders of fractional integration across the different windows together with two standard error bands. As the figure shows, we find strong evidence of long-memory in our multivariate FIVAR specification. The fractional orders are high and massively significant, with the $I(0)$ specification decisively rejected by the data in all rolling windows. However, the estimated coefficients lie inside the stationary region ($0 \le d_n < 0.5$) in all rolling sample estimations, with the nonstationary null generally rejected at standard confidence levels. Overall, our estimation results show that petroleum volatilities are highly persistent but still stationary, mean-reverting, with volatility shocks vanishing slowly in the long run.

As for the evolution of the fractional orders over time, the three-parameter estimates are relatively stable. There is, however, a slight decrease in persistence at the end of 2013. This decline coincides in time with the collapse of petroleum prices after the shale-oil glut.[10] However, the estimated orders of integration are large and significant even during this episode. Overall, our results show a strong presence of long-memory in petroleum volatilities, robust to possible breaks.

Fig. 3 depicts the *total connectedness* index. Barunik et al. [6] noted that petroleum market volatilities are expected to be linked because gasoline and heating oil are sub-products of crude oil. As Fig. 3 shows, the *total connectedness* index in the FIVAR is relatively large across rolling estimations. On average, shocks transmitted across markets explain around two-fifths of the total volatility variances. Connectedness does present some variation over time. The index increased in the post-financial crisis period, peaking at 52% in the late 2013s. The index decreased steadily from this date, reaching a minimum of 40% by the end of 2017, and recovered after that. Petroleum volatilities have recently become strongly connected, coinciding with the 2020 Russia-Saudi Arabia oil price war, but more data is required to confirm this result.

Fig. 3 also shows that neglecting long-memory persistence leads to underrating the importance of own shocks in the system variance, magnifying spillovers. The *total connectedness* index in the traditional VAR is higher than in the FIVAR model in most of the rolling estimations. Interestingly, the index also presents a sudden

[8] In particular, the typical H = 10 forecast horizon yields virtually identical connectedness measures. See Supplement.

[9] Although there are techniques aimed to distinguish between the two types of processes, they have not yet been extended to the multivariate case. Notice that a break in a univariate process may not be present in a multivariate. Besides, as noted in Baillie and Morana [92] both long-memory and a break can be present in the data. Our rolling window estimations account for this possibility.

[10] China's economic slowdown and some conflicts in the Middle East have also been signalled as factors explaining the 2014 price collapse [90].

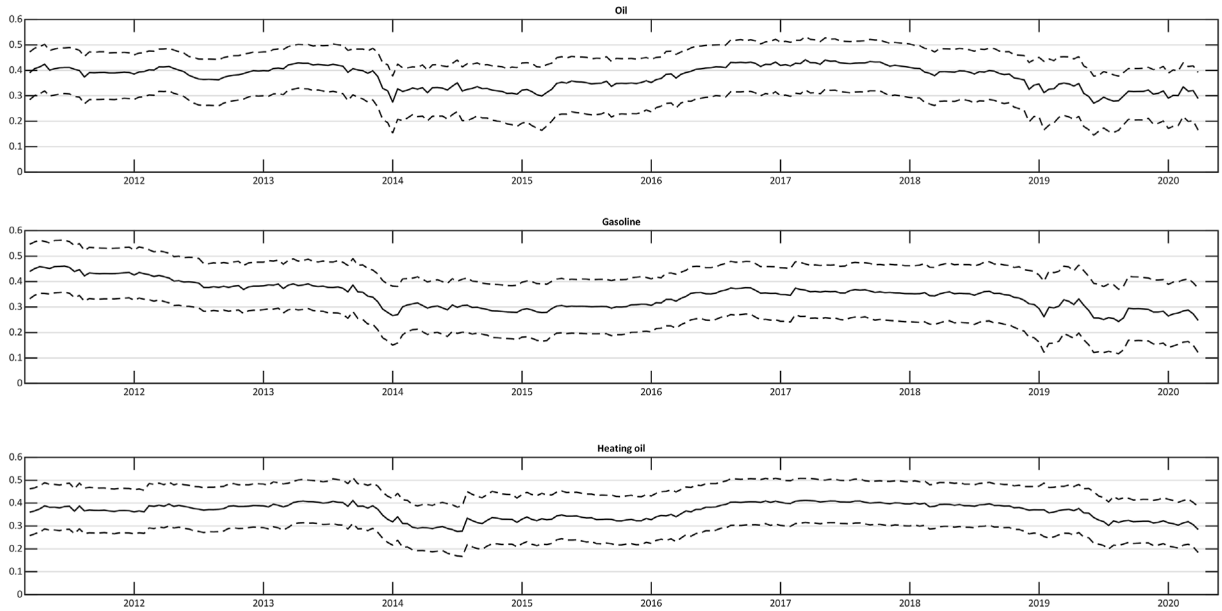

Fig. 2. Estimated long-memory parameters across subsamples. The dashed area is the two-standard error confidence band.

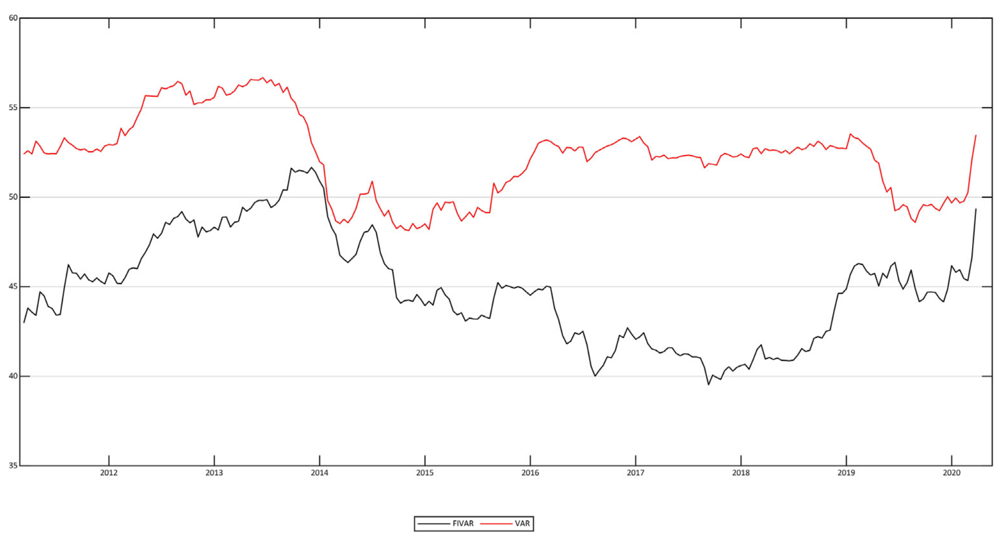

Fig. 3. TOTAL connectedness index: FIVAR and VAR. TOTAL connectedness quantifies the contribution of transmission in the overall system variance.

drop at the end of 2013 but recovers relatively fast, while in the FIVAR model keeps falling for a rather long period. As a result, the most significant discrepancies between the two specifications lie in the second half of the rolling estimations.

Differences between the FIVAR and VAR can also be appreciated in Fig. 4, which presents time-varying indices of *directional* connectedness. We collect *FROM, TO,* and *NET connectedness* indices computed from the FIVAR model on the left-hand side panels of Fig. 4. The corresponding indexes calculated in the VAR model are depicted on the right.

Directional indices from the FIVAR model show that gasoline and heating oil markets are not mere recipients of spillovers that originate in the oil market. Although gasoline is generally the net recipient in the system, we do not observe significant disparities in the contribution of the different markets to total connectedness. As a result, the *net connectedness* across subsamples is close to zero for the three volatilities. Notice that the current episode of high-system connectedness is originated in the three markets simultaneously.

Comparing the left and right panels of Fig. 4, we can observe that the VAR magnifies transmission and leads to a misunderstanding of the relative importance of the different markets. In the VAR, shocks that originated in the oil market contribute significantly more than those in the other two markets, both in total and net terms. Notice that the discrepancies in net connectedness are huge in the second half of the rolling estimations, consistent with Fig. 3.

As a final step, we study the volatility linkages in the frequency domain. The results are depicted in Fig. 5. The first row of the figure presents *within connectedness* at the high, medium, and low-frequency bands. We report in the second row the decomposition

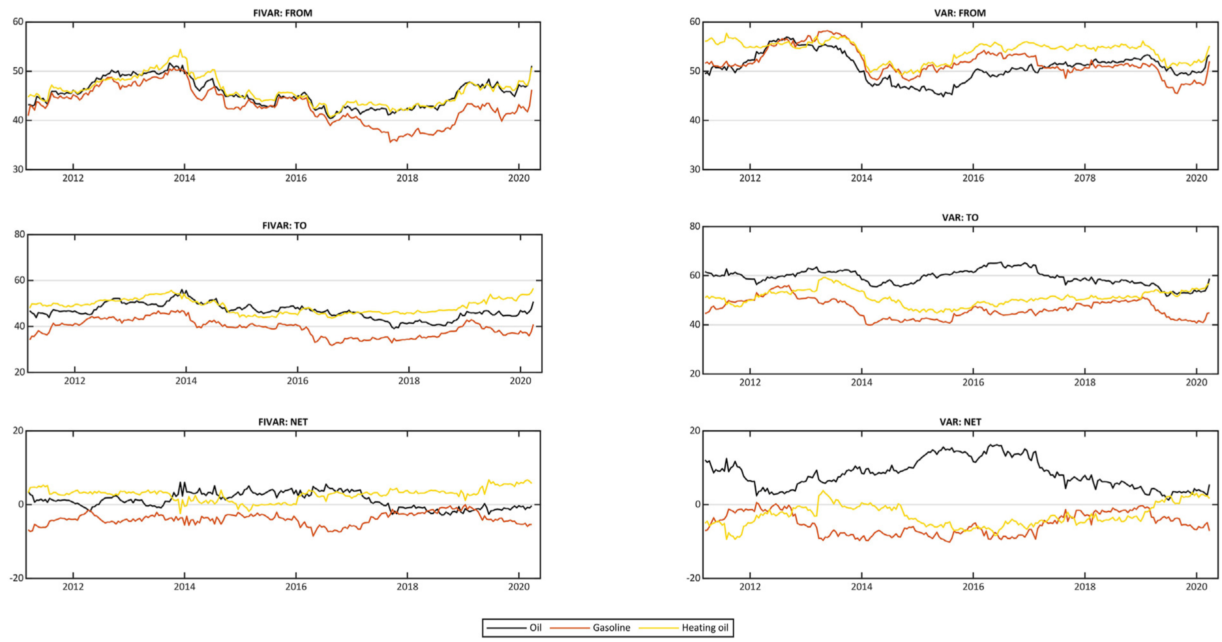

Fig. 4. Directional TO, FROM, and NET connectedness: FIVAR and VAR. Directional TO (FROM) measures the percentage contribution of shocks transmitted to (from) a given market. NET connectedness is the difference between the FROM and TO indices.

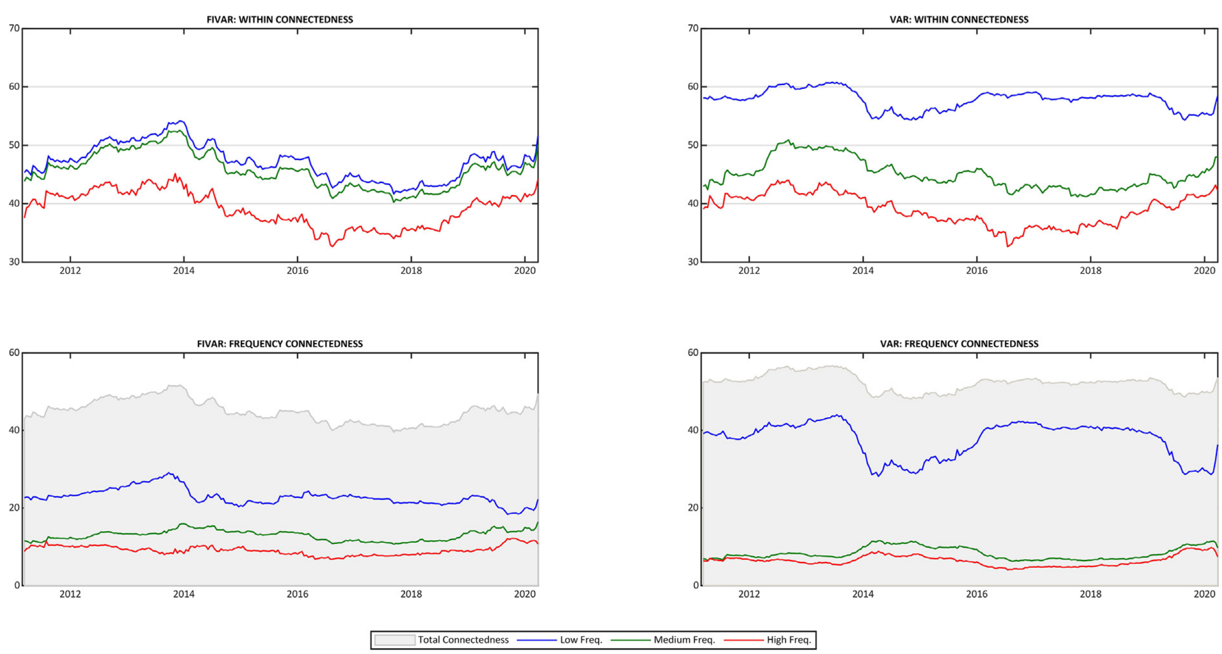

Fig. 5. Connectedness in the frequency domain: FIVAR and VAR. WITHIN connectedness quantifies the relative contribution of transmission for the fluctuations of petroleum volatilities within the band. FREQUENCY connectedness measures the contribution of transmission at the given range in the total variance and adds up the TOTAL connectedness index when aggregated over the bands.

of *total connectedness* into the corresponding three *frequency connectedness* components.[11]

Within connectedness measures the relative importance of spillovers in petroleum volatilities' fluctuations at high, medium, and low frequencies. As shown in Fig. 5 below, volatilities are similarly connected across bands in the FIVAR model. On average, spillovers explain around 40% of the fluctuations at high frequencies. Connectedness is slightly higher at medium and low frequencies, but the difference is not large. Moreover, connectedness evolves similarly within the three bands, presenting the same pattern as *the total connectedness* index in Fig. 3.

Comparing the FIVAR and the VAR results, we see that, although the degree of connectedness *within* high and medium frequency ranges is similar in the two specifications, the VAR model vastly

[11] The estimated integration orders remain in the stationary region in all rolling samples; therefore, variances are finite.

overstates connectedness *within* low frequencies.

The difference between the two specifications becomes even more critical when considering the bands' relative importance on the aggregate fluctuations. This result is observed in the second row of Fig. 5. The grey shadowed area is the *total connectedness* index, which, as noted earlier, is higher in the VAR. The figure also plots *frequency connectedness* indices at high-, medium-, and low-frequency bands. Notice that *frequency connectedness* split up *total connectedness* into three components. Namely, a short-, a medium-, and a long-term component, each quantifying the part of the total variance in the system explained by shock transmission at high, medium, and low frequencies, correspondingly.

In the FIVAR model, connectedness is mainly created at low frequencies, consistent with Krehlik and Barunik [7]. The short-term and medium-term components of total connectedness account, on average, around ten percent of the fluctuations each. The contribution of the long-term component is notoriously larger (about 20%). Thus, we find that, although shocks transmitted across markets explain similar percentages of the high, medium, and low-frequency fluctuations, transmission at low frequencies is more important for the total fluctuations. As the right-hand side plot shows, this result qualitatively stands for the VAR, but with an enormous discrepancy in the magnitudes. Notice that the long-term component in the VAR explains around 40% of the total system variance, which is twice as large as in the FIVAR.

4.3. Discussion and implications of the empirical findings

The volatilities of petroleum commodities are critical inputs for option pricing, portfolio construction, and risk management operation. Consequently, the results of the previous section have important implications for both investors and policymakers. For example, Fig. 2 shows that petroleum volatilities are best described by a mean-reverting fractionally integrated process. This result implies that petroleum volatilities take substantial time to forget shocks, no matter the market they originated. Visual illustration of the long memory in volatility series can be found even in Fig. 1: series diverge from their means for long periods of time that means that the phases of strong volatility have a long duration. Thus, the long memory must be explicitly considered for adequate tracking and forecasting of volatility that is important for all market participants. From a practical point of view, long memory in volatilities indicates that trends in prices, or periods of the information transmission, last considerable periods of time, in the same way as relatively calm periods. The strong evidence of long-memory also matters from an investor's perspective since it has significant implications for asset pricing as volatility enters the risk premium [81–83].

Given the enormous importance of petroleum for the economy, strong evidence of long memory is crucial for policymakers. Since volatility is associated with risk, instability, information transmission, and its absorption by the market, its efficient forecast may serve as a warning system for the oncoming crisis and its posterior propagation to the economy. For example, if a new observation on volatility is much higher (outside of the accepted confidence bands) than its forecast made with a long memory model, it can be considered as a signal for strong changes in the market, possible crises of the beginning of a boom. As well, volatility forecasts can be used to track the current economic situation and the way the new information, such as announcements about the introduction of new policies, is processed by the public.

If the volatilities are restricted to be I(0), the forecasts derived from the misspecified model are going to be erroneous since they implicitly restrict that past is forgotten fast and do not influence the future estimates. Thus, the conclusions on the future behavior of volatilities are going to be misleading.

Concerning connectedness indices, we find that volatilities are highly connected, as shown in Fig. 3. The degree of connectedness was stable across sub-samples (slightly over 40%), except for a slight decline after the oil crash of 2014. Therefore, a large part of the volatility fluctuations of petroleum commodities is due to shocks originating in another petroleum market.

Although often disregarded, high volatility connectedness does not directly imply systemic risk. The reason is that shocks may have an opposite sign in the emitter and recipient markets, making them correlate negatively. However, as Krehlnik and Barunik [7] argued, shocks are expected to induce responses of the same sign in all petroleum commodities.[12]

Following this interpretation, our estimates indicate that the risk of contagion is relatively high. Also, directional indices from the proposed FIVAR indicate that all markets are equally important in transmitting volatility. Thus, the gasoline and heating-oil markets should not be and should not be overlooked by stakeholders in the oil market. Overall, these findings are consistent with the view that gasoline and heating-oil commodities should be an integral part of a diversified portfolio of oil assets, increasing the risk-adjusted performance of the hedged portfolio. As connectedness between petroleum volatilities is high and shocks are expected to have the same sign in all markets, an investor may hedge holdings (a long position) in one market with a short sell in any of the other two markets.

However, our results also indicate that petroleum volatilities are significantly less connected than estimated in the traditional VAR. Short-memory specifications, such as the VAR, understate the importance of own-shocks, magnifying spillovers. Disregarding the persistence of petroleum volatilities may lead to misunderstanding their reaction to shocks transmitted across markets and, therefore, inaccurate risk management. In practice, the result suggests that more gasoline or heating-oil assets are required in short positions to reduce investors' risk with crude oil long position (or *vice versa*) and, thus, higher hedging costs. Consequently, the hedge is less effective than the traditional VAR model stipulates. This result is particularly relevant for the market participants acting in the long run, as the most considerable discrepancies between the FIVAR and VAR specifications are found in the low-frequency range.

The most important long-term participants are governments, different types of regulatory organisms, and big financial institutions. In either case, the precise estimate of the spillovers between markets may strongly influence the participants' decisions. Thus, for example, policymakers may want to apply fuel-prices stabilization mechanisms to smooth price variations. While there are different ways to implement such policies, they all have high fiscal costs during periods of sustained increases in international petroleum prices. Thus, a reliable forecast of the future price and knowledge on how these markets interrelate may alleviate the fiscal burden of such policies. Also, as Marchese et al. [21] point out, high volatility transmission between crude oil and refined products markets is essential for agents trading in crack spreads, i.e., refiners or oil trading companies, as they are exposed to oil and other refined product shocks. According to our results, it is therefore crucial for these companies to account for the actual persistence of petroleum volatilities, as the large discrepancy between VAR and FIVAR connectedness matters for their hedging strategies,

[12] Under relatively weak assumptions, Krehlik and Barunik [7] show that volatility shocks across petroleum markets may have effects of different signs, only if increasing costs of one commodity reduce the price of the other, which is hard to sustain.

especially as they care about the long-term.

Finally, it is to be observed that omitting persistence also leads to a misjudging of the relative contribution of different markets. The FIVAR results indicate that gasoline and heating-oil cannot be understood as mere recipients of volatility shocks arising in the oil market and must be closely monitored in combination with oil.

5. Conclusion

This paper has assessed weekly volatility spillovers across petroleum futures in a FIVAR model, thus relaxing the questionable assumptions on volatility persistence in previous studies. To do so, we have relied on Diebold and Yilmaz [22,23] framework, the standard method to assess volatility spillovers. However, unlike previous studies, we have computed connectedness measures based on a FIVAR to account for long-memory volatility persistence. We have also evaluated connectedness by frequency ranges by extending the Barunik and Krehlik [24] methodology to long-memory multivariate specifications.

We have found that petroleum volatilities are well characterized by a combination of short- and long-memory, with the long-memory component imparting substantial persistence to the volatility series. Connected measures have shown that while petroleum volatilities are significantly connected, they are much less connected than indicated by the standard VAR, particularly at low frequencies.

Overall, our results have shown that the proper modeling of persistence is vital for risk management. As long-memory is a stylized characteristic of many financial assets, additional studies considering this issue are required. It would be an interesting extension to investigate volatility spillovers between the oil and the financial market within the DY framework, as in Xu et al. [43]; but explicitly considering long-memory. Structural identification of demand and supply in the oil market, as by Kilian and Park [84]; might be included in the analysis, which would help disentangle whether spillover effects from oil come from supply or demand. We consider this an exciting avenue for future research.

Credit author statement

Yuliya Lovcha: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Writing- Reviewing and Editing. Alejandro Perez-Laborda: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Writing-Reviewing and Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.energy.2021.122950.

References

[1] Lin SX, Tamvakis MN. Spillover effects in energy futures markets. Energy Econ 2001;23:43–56.
[2] Haigh MS, Holt MT. Crack spread hedging: accounting for time-varying volatility spillovers in the energy futures markets. J Appl Econom 2002;17:269–89.
[3] Hammoudeh S, Li H, Jeon B. Causality and volatility spillovers among petroleum prices of WTI, gasoline, and heating oil in different locations. N Am J Econ Finance 2003;14:89–114.
[4] Zhang B, Wang P. Return and volatility spillovers between China and world oil markets. Econ Modell 2014;42:13–420.
[5] Karali B, Ramirez OA. Macro determinants of volatility and volatility spillover in energy markets. Energy Econ 2014;46:413–21.
[6] Barunik J, Kocenda E, Vacha L. Volatility spillovers across petroleum markets. Energy J 2015;36:309–29.
[7] Krehlik T, Barunik J. Cyclical properties of supply-side and demand-side shocks in oil-based commodity markets. Energy Econ 2017;65:208–18.
[8] Magkonis G, Tsouknidis DA. Dynamic spillover effects across petroleum spot and futures volatilities, trading volume, and open interest. Int Rev Financ Anal 2017;52:104–18.
[9] Zhang D, Ji Q, Kutan AM. Dynamic transmission mechanisms in global crude oil prices: estimation and implications. Energy 2019;175:1181–93.
[10] An S, Gao X, An H, An F, Sun Q, Liu S. Windowed volatility spillover effects among crude oil prices. Energy 2020;2000:117521.
[11] Choi K, Hammoudeh S. Long-memory in oil and refined products markets. Energy J 2009;30:97–116.
[12] Kang SH, Kang SM, Yoon SM. Forecasting volatility of crude oil markets. Energy Econ 2009;31:119–25.
[13] Cheong CW. Modeling and forecasting crude oil markets using ARCH-type models. Energy Pol 2009;37:2346–55.
[14] Cunado J, Gil-Alana LA, Perez de Gracia F. Persistence in some energy futures markets. J Futures Mark 2010;30:490–507.
[15] Wei Y, Wang Y, Huang D. Forecasting crude oil market volatility: further evidence using GARCH-class models. Energy Econ 2010;32:1477–84.
[16] Arouri MEH, Lahiani A, Levy A, Nguyen DK. Forecasting the conditional volatility of oil spot and futures prices with structural breaks and long-memory models. Energy Econ 2012;34:283–93.
[17] Kang SH, Yoon SM. Modeling and forecasting the volatility of petroleum futures prices. Energy Econ 2013;36:354–62.
[18] Charfeddine L. True or spurious long-memory in volatility: further evidence on the energy futures markets. Energy Pol 2014;71:76–93.
[19] Charfeddine L. Breaks or long-range dependence in the energy futures volatility: out-of-sample forecasting and VaR analysis. Econ Modell 2016;53:354–74.
[20] Gil-Alana LA, Gupta R, Olubusoye OE, Yaya OS. Time series analysis of persistence in crude oil price volatility across bull and bear regimes. Energy 2016;109:29–37.
[21] Marchese M, Kyriakou I, Tamvakis M, Di Iorio F. Forecasting crude oil and refined products volatilities and correlations: new evidence from fractionally integrated multivariate GARCH models. Energy Econ 2020;88:104757.
[22] Diebold FX, Yilmaz K. Better to give than to receive: forecast-based measurement of volatility spillovers. Int J Forecast 2012;28:57–66.
[23] Diebold FX, Yilmaz K. On the network topology of variance decompositions: measuring the connectedness of financial firms. J Econom 2014;182:119–34.
[24] Barunik J, Krehlik T. Measuring the frequency dynamics of financial connectedness and systemic risk. J Financ Econom 2018;16:271–96.
[25] Ortu F, Tamoni A, Tebadi C. Long-run risk and the persistence of consumption shocks. Rev Financ Stud 2013;26:2876–915.
[26] Dew-Becker I, Giglio S. Asset pricing in the frequency domain: theory and empirics. Rev Financ Stud 2016;29:2029–68.
[27] Bandi FM, Chaudhuri SE, Lo AW, Tamoni A. Spectral factor models. J Financ Econ 2021;142:214–38.
[28] Andersen TG, Bollerslev T, Diebold FX, Labys P. Modeling and forecasting realised volatility. Econometrica 2003;71:529–626.
[29] Liu HH, Chen YC. A study on the volatility spillovers, long-memory effects and interactions between carbon and energy markets: the impacts of extreme weather. Econ Modell 2013;35:840–55.
[30] Dark J. Multivariate models with long memory dependence in conditional correlation and volatility. J Empir Finance 2018;48:162–80.
[31] Cipollini A, Lo Cascio I, Muzzioli S. Risk aversion connectedness in five European countries. Econ Modell 2018;71:68–79.
[32] Malik F, Ewing BT. Volatility transmission between oil prices and equity sector returns. Int Rev Financ Anal 2009;18:95–100.
[33] Sadorsky P. Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. Energy Econ 2012;34:248–55.
[34] Khalfaoui R, Boutahar M, Boubaker H. Analyzing volatility spillovers and hedging between oil and stock markets: evidence from wavelet analysis. Energy Econ 2015;49:540–9.
[35] Ewing BT, Malik F. Volatility spillovers between oil prices and the stock market under structural breaks. Global Finance J 2016;29:12–23.
[36] Antonakakis N, Chatziantoniou I, Filis G. Oil shocks and stock markets: dynamic connectedness under the prism of recent geopolitical and economic unrest. Int Rev Financ Anal 2017;50:1–26.
[37] Antonakakis N, Cunado J, Filis G, Gabauer D, Perez de Gracia F. Oil volatility, oil and gas firms and portfolio diversification. Energy Econ 2018;70:499–515.
[38] Chang K, Ye Z, Wang W. Volatility spillover effect and the dynamic correlation between regional emissions allowances and fossil energy markets: new evidence from China's emissions trading scheme pilots. Energy 2019;185:1314–24.
[39] Dutta A, Bouri E, Noor MdH. Return and volatility linkages between CO2 emission and clean energy stock prices. Energy 2018;164:803–10.
[40] Ferrer R, Shahzad J, Lopez R, Jareño F. Time and frequency dynamics of

connectedness between renewable energy stocks and crude oil prices. Energy Econ 2018;76:1–20.
[41] Barunik J, Kocenda E. Total, asymmetric and frequency connectedness between oil and forex markets. Energy J 2019;40:157–74.
[42] Ashfaq S, Tang Y, Maqbool R. Volatility spillover impact of world oil prices on leading Asian energy exporting and importing economies' stock returns. Energy 2019;188:116002.
[43] Xu W, Ma F, Chen W, Zhang B. Asymmetric volatility spillovers between oil and stock markets: evidence from China and the United States. Energy Econ 2019;80:310–20.
[44] Wang X, Wang Y. Volatility spillovers between crude oil and Chinese sectoral equity markets: evidence from a frequency dynamics perspective. Energy Econ 2019;80:995–1009.
[45] Ewing BT, Malik F, Ozfidan O. Volatility transmission in the oil and natural gas markets. Energy Econ 2002;24:525–38.
[46] Lin B, Li J. The spillover effects across natural gas and oil markets: based on the VEC-MGARCH framework. Appl Energy 2015;155:229–41.
[47] Perifanis T, Dagoumas A. Price and volatility spillovers between the US crude oil and natural gas wholesale markets. Energies 2018;11:2757.
[48] Lovcha Y, Perez-Laborda A. Dynamic frequency connectedness between oil and natural gas volatilities. Econ Modell 2020;84:181–9.
[49] Le Pen Y, Sévi B. Volatility transmission and volatility impulse response functions in European electricity forward markets. Energy Econ 2010;32: 758–70.
[50] Apergis N, Barunik J, Lau M. Good volatility, bad volatility: What drives the asymmetric connectedness of Australian electricity markets? Energy Econ 2017;66:108–15.
[51] Batten JA, Brzeszczynski J, Ciner C, Lau MCK, Lucey B, Yarovaya L. Price and volatility spillovers across the international steam coal market. Energy Econ 2019;77:119–38.
[52] Li J, Xie C, Long H. The roles of inter-fuel substitution and inter-market contagion in driving energy prices: evidences from China's coal market. Energy Econ 2019;84:104525.
[53] Reboredo JC. Volatility spillovers between the oil market and the European Union carbon emission market. Econ Modell 2014;36:229–34.
[54] Ji Q, Zhang D, Geng J. Information linkage, dynamic spillovers in prices and volatility between the carbon and energy markets. J Clean Prod 2018;198: 972–8.
[55] Chulia H, Furio D, Uribe JM. Volatility spillovers in energy markets. Energy J 2019;40. 127-12.
[56] Lin B, Chen Y. Dynamic linkages and spillover effects between CET market, coal market and stock market of new energy companies: a case of Beijing CET market in China. Energy 2019;172:1198–210.
[57] Wang Y, Guo Z. The dynamic spillover between carbon and energy markets: new evidence. Energy 2019;149:24–33.
[58] Diebold FX, Liu L, Yilmaz K. Commodity connectedness. Central banking, analysis, and economic policies book series. In: Mendoza EG, Pastén E, Saravia D, editors. Monetary policy and global spillovers: mechanisms, effects and policy measures. edition 1, vol. 25; 2018 [chapter 4].
[59] Barbaglia L, Croux C, Wilms I. Volatility spillovers in commodity markets: a large t-vector autoregressive approach. Energy Econ 2019;85:104555.
[60] Kang SH, Tiwari AK, Albulescu CT, Yoon SM. Exploring the time-frequency connectedness and network among crude oil and agriculture commodities V1. Energy Econ 2019;84(C).
[61] Toyoshima Y, Hamori S. Measuring the time-frequency dynamics of return and volatility connectedness in global crude oil markets. Energies 2019;11: 2893.
[62] Granger CWJ, Joyeux R. An introduction to long-memory time series models and fractional differencing. J Time Anal 1980;1:15–39.
[63] Hosking JRM. Fractional differencing. Biometrika 1981;68:165–76.
[64] Abbriti M, Gil-Alana LA, Lovcha Y, Moreno A. Term structure persistence. J Financ Econom 2016;19:331–52.
[65] Lovcha Y, Perez-Laborda A. Monetary policy shocks, long-memory, and inflation persistence. J Macroecon 2018;55:117–27.
[66] Hosoya Y. The quasi-likelihood approach to statistical inference on multiple time-series with long-range dependence. J Econom 1996;73:217–36.
[67] Lobato I. A semiparametric two-step estimator in a multivariate long memory model. J Econom 1999;90:129–53.
[68] Lovcha Y, Perez-Laborda A. Hours-worked productivity puzzle: identification in fractional integration settings. Macroecon Dyn 2015;19:1593–621.
[69] Pesaran MH, Shin Y. Generalized impulse response analysis in linear multivariate models. Econ Lett 1998;58:17–29.
[70] Sargent TJ. Macroeconomic theory. second ed. Academic Press; 1987.
[71] Kaul G, Nimalendran M. Price reversals: Bid-ask errors or market overreaction? J Financ Econ 1990;28:67–93.
[72] Garman MB, Klass MJ. On the estimation of security price volatilities from historical data. J Bus 1980;53:67–78.
[73] Diebold FX, Yilmaz K. Measuring financial asset return and volatility spillovers, with application to global equity markets. Econ J 2009;119:158–71.
[74] Liu LY, Patton AJ, Sheppard K. Does anything beat 5-minute RV? A comparison of realized measures across multiple asset classes. J Econom 2015;187: 293–311.
[75] Alizadeh S, Brandt MW, Diebold FX. Range-based estimation of stochastic volatility models. J Finance 2002;57:1047–91.
[76] Brandt M, Diebold FX. A no-arbitrage approach to range-based estimation of return covariances and correlations. J Bus 2006;79:61–74.
[77] Diebold FX, Yilmaz K. Trans-Atlantic equity volatility connectedness: U.S. and European financial institutions, 2004-2014. J Financ Econom 2016;14: 81–127.
[78] Demirer M, Diebold FX, Liu L, Yilmaz K. Estimating global bank network connectedness. J Appl Econ 2018;33:1–15. 2018.
[79] Diebold FX, Inoue A. Long memory and regime switching. J Econom 2001;105: 131–59.
[80] Nunes LC, Kuan CM, Newbold P. Spurious breaks. Econom Theor 1995;11: 736–49.
[81] Bollerslev T, Mikkelsen HO. Modeling and pricing long-memory in stock market volatility. J Econom 1996;73:151–84.
[82] Taylor SJ. Consequences for option pricing of a long-memory in volatility. In: Handbook of financial econometrics and statistics. New York: Springer SBM; 2015. p. 903–33.
[83] Christensen B, Nielsen M. The effect of long memory in volatility on stock market fluctuations. Rev Econ Stat 2007;89:684–700.
[84] Kilian L, Park C. The Impact of oil price shocks on the U.S. stock market. Int Econ Rev 2009;50:1267–87.
[85] Johansen S. A representation theory of a class of vector autoregressive models for fractional processes. Econom Theor 2008;24:651–76.
[86] Johansen S, Nielsen MØ. Likelihood inference for a fractionally cointegrated vector autoregressive model. Econometrica 2012;80:2667–732.
[87] Cromwell JB, Labys WC, Kouassi E. What color are commodity prices? A fractal analysis. Empir Econ 2000;25:563–80.
[88] Mulligan RF. Fractal analysis of highly volatile markets: an application to technology equities. Q Rev Econ Finance 2004;44:155–79.
[89] Onali E, Goddard J. Are European equity markets efficient? New evidence from fractal analysis. Int Rev Financ Anal 2011;20(2):59–67.
[90] Baffes J, Kose MA, Ohnsorg F, Stocker M. The great plunge in oil prices: causes, consequences, and policy responses. Pol Res Notes 2015;94725. The World Bank.
[91] Zhang D. Oil shocks and stock markets revisited: Measuring connectedness from a global perspective. Energy Econ 2017;62:323–33.
[92] Baillie RT, Morana C. Modelling long memory and structural breaks in conditional variances: An adaptive FIGARCH approach. J Econ Dyn Control 2009;33:1577–92.