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Volatility Spillovers in a Long-Memory VAR: an Application to Energy Futures Returns

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Abstract: In this paper, we assess volatility spillovers across energy markets accounting for the persistence of the volatility series. To do so, we compute Diebold and Yilmaz (2015) measures of connectedness based on the forecast-error variance decomposition of an estimated fractionally integrated VAR (FIVAR). We use this method to study volatility spills among oil, unleaded gasoline, heating oil, and natural gas. Our main empirical findings are: 1) Accounting for persistence is essential to assess the magnitude of the spillover effects in these markets; 2) The traditional VAR magnifies the other's contribution to the volatility variance; 3) There are substantial spillover effects across petroleum markets, but the link between these markets and the natural gas market appears to be broken in post 2008-crisis data.

Keywords: fractional integration, spillovers, energy commodities

JEL Classification: G1, C5, Q4

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1. INTRODUCTION

The analysis of volatility spillovers has recently attracted a lot of interest; as markets become more interconnected, volatility in one market tends to trigger volatility in the others, a phenomenon that becomes visible in periods of turmoil. Obviously, the existence of these linkages can be employed by investors and financial institutions to manage portfolios and designing strategies for hedging against risk.

In a series of papers, Diebold and Yilmaz (2009, 2012, and 2014) introduced several measures based on VAR forecast error variance decompositions (FEVD) aimed to study spillovers.[1] This methodology (henceforth noted as DY) provides a quantification of the magnitude of the spillovers and of its direction, and is currently employed in an increasing number of studies (see e.g., Antonakakis et al., 2016). However, the VAR model on which the DY measures are based imposes a fast exponential decline to shocks of the different series, which is at odds with the observed persistence of squared (or absolute) returns. There is overwhelming evidence that markets take a lot of time to forget volatility shocks (months), and many studies demonstrate that return volatility series contain a strong long-memory (LM) component. In fact, LM models frequently perform better than other models in tracking and forecasting volatility (see e.g., Breidt et al., 1994; Baillie et al., 1996; Andersen et al., 2003);

In this paper, we account for the persistence of the volatility series when assessing volatility spillover effects among four energy future contracts: crude oil, unleaded gasoline, heating oil, and natural gas. To do so, we employ DY measures of connectedness based on FEVD decompositions from a fractionally integrated VAR (FIVAR). In this way, we allow for the possibility of LM, with the responses of the

[1] Diebold and Yilmaz (2015) summarize the methodology.

volatilities to shocks declining at a slow hyperbolical rate, which appears to be more compatible with the actual behavior of these series. Note that the responses to shocks determine the forecast error variances, which are the underlying concept behind the DY measures.

Energy futures have become a popular asset class for portfolio investors (Vivian and Wohar, 2012). This overgoing *financialization* has renewed the interest in understanding how these markets are related. However, most of the existing literature focuses on prices, while the research related to their volatility connections is still scarce. Volatility flows *between* oil and natural gas have been studied in Ewing et al. (2002), Lin and Li (2015), and Zhu et al. (2018). The former two works found evidence of volatility spillovers using a multivariate GARCH. However, Zhu *et al*. (2018) recently argued that the volatilities of these two commodities are currently decoupled. The authors found no evidence of (Granger) causal links in post-2007 data, which is consistent with price independencies documented in Batten et al. (2017). As for the petroleum markets, the literature is also dominated by GARCH modeling, and mostly concentrated in studying volatility spillovers between returns traded at different centers (see e.g., Chang et al. 2010; Hammoudeh et al., 2003; Lin and Tamvakis, 2001). In this sense, our work is more closely related to Barunik et al. (2016) and Magkonis and Tsouknidis (2017). The later work analyzed spillover effects across petroleum-based commodities and among spot-futures volatilities, trading volume, and open interest. The authors stressed the importance of computing dynamic spillovers for petroleum commodities. Barunik et al. (2016), on the other hand, focuses on petroleum futures, but employs realized semi-variances in combination with DY indices to stress the asymmetric effect of good and bad spillovers. The authors found that asymmetries play an important role before the 2008-crisis but their importance declined strongly after this date. We depart from these interesting studies in two ways. As in Barunik et al. (2016), we concentrate on future contracts, but unlike asymmetries, we study the persistence and apparent LM of the volatility series. Second, we also examine the relation between petroleum and natural gas markets volatilities, which is currently under discussion.

In terms of its methodology, our paper belongs to the literature employing multivariate fractionally integrated models for the assessment of spillovers. Although fractionally integrated GARCH models have been successfully employed to study volatility connections (see, e.g., Brunetti and Gilbert, 2000; Liu and Chen, 2013), the extension of the DY indices to the fractional integration framework has still received very little attention.[2] To our knowledge, only Cipollini et al. (2018) addressed this issue. The authors employed a FIVAR model to study vulnerability to systematic risk for five European stock markets, finding only small differences in the DY measures computed using the FIVAR and the VAR models.[3] However, the reported evidence of LM is rather weak, with small, sometimes non-significant, estimated orders of fractional integration in large part of their sample, which in part explains the unobserved differences between the two specifications. We depart from Cipollini et al. (2018) in two important ways. The first one is methodological. The authors estimated univariate models to obtain the LM parameters of the FIVAR, while the autoregressive component was estimated in a second step fitting a VAR to the (fractionally) differenced series. As in Abritti et al. (2016), we estimate the short- and long-memory parameters together in a single step, without relying on univariate specifications, which is a clear advantage in

[2] Outside the fractional integration framework, Caloia et al. (2018) recently employed DY measures based on a vector HAR model to account for the persistence of the semi-volatility series assessing spillover effects between five EMU stock markets.

[3] More specifically, Cipollini et al. (2018) find no differences between the two specifications when the models were estimated over their entire sample. Using rolling-samples, the FIVAR and VAR measures slightly diverge in a relatively small period after the 2008 crises, which is correlated with larger orders of fractional integration. Yet, the observed differences are still mild.

terms of efficiency over their two-step procedure. Second, we find strong evidence of LM in our data, which is stable over the whole sample. In fact, the presence of a LM component in the volatility of energy returns is well documented in the literature (see e.g., Charfeddine, 2016; Choi and Hammoudeh, 2009; Cunado et al., 2010; Gil-Alana et al., 2016; Kang et al., 2009). We find that accounting for this persistence leads to substantial differences in the DY indices computed in FIVAR and VAR specifications.

Our findings can be summarized as follows.

1. Consistent with previous studies, we find overwhelming evidence of LM in the volatilities of the four future returns, with the I(0) assumption decisively rejected by the data.
2. Accounting for LM is necessary to assess the magnitude of the spillovers. In particular, the traditional VAR understates the contribution of own-shocks, magnifying the spillovers effects.
3. As in Barunik et al. (2008), we find substantial spillovers across petroleum futures, but the link between petroleum commodities and natural gas in post-appears to be broken in post-2008 data. Thus, the results of the LM model support the thesis of Batten et al. (2017) and Zhu et al. (2018) obtained with Granger (non-) causality testing.

The remainder of the paper is organized as follows. In Section 2, we discuss the econometric framework. The empirical application is provided in Section 3. Finally, Section 4 offers some concluding remarks.

2. METHODOLOGY

2.1 The FIVAR Model and the Estimation Procedure

The FIVAR model is the multivariate extension of the well-known autoregressive ARFIMA. In this paper, we employ an unrestricted specification that allows for different orders of integration of the series, as in Abritti et al. (2016), Golinski and Zaffaroni (2016), or Lovcha and Perez-Laborda (2015).[4] Let the vector $Y_t = \left[y_{1t},...,y_{Nt}\right]'$ contain all the volatility series. An unrestricted FIVAR model for Y_t can be written as:

$$\begin{aligned} D(L)Y_t &= u_t \\ u_t &= F(L)u_{t-1} + \xi_t \ , \end{aligned} \tag{1}$$

where $D(L)$ is a diagonal matrix with elements given by $(1-L)^{d_i}$, and $d_i \in [0,1]$ is the order of fractional integration of the *i*th series in the vector. The larger this parameter, the more persistent y_i. In particular, if $d_i = 0$ or $d_i = 1$, the series exhibits standard I(0) or I(1) properties. Instead, if $0 < d_i < 1$, the series has LM properties, and the response of the variable to a shock takes more time to disappear than if the process was I(0). 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 Σ as the variance-covariance matrix.

To estimate the process given by (1) and (2), we use the approximate frequency domain maximum likelihood, proposed by Boes et al. (1989). A discussion of the multivariate version of the procedure can be found in Hosoya (1996). The method has various advantages over existing alternatives. First, in order to circumvent the complicated likelihood function of autoregressive fractionally integrated time series models, the estimation is produced in the frequency domain, on the contrary, with no need of latent variables. More importantly, using this method, all the parameters of the

[4] Fractional co-integrated models, as the ones in Johansen (2008) or in Johansen and Nielsen (2011), impose equal coefficients of fractional integration for all variables.

FIVAR model, long memory and short memory, are estimated simultaneously, which is a clear advantage over two-step procedures.

Collecting all model parameters in θ, an approximate (Whittle) log-likelihood function based on Y_t is given, up to a constant of multiplication by:

$$\ln L\left(\omega_j,\theta\right) = -\sum_{j=0}^{T/2}\left[\ln\det f_Y\left(\omega_j,\theta\right) + trf_Y^{-1}\left(\omega_j,\theta\right)I_T\left(\omega_j,Y\right)\right], \tag{2}$$

where $\omega_j = 2\pi j/T$, $j = 1...T/2$ is an equispaced set of Fourier frequencies. The spectral matrix $f_Y\left(\omega_j,\theta\right)$ is given by:

$$f_y\left(\omega_j,\theta\right) = \left(2\pi\right)^{-1} D\left(e^{i\omega_j}\right)^{-1}\left(I - F\left(e^{i\omega_j}\right)\right)^{-1}\Sigma\left(I - F\left(e^{-i\omega_j}\right)\right)^{-1} D\left(e^{-i\omega_j}\right)^{-1}, \tag{3}$$

where i denotes the imaginary unit, $D\left(e^{i\omega}\right)$, a diagonal matrix with the n-diagonal element given by $\left(1-e^{i\omega_j}\right)^{d_n}$ and $F\left(e^{i\omega_j}\right) = F_1 e^{i\omega_j} + ... + F_p e^{pi\omega_j}$.

Finally, $I_T\left(\omega_j,Y\right)$ in the equation (2) is the periodogram matrix, computed as the product of $x\left(\omega_j,Y\right)$ by its complex conjugate:

$$I_T\left(\omega_j,Y\right) = x\left(\omega_j,Y\right)x\left(\omega_j,Y\right)^*, \tag{4}$$

where $x\left(\omega_j,Y\right)$ is the finite Fourier transform of $Y_{n,t}$:

$$x_n\left(\omega,y_{n,t}\right) = \frac{1}{\sqrt{2\pi T}}\sum_{t=1}^{T} y_{n,t}e^{-i\omega(t-1)}. \tag{5}$$

Abbriti et al. (2016) and Lovcha and Perez-Laborda (2015) contain more details on the estimation procedure.

2.2 Diebold-Yilmaz Measures of Connectedness

The DY framework can be easily applied to the FIVAR model as it is applied to the VAR. To deal with correlation in the residuals, we rely on the generalized framework of Pesaran and Shin (1998), which does not require the orthogonalization of the shocks.

In particular, let the MA(∞) representation of the FIVAR model in (1) be:

$$Y_t = D(L)^{-1}\left[I - F\left(L\right)\right]^{-1}\xi_t = \Lambda\left(L\right)\xi_t\,. \tag{6}$$

The elements of the matrix $\Lambda\left(L\right)$ are infinite polynomials whose coefficients are the impulse responses (IRF) of the variables to the (possibly correlated) innovations. These IRFs can be computed in the FIVAR model noting that the diagonal elements of the matrix $D\left(L\right)$ can be expanded using the gamma function $\Gamma\left(\cdot\right)$:

$$(1-L)^{d_n} = \sum\nolimits_{k=0}^{\infty} D_{n,k}L^k;\quad D_{n,k} = \Gamma\left(k-d_n\right)\big/\Gamma\left(k+1\right)\Gamma\left(-d_n\right). \tag{7}$$

The remainder of this section closely follows Diebold and Yimaz (2015). We refer to this work for a further discussion. The proportion of the H-step ahead forecast error variance of variable y_i accounted for by the innovations in y_j could be computed from the generalized IRF as:

$$d_{ij}^{H} = \sigma_{ii}^{-1}\sum\nolimits_{h=0}^{H-1}\left(e'_i\,\Lambda_h\Sigma e_j\right)^2\Big/\sum\nolimits_{h=0}^{H-1}\left(e'_i\,\Lambda_h\Sigma\Lambda'_h\,e_i\right).$$

Since the own-and-cross shares do not sum to one, the contributions are typically normalized by the row-sum: $\tilde{d}_{ij}^{H} = d_{ij}^{H}\Big/\sum\nolimits_{j=1}^{N} d_{ij}^{H}$, yielding a $N\times N$ matrix of normalized contributions known as the *connectedness table*.

Each entry of this table measures the *pairwise directional connectedness* from variable y_j to variable y_i:[5]

$$C_{i\leftarrow j}^{H} = \tilde{d}_{ij}^{H} .$$

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

$$C_{i\leftarrow \bullet}^{H} = \sum_{j=1;\, j\neq i}^{N} d_{ij}^{H}$$

and, similarly, the off-diagonal column sum is the *total directional connectedness to* others from y_j:

$$C_{\bullet\leftarrow j}^{H} = \sum_{i=1;\, i\neq j}^{N} d_{ij}^{H} .$$

Net connectedness can be obtained as the difference between the *to* and *from* measures. Finally, the *total connectedness* index is defined as the sum of off-diagonal elements (total of off-diagonal variation) relative to the total sum (total variation) of elements:

$$C^{H} = \frac{1}{N}\sum_{\substack{i,j=1\\ i\neq j}}^{N} d_{ij}^{H} .$$

This index measures the extent to which the system is connected. Thus, if $C^{H} = 0$, the components are independent are there are no spillover effects in the system. On the contrary, if $C^{H} = 1$, the system is perfectly connected and all the forecast error variance comes from spillover effects.

[5] Note that, in general, $C_{i\leftarrow j}^{H} \neq C_{j\leftarrow i}^{H}$, and by construction, $\sum_{j=1}^{N} d_{ij}^{H} = 1$ and $\sum_{i,j=1}^{N} d_{ij}^{H} = N$.

3. VOLATILITY SPILLS ACROSS ENERGY FUTURES

We examine weekly volatility connections among four types of energy commodity futures: WTI crude oil, reformulated RBOB gasoline, heating oil, and natural gas. Our underlying daily data has been extracted from Thomson-Reuters Eikon and covers September 2008 to February 2018.[6]

Table 1
Summary Statistics

	Oil	Gasoline	Heating oil	Natural gas
Mean	32.414	31.844	26.899	40.047
Median	27.094	27.295	23.680	35.151
Maximum	167.518	126.564	96.051	135.342
Minimum	7.541	7.395	6.258	14.220
S.D.	20.200	17.680	13.975	18.361
Skewness	2.278	1.847	1.521	1.852
Kurtosis	7.699	4.405	2.844	5.043
Jarque Bera	1620.1	670.1	351.9	793.0

As in Diebold and Yilmaz (2009) or Yimaz (2010), we follow Garman and Klass (1980) and estimate weekly return volatilities using weekly high, low, opening and closing prices obtained from underlying daily high, low, open and close data, from the Monday open to the Friday close:

$$\begin{aligned}\tilde{\sigma}^2 &= 0.511\left(H_t - L_t\right)^2 - 0.019\left[\left(C_t - O_t\right)\left(H_t - L_t - 2O_t\right) - 2\left(H_t - O_t\right)\left(L_t - O_t\right)\right] \\ &-0.383\left(C_t - O_t\right)^2\end{aligned},$$

where H_t and L_t are the logarithms of Monday to Friday high and low prices, O_t is the Monday open price, and C_t is the Friday close (also in natural logs), resulting in 494 weekly volatility observations. Annualized standard deviations can be computed as $\tilde{\sigma} = 100\sqrt{52 \times \tilde{\sigma}^2}$. We provide summary statistics for volatilities in Table 1.

[6] The sample corresponds to the largest set available. Note that asymmetries do not play a fundamental role in the studied period (Barunik et al. 2016).

3.1 Full-Sample Results

Following the methodology explained in Section 2, we estimate a FIVAR model of the weekly volatilities of the four energy futures: WTI oil, unleaded gasoline, heating oil, and natural gas. For the autoregressive part, we select one lag according to SIC criteria.

Table 2
Selected FIVAR Estimation Results

Oil	Gasoline	Heating oil	Natural gas
0.4	0.32	0.35	0.47
(0.04)	(0.04)	(0.03)	(0.05)

Notes: The table provides the estimated orders of fractional integration. Standard errors in parenthesis.

Selected estimation results may be found in Table 2, which reports the estimated orders of FI of the four series. Corresponding standard errors are provided in parenthesis. Consistent with univariate studies, the presence of LM in the data is strong. The orders of integration are relatively high and greatly significant. Oil, unleaded gasoline, and heating oil have fractional orders of 0.4, 0.32, and 0.35 respectively, while the order of integration of natural gas is slightly larger (0.47), just on the border of the non-stationary region.[7] After, we test the VAR specification against the FIVAR alternative by bootstrapping the empirical distribution of the likelihood ratio test statistic.[8] The VAR null is rejected at usual significance levels. Overall, we find overwhelming evidence of long-memory with the standard I(0) framework decisively rejected by the data.

[7] If $0.5 \leq d_i < 1$, the series is no longer stationary, although it is still mean-reverting.

[8] For testing this hypothesis, we assume one autoregressive lag in the VAR, ensuring that the two models are nested. For the LR statistic, we estimate both models in the frequency domain and compute the values of the likelihood function. We bootstrap the empirical distribution of this statistic using both residual-based and frequency-domain bootstrap methods, generating 500 bootstrap replications in each case.

Once the presence of LM in the data has been confirmed, we examine spillovers within the DY framework. The resulting *connectedness table* is reported in the first part of Table 3.[9]

Table 3
Volatility Connectedness: FIVAR and VAR

FIVAR

	Oil	Gasoline	Heating oil	Natural gas	**FROM:**
Oil	56.6	15.3	28.1	0.0	43.4
Gasoline	18.5	58.0	23.2	0.3	42.0
Heating oil	27.4	19.5	52.8	0.3	47.2
Natural gas	0.1	0.2	0.5	99.2	0.8
TO :	46.0	35.0	51.8	0.6	**C = 33.4**

VAR

	Oil	Gasoline	Heating oil	Natural gas	**FROM:**
Oil	46.7 (-17.6)	22.8 (49.5)	29.6 (5.5)	0.9 (2139)	53.3 (22.9)
Gasoline	28.0 (50.9)	46.1 (-20.4)	25.0 (8.0)	0.8 (179.0)	53.9 (28.1)
Heating oil	32.0 (16.8)	21.2 (8.9)	45.0 (-14.7)	1.7 (474.1)	55.0 (16.4)
Natural gas	2.6 (4736.9)	1.0 (339.2)	5.1 (834.1)	91.3 (-7.9)	8.7 (945.6)
TO:	62.6 (36.0)	45.1 (28.8)	59.7 (15.3)	3.4 (438.3)	**C = 42.7 (28)**

Notes: The results are based on 10-week ahead forecasts. The *ij*-th entry of the upper-left 4x4 sub-matrix gives the *ij*-th pairwise directional connectedness. The FROM column gives total directional connectedness from others. The TO row gives the total directional connectedness to others. Net connectedness can be computed subtracting the FROM column to the TO row. The bottom-right element C (in boldface) is the total connectedness. Values in parenthesis indicate % change with respect to the corresponding measure in the FIVAR.

As can be seen in the table, the *total connectedness* in the FIVAR system is 32.4%. Interestingly, connectedness is completely driven by the close link between petroleum markets. Note that both gasoline and heating-oil are products of crude oil, so shocks across these markets are transmitted quickly. Oil, gasoline, and heating oil contribute to the forecast error variance of the other petroleum volatilities with more or less the same amount spillovers that they receive, which is consistent with the evidence provided in Barunik *et al.* (2016). Yet, the gasoline market is net receiver, while crude

[9] We employ a 10-week ahead forecast horizon for the connectedness table, as in Diebold and Yilmaz (2009).

oil and heating oil are net transmitters of spillovers. On average, around 45% of the variability comes from spillovers from other petroleum commodities. On the contrary, we virtually find no volatility spillovers effects from petroleum markets to natural gas market or vice versa. As can be seen in the table, the *total directional connectedness from* and *to* natural gas is very small (0.8 and 0.6, respectively). Thus, our results suggest that the link between these markets is broken in post-2008 crisis data.

To facilitate comparison with the standard framework, the second half of Table 2 contains the connectedness measures calculated from the FEVD of a canonical VAR.[10] In order to assess the relative importance of the discrepancies, the table also provides the percentage of variation with respect to the corresponding measure in the FIVAR (in parenthesis). As can be observed in the table, the VAR model significantly understates the own-contributions to the FEVD. As a result, the spillovers are largely magnified. The *total connectedness* in the VAR model is full 10 points higher (from 33.4 to a 42.7), which is a lot for a magnitude bounded by 0 and 100, and it implies a variation of almost 30% with respect to the FIVAR. The difference is even greater for certain commodities. For instance, the *total directional connectedness* of oil *to* others is more than 15 points higher. Yet, in relative terms, the largest discrepancies are in the spillovers from and to natural gas. Note that the magnitude of the volatility linkages between petroleum and natural gas volatilities in the VAR model is not negligible, and is directed from petroleum markets to natural gas (the net connectedness of natural gas in the VAR model is -5.3).

[10] We select two lags according to the same criteria employed in the FIVAR (SIC). However, the results are robust to using exactly the same number of lags in the two models.

3.2 Rolling-Sample Analysis

The full sample analysis provides an overall picture of the volatility relationships between 2008 and 2018, yet it may well be that connectedness varies with time. As typically done in this literature, we carry out rolling estimations over a 250-week window. The objective here is twofold. From one side, the resulting time-series of connectedness indices allow us to study the extent of the spillover variation and assess whether the discrepancies found between the FIVAR and VAR specifications are stable. On the other, we can also evaluate the robustness of presence of LM to possible breaks in the data. It has been argued that LM may sometimes appear as a spurious phenomenon caused by a break (Diebold and Inoue, 2001). Yet, the opposite effect is also well documented (Nunes et al., 1995).[11] In addition, the results obtained by the previous literature suggest that, even in the event of any structural change, the presence of LM components in the volatility of returns would be robust to structural changes. Choi and Hammoudeh (2009), for example, provide evidence of LM in the absolute and squared petroleum futures returns, with structural breaks having only a small marginal effect on the fractionally integrated parameters. Nevertheless, finding significant presence of LM in the different rolling-samples will make irrelevant the practical importance of this possible critique to our full sample results.

Figure 1 plots the resulting orders of fractional integration across the different windows together with two standard error bands. As can be seen in the figure, the evidence of LM is strong. The fractional orders are relatively high and significant. Moreover, they are also quite constant across the different subsamples, with values

[11] Although there are techniques aimed to distinguish between the two types of processes (see e.g., Qu, 2011, and references therein), they have not yet been extended to the multivariate case. This is important since, as far as any structural break found using a univariate specification is explained by a change in the composition of shocks, this is not a concern in the multivariate model.

always close to those estimated in the whole sample. Thus, the rolling-estimates of the multivariate model suggest that structural breaks (if any) play only a marginal role on the LM characteristics of the volatility series, which is in line with the results of the preceding univariate studies.

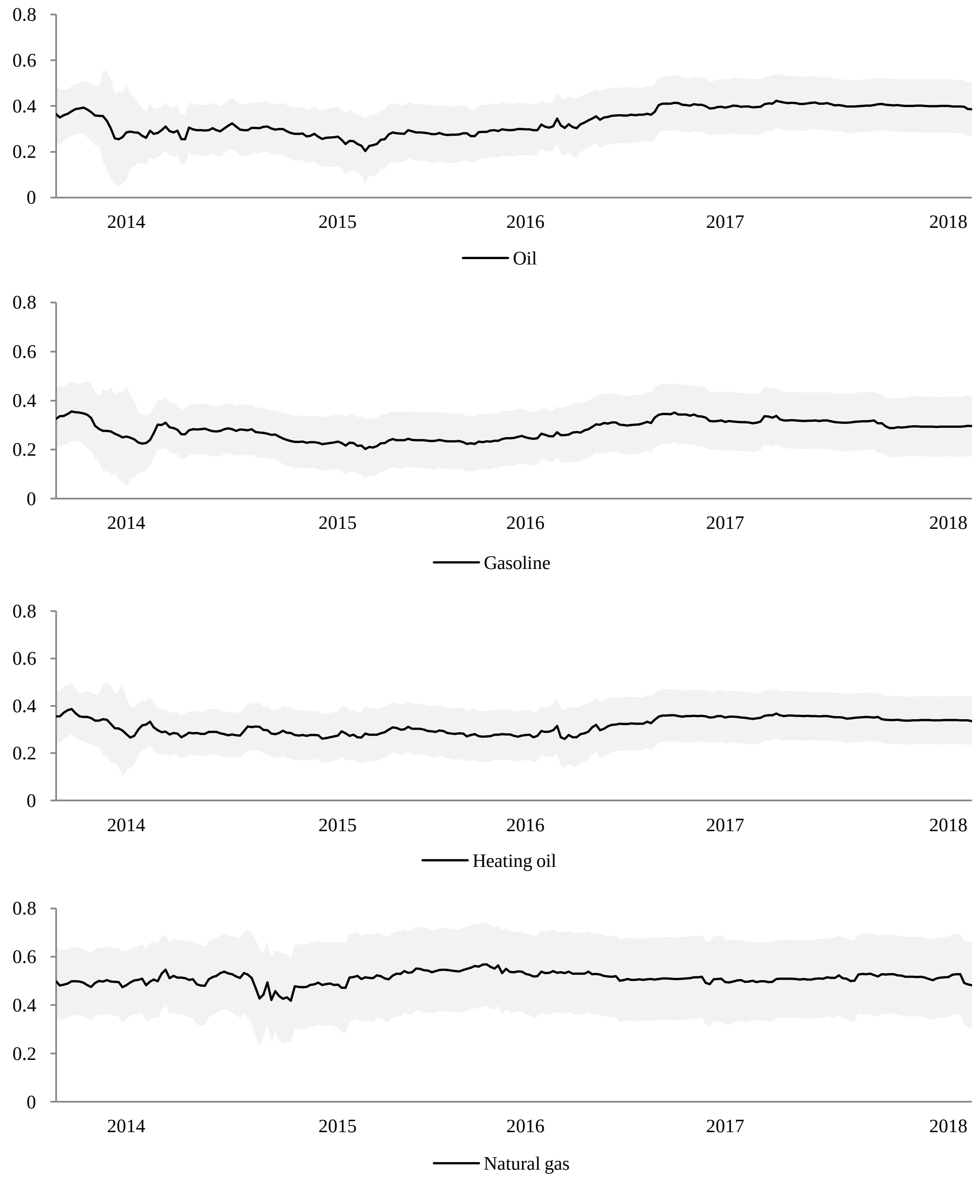

Fig. 1. Rolling-estimation orders of fractional integration. The shadowed area is the two standard error band.

The time-varying version of the *total connectedness* index is depicted in Figure 2. The figure also includes the corresponding measure computed in the VAR. Note that, although the LM parameters are rather stable, the *total connectedness* in the system presents a significant declining trend, ranging from 39% (the window ending in August 2013) to 28% (the window ending in February 2018). Interestingly, this decline is also present in the VAR (from 47% to 39%), but with a completely different pattern. The index computed in the VAR presents a considerably faster decline in the first quarter of the subsamples. As a result, the gap between the indexes computed in the two models is progressively closing; however, it remains almost a plateau after. As a result, the larger discrepancies between the two specifications are found in the last quarter of the rolling-estimations.[12]

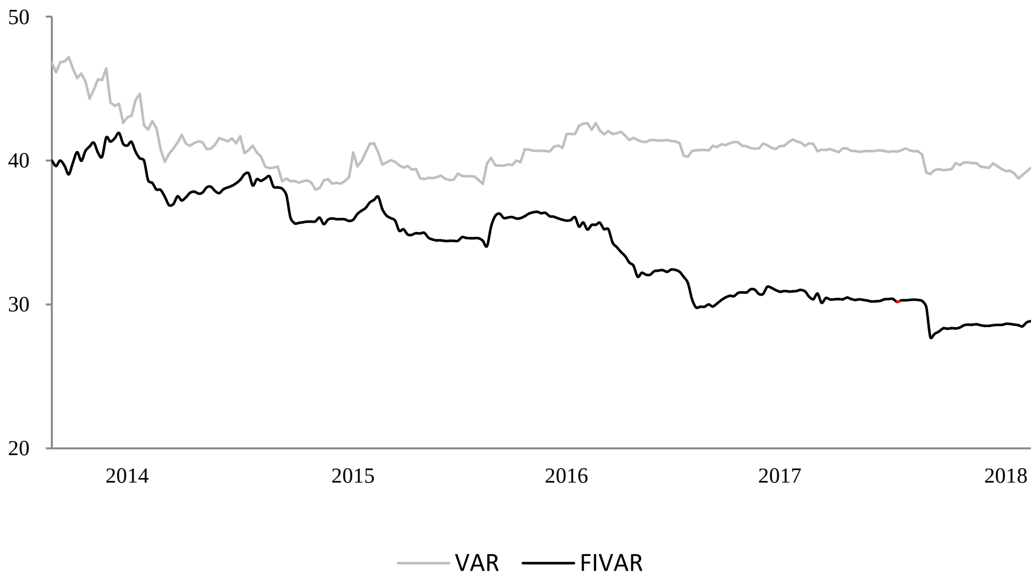

Fig. 2. Rolling-estimation total connectedness.

[12] The minimum distance is found in the samples ending in January 2014 and August 2014 (2 points), coinciding with small dips in the estimated persistence of petroleum and natural gas volatilities. The maximum divergence is found in the sample ending in October 2017 (12 points).

Finally, we employ the rolling-sample estimates to shed more light on the relationship between petroleum and natural gas volatilities. Figure 3 depicts the time pattern of the *total directional connectedness* to natural gas volatility *from* the petroleum markets and vice versa. Note, that although these two measures are never large, their values are significantly larger than the magnitudes obtained using the whole sample in the first third of rolling-samples, reaching maximums of 12.4% and 10.1%, respectively. However, the two measures experienced a progressive decline so that the volatility spillover effect between the natural gas and petroleum markets is virtually nonexistent in any direction for recent subsamples.

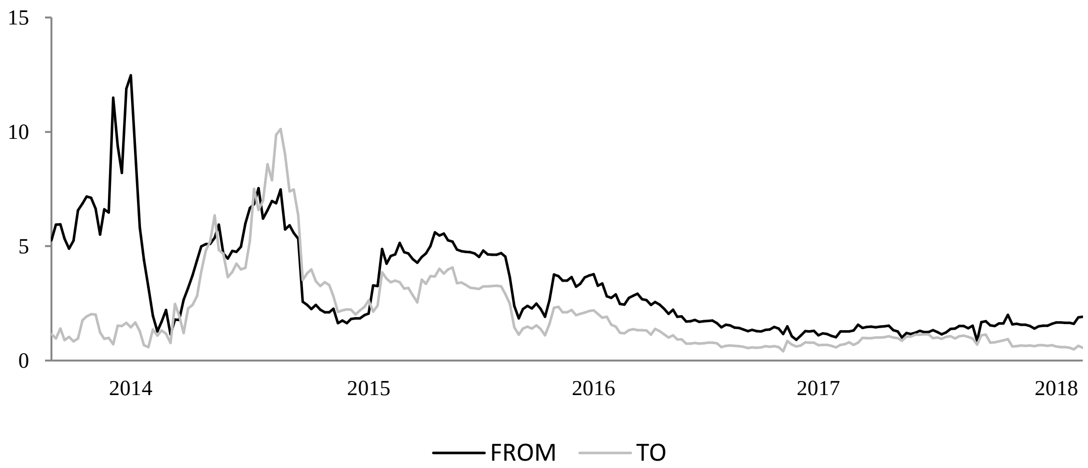

Fig.3. Dynamic Total Directional Connectedness FROM-TO Natural Gas computed in the FIVAR model. Net spillover effects can be computed as the difference between TO and FROM

4. CONCLUSIONS

It is now well understood that return volatility usually presents a degree of persistence that, although still consistent with an essential stationary process, cannot be properly captured by standard autoregressive specifications. In this paper, we have proposed a FIVAR model combining both long and short-memory components to assess volatility spillovers across energy futures markets within the DY framework. We have found that the different return volatility series are well characterized by this combination, with LM providing important persistence to shocks, yet still in a context of mean-reversion. Our results suggest that neglecting this type of persistence results in a misleading assessment of spillovers. In particular, the canonical VAR understate the own-contributions to the forecast error variance, magnifying the magnitude of spillover effects. From the empirical view, we have shown that while petroleum markets present substantial volatility linkages, the relation between these markets and natural gas appear to be broken in post-2008 data, indicating that there are no volatility spillovers that can be employed by market participants to find optimal hedging positions.

Like all empirical work, our approach suffers from several shortcomings. The most important, in our opinion, is that the LM model is not well-suited for the analysis of very short sample spans and is computationally more demanding than the VAR, which may complicate the joint analysis of many volatility series. Yet, the strong support of LM in the literature suggests that additional empirical studies taking into consideration these issues are required. In this respect, it would be interesting to assess the influence of LM on the assessment of the spillovers between the oil and the financial market volatilities. We consider this issue an interesting avenue for future research.

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