Connectedness measures via MIDAS SVAR

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Methodological approach

- Our methodological approach bridges the work of Ghysels (2016), Foroni, Ghysels and Marcellino (2014) and Foroni and Marcellino (2014) on Mixed Data Sampling Structural Vector Autoregressive models (MIDAS-SVAR), with that of Diebold and Yilmaz (2014) on connectedness.

- We apply the aforementioned methods in the empirical setting of Antonakakis, Chatziantoniou & Filis (2017) and Wang, Wu & Yang (2013) in order to **examine the impact of higher frequency variables to connectedness measure, and their contribution to the identification and analysis of shocks (in the oil-stock market context)**.

Variables

- We take into consideration:
  - a supply-side shock (**SSS**) proxied by global oil production,
  - an aggregate demand shock (**ADS**) proxied by global economic activity,
  - an oil specific shock (**OSS**), proxied by oil price

  and we estimate their impact on stock market returns (**SMR**).
- We distinguish three different cases for comparison:
  - In the first case we have **monthly** observations for all variables.
  - In the second case we have **monthly** observations for supply-side and aggregate demand shocks and **bi-weekly** observations for oil specific shocks and stock market returns respectively.
  - In the third case we have **monthly** observations for supply-side and aggregate demand shocks and **weekly** observations for oil specific shocks and stock market returns respectively.

Structural VAR

- The AB-model representation of the general p - th order structural VAR model (see inter alia Amisano and Giannini 1997; Favero 2000 and Lütkepohl 2006):

$$A_0 y_t = \sum_{i=1}^{p} A_i y_{t-i} + B v_t$$

- A reduced form of the underlying structural model:

$$y_t = \sum_{i=1}^{p} C_i y_{t-i} + u_t$$

with $C_i = A_0^{-1} A_i$.

- The moving average (MA) representation of the SVAR model can be written as:

$$y_t = \sum_{i=0}^{\infty} G_i v_{t-i}$$

where $G_i = C_1 G_{i-1} + C_2 G_{i-2} + \ldots + C_p G_{i-p}$, $G_0 = \mathrm{I}_{N\times N}$ and $G_i = 0$ for $i < 0$.

Structural VAR

- y_t: A Nx1 vector of endogenous variables, which we use as proxies to extract shocks.
- N = 4, 6 and 10 for each one of the cases under consideration.
- The *NxN* matrices A_0 and B depict the restrictions imposed upon the variables, i.e. the contemporaneous structural relationships of all the variables, regardless of their frequency, in the model.
- A_i, C_i and G_i are autoregressive coefficient matrices.
- The Nx1 vectors v_t and u_t are the **unobserved** serially uncorrelated structural disturbances and the **observed** reduced form errors respectively. The latter can be written as a linear combination of the former as:

$$A_0 u_t = B v_t \Leftrightarrow u_t = A_0^{-1} B v_t$$

- We can also write the variance-covariance matrices as:

$$\Sigma_v = \mathrm{I}_N \quad \text{and} \quad \Sigma_u = A_0^{-1} B \mathrm{I} B' A_0^{-1\prime}$$

Structural VAR

- We use Cholesky decomposition as in Diebold & Yilmaz (2009), which helps us derive variance decompositions dependent on the chosen ordering of the variables.
- For the first case, that of monthly-observed variables, we adopt the variable ordering in Antonakakis et al. (2017). This goes from the least endogenous to the most endogenous (top-down):

$$\begin{pmatrix} 1 & & & \\ * & 1 & & \\ * & * & 1 & \\ * & * & * & 1 \end{pmatrix} \begin{pmatrix} u_t^{oil\ production} \\ u_t^{global\ economic\ activity} \\ u_t^{oil\ price} \\ u_t^{stock\ market\ returns} \end{pmatrix} = \begin{pmatrix} * & & & \\ & * & & \\ & & * & \\ & & & * \end{pmatrix} \begin{pmatrix} v_t^{SSS} \\ v_t^{ADS} \\ v_t^{OSS} \\ v_t^{SMR} \end{pmatrix}$$

- There are also alternative identification schemes that are invariant to the ordering of the variables (Koop et al. 1996, Pesaran and Shin 1998)

Structural VAR

- Asterisks denote the estimated unrestricted coefficients and empty entries correspond to zeros according to the specification of the imposed relations among the variables. The left-hand side matrix A_0 contains the intra-month relations and dynamics among the variables, while the right-hand side matrix B includes the simultaneous effects of the structural shocks both among the variables and intra-month.
- By construction, matrix A_0 depicts the flow of information contributions from variables ordered on top to the variables ordered underneath them in vector u_t.
- Taking into consideration that the product $A_0^{-1}B$ is a *N*x*N* lower triangular matrix consisting of all the unrestricted elements to be estimated, B matrix is the “complement” of A_0 in all three cases.

- In general, one can use the SVAR framework for policy analysis or forecasting. Today we will use it for policy analysis.

Variance Decomposition

- Variance decomposition gives a different aspect for examining the dynamics of a SVAR model.
- (Forecast error) variance decomposition tell us the proportion of the movements in a variable due to its "own" shocks versus shocks from other variables.
- It determines how much of the K-step ahead forecast error variance of a given variable is explained by innovations to each variable for $K = 1, 2, \dots$.
- A shock in one variable would directly affect the variable itself but it would also be transmitted to all other variables in the system through the dynamic structure of SVAR.
- If v_1 shocks explain none of the forecast error variance of y_2 at all forecast horizons, then y_2 is exogenous. In that case y_2 evolves independently of v_1 and y_1.

Variance Decomposition

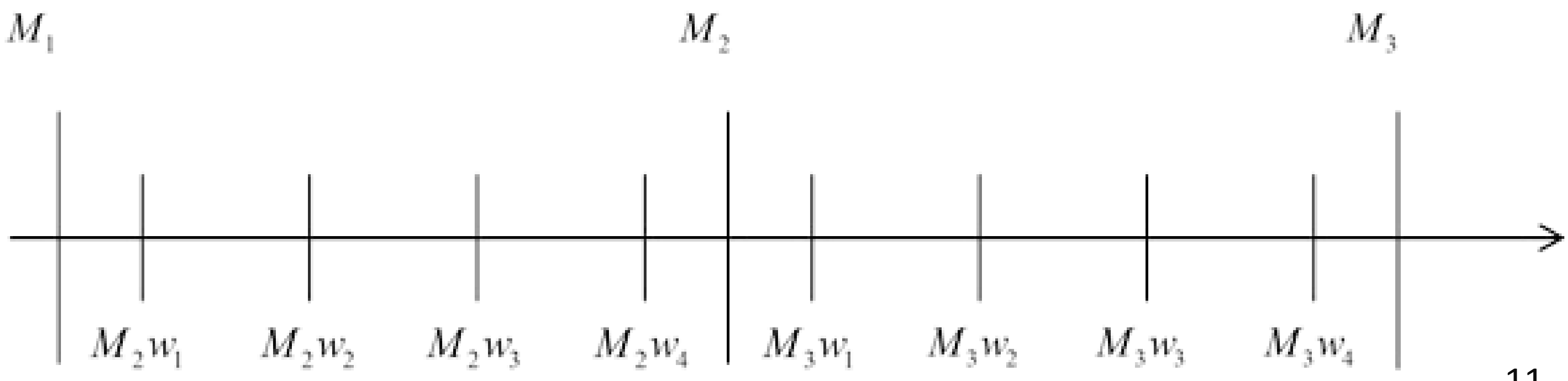
- On the other hand, v_1 shocks could explain all of the forecast error variance of y_2 at all horizons, so that y_2 is entirely endogenous.
- In practice, it is usually observed that own series shocks explain almost all of the forecast error variance at short horizons and smaller proportions at longer horizons.
- We would expect that if v_1 shocks have little contemporaneous effect on y_2, they would affect y_2 with a lag.

MIDAS models

- A typical time series regression involves data sampled at the same frequency (e.g. monthly).
- Variables available at a different frequency (e.g. weekly) may be valuable, but cannot be used directly.
- Typically, one would aggregate (linearly, with equal weights or not) all the high-frequency variables to the same low (monthly) frequency before regressing.
- In the process, a lot of potentially useful information might be discarded, thus rendering the relation between the variables difficult to detect.
- MIxed DAta Sampling (MIDAS) regression models can accommodate variables sampled at different frequencies;
  - Introduced in both filtering and regression contexts (Ghysels, Santa-Clara & Valkanov, 2002, 2004, 2005; see Andreou, Ghysels & Kourtellos, 2011 for a review)
  - Related to the temporal aggregation literature (Sims, 1971; Geweke, 1978)
  - Share some characteristics with Autoregressive Distributed Lag models

MIDAS-SVAR (the information flow)

The MIDAS-SVAR approach offers a better use of available information; specifically, the combination of available data in different frequencies, in the same model. In the figure below, the depiction of the information flow and its subsequent transformation to information packages or vectors helps our better understanding of the mechanics of this transformation and its application. Consider two variables, one "slow" with monthly observations and one "fast" with four weekly observations within a month. Let M_i be the observation of the *i*-th month ("slow" variable) and $M_i w_j$ be the observation of the *j*-th week of *i*-th month ("fast" variable).



MIDAS-SVAR (information packages)

This body of information can be segmented and aligned properly in order to form ***information packages*** or ***vectors*** comprised of the amount of information received in a period of one month, with an ordering based on the endogeneity of each variable and the time point of the observation (for "fast" variables). So we achieve a transition from observations per time point (dates) to groups of observations per time frame (monthly periods) or vectors, as follows:

$$\begin{pmatrix} M_1 \\ M_2 w_1 \\ M_2 w_2 \\ M_2 w_3 \\ M_2 w_4 \end{pmatrix}, \quad \begin{pmatrix} M_2 \\ M_3 w_1 \\ M_3 w_2 \\ M_3 w_3 \\ M_3 w_4 \end{pmatrix}, \quad \dots \quad , \begin{pmatrix} M_{n-1} \\ M_n w_1 \\ M_n w_2 \\ M_n w_3 \\ M_n w_4 \end{pmatrix}$$

MIDAS-SVAR (information packages)

- Expanding this example by two more variables, one slow in the position of the second variable and one fast in the position of the fourth variable respectively, we get the ordering of the models in our study.
- A key issue is the number of observations within a given month, which varies from four to five.
- We keep the last four observations of the month in the cases of five observations per month, in order to retain a uniform pattern for all the months, to keep only actual data and to avoid any synthetic data created by interpolation techniques.
- We choose to keep the last quartet instead of the first in order to maintain the information flow alignment across consecutive information packages or vectors.

MIDAS-SVAR (monthly – bi-weekly)

$$\begin{pmatrix} 1 & & & & & \\ * & 1 & & & & \\ * & * & 1 & & & \\ * & * & * & 1 & & \\ * & * & * & & 1 & \\ * & * & * & * & * & 1 \end{pmatrix} \begin{pmatrix} u_t^{oil\ production} \\ u_t^{global\ economic\ activity} \\ {}_{bw1}u_t^{oil\ price} \\ {}_{bw2}u_t^{oil\ price} \\ {}_{bw1}u_t^{stock\ market\ returns} \\ {}_{bw2}u_t^{stock\ market\ returns} \end{pmatrix} = \begin{pmatrix} * & & & & & \\ & * & & & & \\ & & * & & & \\ & & & * & & \\ & & & * & * & \\ & & & & & * \end{pmatrix} \begin{pmatrix} v_t^{SSS} \\ v_t^{ADS} \\ {}_{bw1}v_t^{OSS} \\ {}_{bw2}v_t^{OSS} \\ {}_{bw1}v_t^{SMR} \\ {}_{bw2}v_t^{SMR} \end{pmatrix}$$

In this case, the left-hand side matrix A_0 contains the intra-month relations and dynamics among high and low frequency variables. The right-hand side matrix B includes the simultaneous effects of the structural shocks both among the variables and intra-month.

MIDAS-SVAR (monthly – weekly)

$$
\begin{pmatrix}
1 & & & & & & & & & \\
* & 1 & & & & & & & & \\
* & * & 1 & & & & & & & \\
* & * & * & 1 & & & & & & \\
* & * & * & * & 1 & & & & & \\
* & * & * & * & * & 1 & & & & \\
* & * & * & & & & 1 & & & \\
* & * & * & * & & & * & 1 & & \\
* & * & * & * & * & & * & * & 1 & \\
* & * & * & * & * & * & * & * & * & 1
\end{pmatrix}
\begin{pmatrix}
u_t^{oil\ production} \\
u_t^{global\ economic\ activity} \\
{}_{w1}u_t^{oil\ price} \\
{}_{w2}u_t^{oil\ price} \\
{}_{w3}u_t^{oil\ price} \\
{}_{w4}u_t^{oil\ price} \\
{}_{w1}u_t^{stock\ market\ returns} \\
{}_{w2}u_t^{stock\ market\ returns} \\
{}_{w3}u_t^{stock\ market\ returns} \\
{}_{w4}u_t^{stock\ market\ returns}
\end{pmatrix}
=
\begin{pmatrix}
* & & & & & & & & & \\
& * & & & & & & & & \\
& & * & & & & & & & \\
& & & * & & & & & & \\
& & & & * & & & & & \\
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& & & * & * & * & * & & & \\
& & & & * & * & & * & & \\
& & & & & * & & & * & \\
& & & & & & & & & *
\end{pmatrix}
\begin{pmatrix}
v_t^{SSS} \\
v_t^{ADS} \\
{}_{w1}v_t^{OSS} \\
{}_{w2}v_t^{OSS} \\
{}_{w3}v_t^{OSS} \\
{}_{w4}v_t^{OSS} \\
{}_{w1}v_t^{SMR} \\
{}_{w2}v_t^{SMR} \\
{}_{w3}v_t^{SMR} \\
{}_{w4}v_t^{SMR}
\end{pmatrix}
$$

Empirical application

- Much like previous studies on oil price shocks and dynamic connectedness with financial markets (see, e.g. Antonakakis et al., 2014, 2017), we examine stock exchanges in a number of (net) oil importing and (net) oil exporting countries.
- Ample empirical evidence suggests that the impact of oil price shocks is different across oil importing and oil exporting countries; for example, Bjornland (2009), Mohanty et al. (2011) and Wang et al. (2013), among others, report that positive oil price shocks are associated with positive returns for the stock markets of net oil–exporting countries, while the opposite holds for the stock markets of the net oil–importers.

Sample Collection

- The time frame of our study spans from January 1998 to September 2017.
- For stock market returns (SMR), we collect weekly, bi-weekly and monthly data of stock market indices for Canada (S&P/TSX), Russia (RTS) and Norway (OSE/OBX), as representatives of net oil exporting countries, and China (SSE), Spain (IBEX35), France (CAC40), Germany (DAX30), Italy (FTSE/MIB), Japan (NIKKEI225), the UK (FTSE100) and the USA (S&P500) as the major net oil importing countries. Stock market indices are deflated by OECD consumer price indices (CPIs) with 2010 as base year. Stock market indices and CPIs are extracted from Datastream.
- U.S. Energy Information Administration is our source of monthly data on world oil production in order to estimate supply-side shocks (SSS), and weekly, bi-weekly and monthly prices of Brent crude oil in order to estimate oil specific shocks (OSS).

Sample Collection

- Given that the U.S. Energy Information Administration reports weekly Brent prices at the end of the trading week (Fridays), the bi-weekly or weekly stock index returns necessary for the MIDAS specifications are also sampled on Fridays.
- Results are virtually indistinguishable if West Texas Intermediate (WTI) oil prices, instead of Brent crude, are employed in the estimation of oil shocks. During the time frame of our study, the correlation coefficients between log returns of WTI and Brent crude are 0.9298, 0.8798 and 0.8283, for the monthly, bi-weekly and weekly frequency respectively.
- For the aggregate demand shocks (ADS) we use as a proxy the global real economic activity in industrial commodity markets index (an index of dry cargo single voyage freight rates - monthly data), from Lutz Kilian's personal website (http://www-personal.umich.edu/~lkilian/), as referenced in Kilian (2009).

Descriptive Statistics

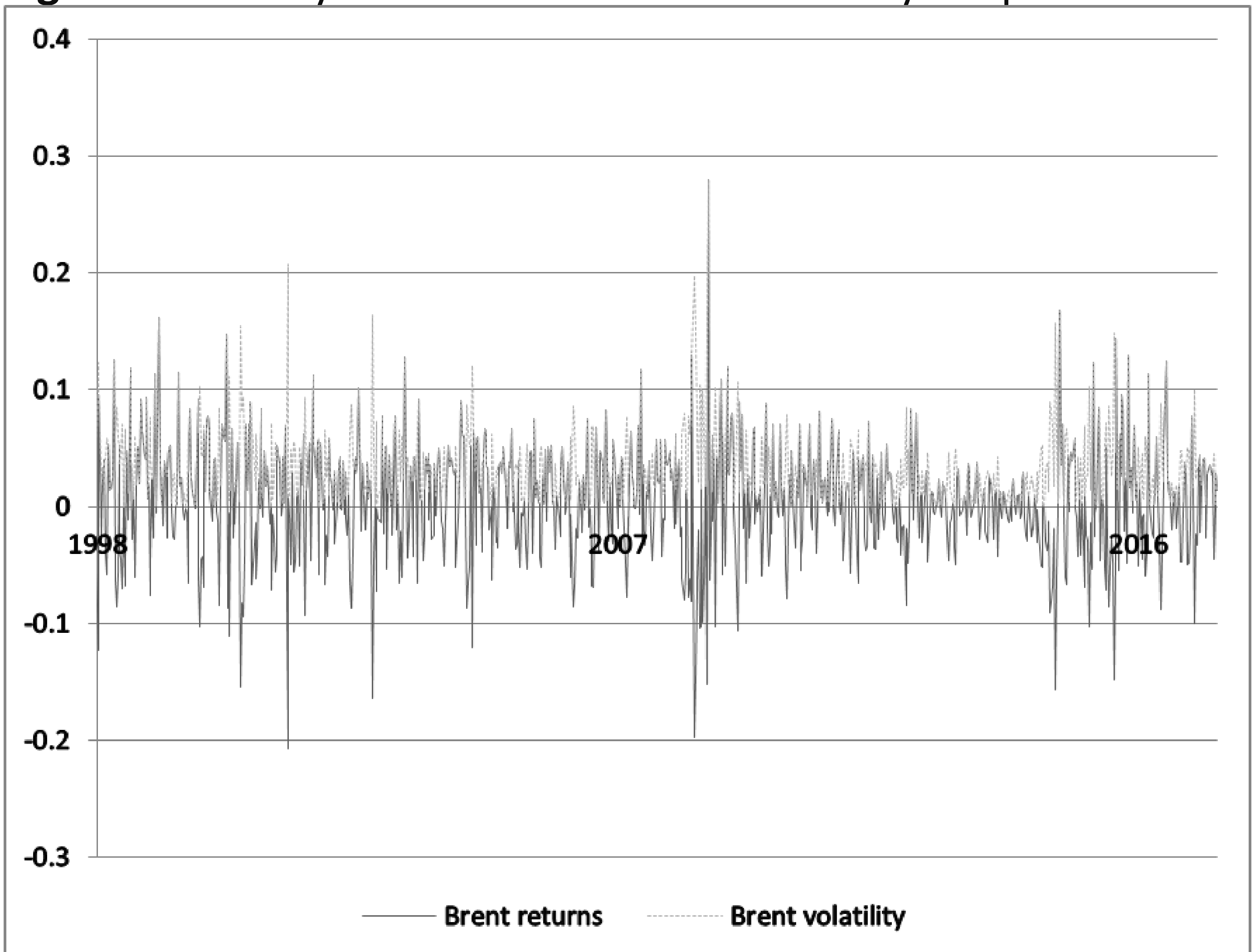
- Descriptive statistics are reported in table 1.
- World oil production, Brent oil prices and stock market indices series are rendered stationary by taking the first differences of natural logarithms as the reported augmented Dickey-Fuller (ADF) statistics testify.
- None of the examined series follows a normal distribution according to the reported Jarque–Bera statistics.
- Skewness appears negative in all series, and kurtosis indicates that our sample distributions appear more leptokurtic, as we shift from low to higher observation frequencies.
- The latter could be considered evidence of the existence of a higher probability of heavily deviated closing prices occurrence and subsequent spillover effects.

Descriptive Statistics

- In our sample period, Brent oil prices and most stock markets (with the exceptions of Russia, Spain, Italy and the UK) exhibited mildly positive mean returns.
- The German stock market outperformed every other, while the Russian stock exchange was the worse-performing during our sample period.
- The Russian stock market exhibited the highest volatility, while the US and the UK stock markets were the least volatile.
- Moreover, as evident from Figure 1, the Brent crude oil price has exhibited a fair amount of volatility during our sample period, especially in the period that followed the 9/11 attack and the 2007-2009 financial crisis.
- This crisis is also evident in the evolution of the returns and volatility series of all examined stock markets (to save space, only the U.S. stock market is plotted in Figure 2).

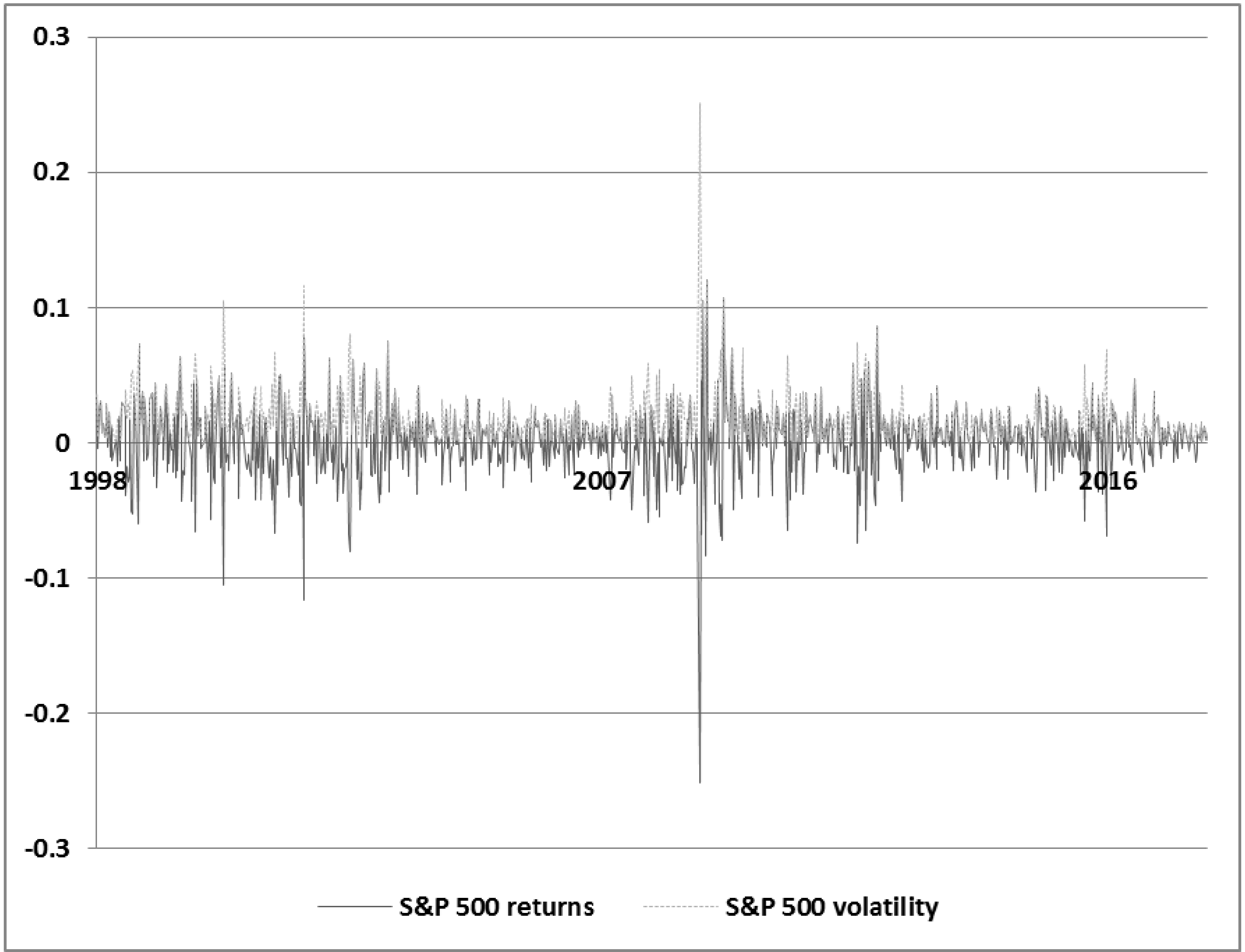
Descriptive Statistics

Figure 1: Weekly returns and realized volatility of spot Brent oil



Descriptive Statistics

Figure 2: Weekly returns and realized volatility of the S&P500 index



Selecting the sampling frequency

- We perform a likelihood ratio (LR) test (Ghysels 2016, Bacchiocchi 2018).
- The test statistic $LR = -2\left(l^r - l^u\right)$, where l^r and l^u are the log-likelihoods of the restricted and the unrestricted models respectively, is asymptotically distributed as X^2 with degrees of freedom equal to the number of the aggregation restrictions (90, 450 and 450 respectively in our applications).
- Rejection of the null hypothesis suggests that data aggregation causes substantial information losses during the process of identification of the structural shocks.
- Our findings suggest that in each case the higher sampling frequency prevails over the lower one, which leads us to the conclusion that the weekly sampling frequency model is the optimal model.

Selecting the sampling frequency

The selection matrices S_{m-b} , S_{m-w} , S_{b-w} which will help us with the aggregation of the high frequency variables in the monthly – biweekly, monthly – weekly and biweekly – weekly comparisons respectively are:

$$S_{m-b} = \begin{bmatrix} \mathrm{I}_{L_1} & 0 & 0 & 0 & 0 & 0 \\ 0 & \mathrm{I}_{L_2} & 0 & 0 & 0 & 0 \\ 0 & 0 & \mathrm{I}_{H_1} & \mathrm{I}_{H_1} & 0 & 0 \\ 0 & 0 & 0 & 0 & \mathrm{I}_{H_2} & \mathrm{I}_{H_2} \end{bmatrix}$$

$$S_{m-w} = \begin{bmatrix} \mathrm{I}_{L_1} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \mathrm{I}_{L_2} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \mathrm{I}_{H_1} & \mathrm{I}_{H_1} & \mathrm{I}_{H_1} & \mathrm{I}_{H_1} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \mathrm{I}_{H_2} & \mathrm{I}_{H_2} & \mathrm{I}_{H_2} & \mathrm{I}_{H_2} \end{bmatrix}$$

Selecting the sampling frequency

$$S_{b-w} = \begin{bmatrix} \mathrm{I}_{L_1} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \mathrm{I}_{L_2} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \mathrm{I}_{H_1^1} & \mathrm{I}_{H_1^1} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \mathrm{I}_{H_2^1} & \mathrm{I}_{H_2^1} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \mathrm{I}_{H_1^2} & \mathrm{I}_{H_1^2} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathrm{I}_{H_2^2} & \mathrm{I}_{H_2^2} \end{bmatrix}$$

Multiplying these matrices by the corresponding C matrices in each case, we obtain the restrictions on the parameters related to the dynamics of the VAR.

LR test results

	monthly - bi-weekly		monthly - weekly		bi-weekly - weekly
CAN	2,640.34		6,701.99		4,061.65
NOR	2,565.49		6,294.82		3,729.33
RUS	2,332.21		5,473.59		3,141.39
CHI	2,560.70		6,231.12		3,670.41
ESP	2,551.76		6,217.22		3,665.46
FRA	2,581.61		6,331.29		3,749.67
GER	2,509.58		6,206.59		3,697.01
ITA	2,563.90		6,218.41		3,654.51
JAP	2,643.29		6,358.94		3,715.64
UK	2,731.68		6,718.69		3,987.01
US	2,661.70		6,621.89		3,960.19
critical value	124.12		522.72		522.72

Log-likelihood ratio tests statistics at 1% significance level.

Impulse Response Functions (IRFs)

- We compute the point estimates of impulse responses for 13 months (current plus 12 months ahead), their accompanying 90% confidence intervals and the means of Impulse Response Distributions (IRD) for all three cases (monthly – bi-weekly, monthly – weekly and bi-weekly – weekly data sampling).
- Then we examine whether both low and high frequency confidence intervals do not include 0 and the low frequency confidence interval is greater than the high frequency confidence interval, i.e. the high frequency confidence interval is tighter.
- We compare the relative confidence intervals in each case as follows:

Impulse Response Functions (IRFs)

Confidence Intervals

- The first two variables in each case are sampled on a monthly basis, therefore the comparison is straightforward. The remaining variables are paired according to their occurrence in time. Specifically, for the monthly – bi-weekly comparison, we compare the monthly sampled oil price with both bi-weekly sampled oil prices, for the monthly – weekly comparison, we compare the monthly sampled oil price with all four weekly sampled oil prices, while for the bi-weekly – weekly comparison, we compare the first bi-weekly sampled oil price with the first and second weekly sampled oil prices and the second bi-weekly sampled oil price with the third and fourth weekly sampled oil prices.
- Obviously, the relative comparisons were also conducted for stock market returns.
- The comparisons results clearly point out that in almost every case the highest sampling frequency offers us a tighter IRF confidence interval.

Impulse Response Functions (IRFs)

Confidence Intervals

	monthly - bi-weekly			monthly - weekly			bi-weekly - weekly	
CAN	391	(83.55%)		1110	(85.38%)		380	(29.23%)
NOR	394	(84.19%)		1166	(89.69%)		515	(39.62%)
RUS	408	(87.18%)		1191	(91.62%)		616	(47.38%)
CHI	413	(88.25%)		1164	(89.54%)		442	(34.00%)
ESP	387	(82.69%)		1119	(86.08%)		483	(37.15%)
FRA	395	(84.40%)		1093	(84.08%)		436	(33.54%)
GER	406	(86.75%)		1171	(90.08%)		547	(42.08%)
ITA	397	(84.83%)		1130	(86.92%)		555	(42.69%)
JAP	403	(86.11%)		1137	(87.46%)		642	(49.38%)
UK	354	(75.64%)		970	(74.62%)		597	(45.92%)
US	26	(5.56%)		55	(4.23%)		35	(2.69%)
Total number of comparisons	468			1300			1300	

Number of comparisons where the 10% confidence interval of the IRF in the higher frequency case is tighter than that in the lower frequency case. In parentheses are reported the percentages of the number of successful comparisons over the total number of comparisons.

Impulse Response Functions (IRFs)

Confidence Intervals

	monthly - bi-weekly			monthly - weekly			bi-weekly - weekly	
CAN	393	(83.97%)		1122	(86.31%)		447	(34.38%)
NOR	396	(84.62%)		1178	(90.62%)		541	(41.62%)
RUS	410	(87.61%)		1203	(92.54%)		624	(48.00%)
CHI	415	(88.68%)		1176	(90.46%)		498	(38.31%)
ESP	389	(83.12%)		1131	(87.00%)		533	(41.00%)
FRA	397	(84.83%)		1105	(85.00%)		487	(37.46%)
GER	408	(87.18%)		1183	(91.00%)		593	(45.62%)
ITA	399	(85.26%)		1142	(87.85%)		601	(46.23%)
JAP	405	(86.54%)		1149	(88.38%)		662	(50.92%)
UK	356	(76.07%)		982	(75.54%)		637	(49.00%)
US	397	(84.83%)		1148	(88.31%)		527	(40.54%)
Total number of comparisons	468			1300			1300	

Number of comparisons where the 10% confidence interval of the IRF in the higher frequency case is tighter than that in the lower frequency case. In parentheses are reported the percentages of the number of successful comparisons over the total number of comparisons.

Impulse Response Functions (IRFs)
Means of IRDs

- Following the according comparisons for the mean of IRDs in each case, we examine whether the mean of the corresponding IRD rises or falls by choosing a higher sampling frequency.
- Our evidence points to the fact that the choice of the highest sampling frequency, in the vast majority of the cases under consideration, leads to the lowest (absolute) mean of IRD, thus we achieve a smoother and less time varying approach to monitor the evolution of a shock on a variable in time.

Impulse Response Functions (IRFs)

Means of IRDs

	monthly - bi-weekly		monthly - weekly		bi-weekly - weekly	
CAN	330	(70.51%)	870	(66.92%)	571	(43.92%)
NOR	304	(64.96%)	1040	(80.00%)	788	(60.62%)
RUS	267	(57.05%)	950	(73.08%)	859	(66.08%)
CHI	405	(86.54%)	1115	(85.77%)	664	(51.08%)
ESP	314	(67.09%)	890	(68.46%)	755	(58.08%)
FRA	267	(57.05%)	756	(58.15%)	640	(49.23%)
GER	277	(59.19%)	787	(60.54%)	762	(58.62%)
ITA	259	(55.34%)	898	(69.08%)	774	(59.54%)
JAP	323	(69.02%)	1009	(77.62%)	749	(57.62%)
UK	270	(57.69%)	761	(58.54%)	711	(54.69%)
US	338	(72.22%)	1014	(78.00%)	599	(46.08%)
Total number of comparisons	468		1300		1300	

Number of comparisons where the absolute mean of the IRD in the higher frequency case is lower than that in the lower frequency case. In parentheses are reported the percentages of the number of successful comparisons over the total number of comparisons.

Connectedness

- We use the context of connectedness as a natural expansion of the spillover index (Diebold & Yilmaz 2009).
- One could say that connectedness measures “directional spillover”.
- One could get the connectedness measure of Diebold & Yilmaz (2012) by essentially standardizing the K-step-ahead error variance decompositions matrix $\Psi(K) = \left[\psi_{ij}(K)\right]_{i,j=1,\ldots,N}$ for $K = 1, 2, \ldots$

Connectedness

$$\psi_{ij}(K) = \frac{\sigma_{jj}^{-1}\sum_{k=0}^{K-1}\left(s_i' G_k \Sigma_u s_j\right)^2}{\sum_{k=0}^{K-1}\left(s_i' G_k \Sigma_v G_k' s_i\right)}$$

- where σ_{jj} is the standard deviation of the error term for the *j*-th equation, s_i is the selection vector, with one as the *i*-th element and zeros otherwise, G_k the coefficients matrix and Σ_u is the variance matrix for the error vector u.
- Since $\sum_{j=1}^{N}\psi_{ij}(K) \neq 1$, we normalize each element of $\Psi(K)$ by the row sum as:

$$\tilde{\psi}_{ij}(K) = \frac{\psi_{ij}(K)}{\sum_{j=1}^{N}\psi_{ij}(K)}$$

- Obviously, $\sum_{j=1}^{N}\tilde{\psi}_{ij}(K) = 1$ and $\sum_{i,j=1}^{N}\tilde{\psi}_{ij}(K) = N$.

Connectedness

- A **total connectedness** measure is calculated by:

$$TC(K) = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\psi}_{ij}(K)}{\sum_{i,j=1}^{N} \tilde{\psi}_{ij}(K)} \cdot 100 = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\psi}_{ij}(K)}{N} \cdot 100$$

- Directional connectedness to element *i* from all other elements *j* is measured by:

$$DC_{i \leftarrow j}(K) = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\psi}_{ij}(K)}{\sum_{i,j=1}^{N} \tilde{\psi}_{ij}(K)} \cdot 100 = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\psi}_{ij}(K)}{N} \cdot 100$$

- Directional connectedness from element *i* to all other elements *j* is measured by:

$$DC_{i \rightarrow j}(K) = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\psi}_{ji}(K)}{\sum_{i,j=1}^{N} \tilde{\psi}_{ji}(K)} \cdot 100 = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\psi}_{ji}(K)}{N} \cdot 100$$

Connectedness

- Subtracting the previous two equations we get the **net directional connectedness** from element *i* to all other elements *j*:

$$NDC_i(K) = DC_{i\to j}(K) - DC_{i\leftarrow j}(K)$$

- **Net pairwise directional connectedness** between elements *i* and *j*:

$$NPDC_{ij}(K) = \left(\frac{\tilde{\psi}_{ji}(K)}{\sum_{i,h=1}^{N} \tilde{\psi}_{ih}(K)} - \frac{\tilde{\psi}_{ij}(K)}{\sum_{j,h=1}^{N} \tilde{\psi}_{jh}(K)} \right) \cdot 100 = \left(\frac{\tilde{\psi}_{ji}(K) - \tilde{\psi}_{ij}(K)}{N} \right) \cdot 100$$

Connectedness

- According to Diebold & Yilmaz (2014) the connectedness table is crucial for clarifying the various connectedness measures and their relationships.
- Its main upper-left *NxN* part consists of the variance decomposition matrix $\Psi(K)$.
- The connectedness table is enveloped with a rightmost column containing row sums or contribution from others, three bottom rows containing column sums or contribution to others, contribution to others including own contribution and NDC respectively, and a bottom-right element containing the TC.
- The off-diagonal entries of $\Psi(K)$ are the parts of the forecast error variance decompositions which measure pairwise directional connectedness.
- Last, on top of each table we report the number of lags chosen for each specification according to Bayesian information criterion.

Empirical Results

- We report our estimates of (SVAR and MIDAS-SVAR) connectedness measures between stock market returns and disaggregated oil price shocks in Table 2.
- Concentrating on total connectedness (*TC*s), our results indicate that if one simply employs a monthly sampling frequency (SVAR), the *TC*s range, on average, between 6.99% (Germany) and 24.48% (Russia). These estimates indicate a low-to-moderate interdependence between oil market shocks and sample stock markets.
- If one extends the estimation to the full monthly-weekly mixed sampling frequencies (MIDAS-SVAR), the *TC*s range, on average, between 16.41% (China) and 23.91% (Norway). This range of interdependence estimates appears more tight and narrow, without altering the nature of the overall result (low-to-moderate interdependence).

Empirical Results

- Net oil exporting sample countries (Canada, Norway and Russia) exhibit total connectedness measures of 15.18%, 22.63% and 24.48% respectively, under the standard approach. These estimates change to 22.77%, 23.91% and 22.86% respectively when the MIDAS-SVAR approach is taken (monthly-weekly). The richer information structure we propose appears to have a very limited effect on the connectedness estimates for (net) oil exporting countries.
- However, for (net) oil importing sample countries, our proposed MIDAS-SVAR approach appears to affect connectedness significantly, in an increasing direction. All countries' stock markets appear more connected to disaggregated oil price shocks in our sample period; the *TC*s of the full monthly-weekly mixed sampling frequencies (MIDAS-SVAR) increase in all cases (more than doubling in China, Spain, Germany, Italy and Japan). Only the measure for the U.S.A. appears moderately affected by the migration to the fuller information set structure of our proposed MIDAS-SVAR approach to connectedness estimation.

Empirical Results

- Overall, our results seem to suggest that by ignoring the (full) potential information structure that our proposed MIDAS-SVAR connectedness measures exploit, one can severely underestimate the dynamic relationship and spillover effect between oil market shocks and stock markets, especially those of oil-importing countries.
- In robustness results, our findings appear unaffected by the use of alternative proxies for oil price (WTI) and to the use of alternative time frames.
- Furthermore, impulse response functions (IRFs) are found to exhibit lower standard errors and narrower confidence intervals for oil-importing and oil-exporting countries alike.

Conclusions

- Accurately and reliably measuring dynamic relationships between financial variables/markets can prove valuable for risk and portfolio managers alike; hence the increased research interest in methods of inferring co-movement, connectedness and spillover effects.
- Recently-proposed measures of connectedness that are based on variance decompositions of vector autoregressive (VAR) approximating models have proven successful in many different empirical contexts (oil market shock propagation, market systemic risk, etc.) and have been adopted by researchers and professionals alike.
- This study proposes a natural extension of such measures, which builds on well-established mixed data sampling econometric methods, the so-called Mixed Data Sampling Structural Vector Autoregressive (MIDAS-SVAR) approach.

Conclusions

- This approach, which essentially augments the information set on which the measures of connectedness are estimated with sample points that are available at a higher observational frequency, is demonstrated in the widely-researched context of spillover effects between oil market shocks and stock markets.
- Our results indicate that by enriching (via the MIDAS-SVAR approach) the information set from which connectedness measures are estimated, we can statistically and economically improve our understanding of dynamic spillover effects and time–varying relationships.
- Measures of connectedness that do not fully exploit the (full) available information structure are shown to severely underestimate the dynamic relationship and spillover effect between oil market shocks and stock markets, especially in the case of (net) oil-importing countries.

- By bridging two recent and distinct methodological approaches from time series modeling, our study essentially improves highly-cited and widely-used connectedness measures and contributes to our better understanding of dynamic structural relationships.

Low frequency series									
Monthly	Observations	Mean	Std. Dev.	Maximum	Minimum	Skewness	Excess Kurtosis	Jarque-Bera	ADF
Real global economic activity	238	3.5910	32.6569	66.7783	-133.1265	-0.2967 *	0.5548 *	6.5444 **	-2.7826 *
Δln(Oil production)	237	0.0011	0.0080	0.0262	-0.0261	-0.1242	0.9087 ***	8.7627 **	-13.8246 ***
Δln(Oil price)	237	0.0056	0.0934	0.2007	-0.3110	-0.7450 ***	0.9753 ***	31.3141 ***	-12.5211 ***
Oil exporting Countries									
Δln(Canada)	237	0.0023	0.0469	0.1084	-0.2629	-1.1713 ***	4.1807 ***	226.7915 ***	-14.1185 ***
Δln(Norway)	237	0.0027	0.0669	0.1600	-0.3719	-1.2136 ***	3.6231 ***	187.8069 ***	-13.6358 ***
Δln(Russia)	237	-0.0061	0.1375	0.5178	-0.9427	-1.8027 ***	10.3720 ***	1190.6920 ***	-12.4547 ***
Oil importing Countries									
Δln(China)	237	0.0027	0.0811	0.2773	-0.2890	-0.0693	1.6135 ***	25.8989 ***	-8.9306 ***
Δln(Spain)	237	-0.0005	0.0624	0.1521	-0.2370	-0.5879 ***	1.0933 ***	25.4554 ***	-15.1034 ***
Δln(France)	237	0.0014	0.0564	0.1346	-0.2345	-0.9351 ***	1.5334 ***	57.7570 ***	-14.7770 ***
Δln(Germany)	237	0.0037	0.0621	0.1683	-0.2817	-0.8578 ***	1.9454 ***	66.4335 ***	-14.0611 ***
Δln(Italy)	237	-0.0021	0.0684	0.2527	-0.2684	-0.4551 ***	1.8689 ***	42.6717 ***	-15.2093 ***
Δln(Japan)	237	0.0014	0.0643	0.1527	-0.2454	-0.4832 ***	0.9319 ***	17.7959 ***	-15.7775 ***
Δln(UK)	237	-0.0001	0.0468	0.1113	-0.2412	-1.0452 ***	2.9652 ***	129.9795 ***	-17.0766 ***
Δln(USA)	237	0.0024	0.0453	0.1164	-0.2628	-1.1327 ***	4.4332 ***	244.7534 ***	-15.6601 ***
High frequency series									
Bi-weekly	Observations	Mean	Std. Dev.	Maximum	Minimum	Skewness	Excess Kurtosis	Jarque-Bera	ADF
Δln(Oil price)	475	0.0029	0.0733	0.1905	-0.3067	-0.6565 ***	1.4428 ***	75.3197 ***	-19.1788 ***
Oil exporting Countries									
Δln(Canada)	475	0.0011	0.0332	0.1014	-0.2805	-1.5919 ***	11.0248 ***	2606.2310 ***	-22.5281 ***
Δln(Norway)	475	0.0013	0.0455	0.1628	-0.3233	-1.1415 ***	5.6884 ***	743.5781 ***	-19.5690 ***
Δln(Russia)	475	-0.0032	0.0889	0.4881	-0.5437	-0.9381 ***	6.5456 ***	917.6366 ***	-18.9115 ***
Oil importing Countries									
Δln(China)	475	0.0014	0.0516	0.1831	-0.2286	-0.2918 ***	2.4122 ***	121.9035 ***	-19.5628 ***
Δln(Spain)	475	-0.0003	0.0433	0.1498	-0.2390	-0.7070 ***	2.6847 ***	182.2143 ***	-20.9679 ***
Δln(France)	475	0.0007	0.0407	0.1385	-0.2699	-1.0537 ***	4.6676 ***	519.0813 ***	-22.3697 ***
Δln(Germany)	475	0.0019	0.0450	0.1529	-0.2864	-1.2648 ***	5.4150 ***	706.9921 ***	-21.7427 ***
Δln(Italy)	475	-0.0011	0.0469	0.1688	-0.2905	-0.8538 ***	4.1797 ***	403.4663 ***	-20.6215 ***
Δln(Japan)	475	0.0006	0.0438	0.1308	-0.3616	-1.3658 ***	9.5438 ***	1950.3700 ***	-21.5549 ***
Δln(UK)	475	-0.0001	0.0328	0.1103	-0.2555	-1.2680 ***	7.9148 ***	1367.1040 ***	-23.6051 ***
Δln(USA)	475	0.0012	0.0338	0.1162	-0.2892	-1.5730 ***	11.4860 ***	2806.9560 ***	-23.3947 ***
Weekly	Observations	Mean	Std. Dev.	Maximum	Minimum	Skewness	Excess Kurtosis	Jarque-Bera	ADF
Δln(Oil price)	951	0.0014	0.0471	0.2461	-0.2316	-0.2260 ***	2.6901 ***	294.8418 ***	-26.0976 ***
Oil exporting Countries									
Δln(Canada)	951	0.0006	0.0255	0.1282	-0.2805	-1.8237 ***	17.8635 ***	13171.7000 ***	-34.5811 ***
Δln(Norway)	951	0.0007	0.0350	0.1683	-0.3233	-1.3426 ***	11.5067 ***	5532.1750 ***	-30.9006 ***
Δln(Russia)	951	-0.0017	0.0628	0.3419	-0.4289	-0.7397 ***	6.9752 ***	2014.6110 ***	-18.8630 ***
Oil importing Countries									
Δln(China)	951	0.0007	0.0342	0.1393	-0.1492	-0.1044	2.2133 ***	195.8445 ***	-28.4700 ***
Δln(Spain)	951	-0.0001	0.0328	0.1359	-0.2390	-0.6751 ***	4.0886 ***	734.6317 ***	-32.4209 ***
Δln(France)	951	0.0004	0.0313	0.1243	-0.2699	-0.8890 ***	6.7579 ***	1934.9370 ***	-33.0171 ***
Δln(Germany)	951	0.0009	0.0339	0.1494	-0.2864	-0.8618 ***	6.8785 ***	1992.5440 ***	-32.2785 ***
Δln(Italy)	951	-0.0005	0.0350	0.1936	-0.2905	-0.8795 ***	7.4527 ***	2323.4990 ***	-30.8728 ***
Δln(Japan)	951	0.0004	0.0326	0.1356	-0.3616	-1.6042 ***	16.2732 ***	10901.2500 ***	-31.9464 ***
Δln(UK)	951	-0.00002	0.0252	0.1258	-0.2555	-1.1999 ***	12.9415 ***	6864.6800 ***	-20.4166 ***
Δln(USA)	951	0.0006	0.0259	0.1136	-0.2892	-1.6543 ***	17.8463 ***	13053.9100 ***	-33.9846 ***

Note: *, ** and *** indicate indicate significance at 10%, 5% and 1% levels, respectively.

Table 1: Descriptive statistics of sample time series. The sample time period is from January 1998 to September 2017 inclusive and ADF stands for the augmented Dickey-Fuller test statistic (with intercept and no trend).

Panel A: Monthly - weekly frequencies

CAN lag = 1

To (i)	From (j) SSS	ADS	ODS_1	ODS_2	ODS_3	ODS_4	SMR_1	SMR_2	SMR_3	SMR_4	From Others
SSS	77.05	5.45	3.34	1.00	2.02	5.45	2.07	1.25	1.88	0.50	22.95
ADS	0.01	87.99	0.34	9.14	1.24	0.00	0.40	0.86	0.01	0.02	12.01
ODS_1	0.12	0.58	83.01	8.29	3.05	0.41	3.21	0.00	0.73	0.59	16.99
ODS_2	0.05	8.30	6.92	68.14	9.21	0.92	3.80	1.51	0.11	1.02	31.86
ODS_3	0.08	2.99	1.27	10.92	78.98	1.09	0.55	1.77	1.86	0.51	21.02
ODS_4	0.82	0.74	0.17	2.03	1.23	91.17	0.34	0.98	1.78	0.73	8.83
SMR_1	0.26	0.21	9.27	12.91	6.06	1.06	63.78	2.87	3.36	0.23	36.22
SMR_2	0.08	5.34	0.04	7.25	5.73	3.08	3.21	70.68	2.31	2.28	29.32
SMR_3	0.45	0.40	0.78	0.27	9.51	5.31	6.50	0.99	72.67	3.11	27.33
SMR_4	0.08	1.36	3.26	5.23	4.06	1.32	2.54	0.12	3.23	78.80	21.20
Contr. to others	1.94	25.38	25.38	57.05	42.10	18.64	22.62	10.34	15.28	8.99	
Contr. incl. own	79.0	113.4	108.4	125.2	121.1	109.8	86.4	81.0	88.0	87.8	TC
NDC	-21.0	13.4	8.4	25.2	21.1	9.8	-13.6	-19.0	-12.0	-12.2	**22.77**

NOR lag = 1

To (i)	From (j) SSS	ADS	ODS_1	ODS_2	ODS_3	ODS_4	SMR_1	SMR_2	SMR_3	SMR_4	From Others
SSS	76.18	4.63	3.66	1.09	1.39	6.21	4.37	0.51	0.50	1.46	23.82
ADS	0.01	84.40	0.62	9.62	0.96	0.02	0.93	3.14	0.05	0.26	15.60
ODS_1	0.13	0.45	76.31	7.42	2.95	0.39	9.13	0.11	2.55	0.57	23.69
ODS_2	0.05	8.01	6.34	66.22	8.07	1.18	5.72	2.81	0.20	1.41	33.78
ODS_3	0.05	2.53	1.18	9.46	76.87	1.03	1.59	2.15	3.95	1.18	23.13
ODS_4	0.84	0.64	0.25	2.36	1.09	89.99	0.38	0.46	3.70	0.30	10.01
SMR_1	0.22	0.07	13.28	8.24	1.56	1.41	68.74	0.89	5.46	0.12	31.26
SMR_2	0.10	3.44	1.28	7.64	4.12	0.66	4.51	69.29	7.82	1.13	30.71
SMR_3	0.08	0.80	1.22	1.03	6.90	4.58	3.94	4.40	75.74	1.30	24.26
SMR_4	0.11	0.15	1.12	5.13	5.40	0.72	4.99	1.43	3.74	77.19	22.81
Contr. to others	1.59	20.72	28.97	51.99	32.44	16.19	35.56	15.89	27.97	7.74	
Contr. incl. own	77.8	105.1	105.3	118.2	109.3	106.2	104.3	85.2	103.7	84.9	TC
NDC	-22.2	5.1	5.3	18.2	9.3	6.2	4.3	-14.8	3.7	-15.1	**23.91**

RUS lag = 1

To (i)	From (j) SSS	ADS	ODS_1	ODS_2	ODS_3	ODS_4	SMR_1	SMR_2	SMR_3	SMR_4	From Others
SSS	69.28	4.57	3.04	1.04	1.41	5.45	8.43	0.44	3.34	3.01	30.72
ADS	0.00	82.61	0.42	8.77	0.80	0.00	0.73	6.46	0.04	0.16	17.39
ODS_1	0.11	0.83	73.51	6.45	2.67	0.22	8.77	3.37	2.33	1.73	26.49
ODS_2	0.05	6.84	5.12	56.98	6.98	0.58	2.05	15.90	2.46	3.04	43.02
ODS_3	0.05	2.25	0.91	9.01	73.86	1.37	3.36	7.65	0.97	0.57	26.14
ODS_4	0.75	0.42	0.03	1.40	1.61	88.90	0.67	1.10	4.20	0.92	11.10
SMR_1	0.05	0.22	5.45	1.54	2.02	0.31	78.02	1.52	9.13	1.74	21.98
SMR_2	0.01	2.11	1.85	9.99	3.73	0.76	2.58	75.76	2.19	1.02	24.24
SMR_3	0.03	0.39	0.61	0.90	0.29	0.99	5.22	3.32	87.59	0.67	12.41
SMR_4	0.09	1.99	1.16	4.01	2.51	0.32	2.12	2.16	0.72	84.90	15.10
Contr. to others	1.14	19.63	18.59	43.10	22.02	10.00	33.94	41.93	25.39	12.86	
Contr. incl. own	70.4	102.2	92.1	100.1	95.9	98.9	112.0	117.7	113.0	97.8	TC
NDC	-29.6	2.2	-7.9	0.1	-4.1	-1.1	12.0	17.7	13.0	-2.2	**22.86**

Panel B: Monthly - bi-weekly frequencies

CAN lag = 1

To (i)	From (j) SSS	ADS	ODS_1	ODS_2	SMR_1	SMR_2	From Others
SSS	84.61	6.33	1.02	5.94	1.47	0.62	15.39
ADS	0.01	90.45	8.69	0.00	0.84	0.01	9.55
ODS_1	0.06	9.30	86.65	0.88	1.55	1.57	13.35
ODS_2	0.78	0.71	1.72	95.35	0.84	0.60	4.65
SMR_1	0.04	6.93	6.80	2.94	80.65	2.63	19.35
SMR_2	0.10	1.37	7.02	0.85	0.06	90.61	9.39
Contr. to others	0.99	24.64	25.26	10.62	4.76	5.43	
Contr. incl. own	85.6	115.1	111.9	106.0	85.4	96.0	TC
NDC	-14.4	15.1	11.9	6.0	-14.6	-4.0	**11.95**

NOR lag = 1

To (i)	From (j) SSS	ADS	ODS_1	ODS_2	SMR_1	SMR_2	From Others
SSS	84.63	5.84	1.06	6.32	0.94	1.22	15.37
ADS	0.02	86.77	9.17	0.00	3.62	0.42	13.23
ODS_1	0.05	9.05	83.75	0.87	3.55	2.73	16.25
ODS_2	0.81	0.57	1.76	96.32	0.43	0.12	3.68
SMR_1	0.10	6.31	9.02	0.67	82.61	1.29	17.39
SMR_2	0.10	0.28	8.20	0.44	1.71	89.27	10.73
Contr. to others	1.08	22.05	29.20	8.30	10.25	5.78	
Contr. incl. own	85.7	108.8	113.0	104.6	92.9	95.0	TC
NDC	-14.3	8.8	13.0	4.6	-7.1	-5.0	**12.78**

RUS lag = 1

To (i)	From (j) SSS	ADS	ODS_1	ODS_2	SMR_1	SMR_2	From Others
SSS	83.32	5.64	1.06	6.47	0.79	2.72	16.68
ADS	0.01	84.32	8.49	0.00	7.01	0.17	15.68
ODS_1	0.04	7.12	70.44	0.77	18.05	3.57	29.56
ODS_2	0.81	0.62	1.79	95.00	0.94	0.85	5.00
SMR_1	0.01	3.03	10.52	0.69	84.89	0.85	15.11
SMR_2	0.07	2.57	4.26	0.26	1.69	91.15	8.85
Contr. to others	0.95	18.97	26.11	8.20	28.48	8.17	
Contr. incl. own	84.3	103.3	96.6	103.2	113.4	99.3	TC
NDC	-15.7	3.3	-3.4	3.2	13.4	-0.7	**15.15**

Panel C: Monthly frequencies

CAN lag = 1

To (i)	From (j) SSS	ADS	ODS	SMR	From Others
SSS	85.46	7.21	2.61	4.72	14.54
ADS	0.03	89.52	9.40	1.05	10.48
ODS	0.02	0.78	89.17	10.03	10.83
SMR	0.14	0.10	24.62	75.14	24.86
Contr. to others	0.19	8.09	36.63	15.80	
Contr. incl. own	85.7	97.6	125.8	90.9	TC
NDC	-14.3	-2.4	25.8	-9.1	**15.18**

NOR lag = 2

To (i)	From (j) SSS	ADS	ODS	SMR	From Others
SSS	74.05	7.48	11.14	7.32	25.95
ADS	0.07	71.10	17.48	11.36	28.90
ODS	0.02	0.37	82.00	17.61	18.00
SMR	0.09	0.15	17.45	82.32	17.68
Contr. to others	0.17	8.00	46.07	36.29	
Contr. incl. own	74.2	79.1	128.1	118.6	TC
NDC	-25.8	-20.9	28.1	18.6	**22.63**

RUS lag = 2

To (i)	From (j) SSS	ADS	ODS	SMR	From Others
SSS	66.85	6.14	14.14	12.87	33.15
ADS	0.02	67.45	20.00	12.52	32.55
ODS	0.03	0.53	76.03	23.42	23.97
SMR	0.01	0.13	8.10	91.76	8.24
Contr. to others	0.06	6.80	42.24	48.80	
Contr. incl. own	66.9	74.3	118.3	140.6	TC
NDC	-33.1	-25.7	18.3	40.6	**24.48**

Panel A: Monthly - weekly frequencies

CHI lag = 1

To (i) \ From (j)	SSS	ADS	ODS_1	ODS_2	ODS_3	ODS_4	SMR_1	SMR_2	SMR_3	SMR_4	From Others
SSS	79.23	4.90	3.70	0.90	1.87	5.59	1.20	0.42	1.27	0.91	20.77
ADS	0.01	87.11	0.52	9.23	0.98	0.01	1.32	0.18	0.45	0.19	12.89
ODS_1	0.12	0.79	84.70	8.71	3.27	0.32	0.72	0.71	0.03	0.63	15.30
ODS_2	0.05	8.38	7.49	71.52	9.66	0.81	1.66	0.17	0.02	0.23	28.48
ODS_3	0.07	3.04	1.24	11.14	81.20	1.54	0.16	0.18	0.84	0.60	18.80
ODS_4	0.75	0.97	0.10	1.73	1.70	89.65	0.45	0.64	1.55	2.45	10.35
SMR_1	0.05	5.46	4.28	4.23	0.48	0.31	80.39	2.82	1.44	0.54	19.61
SMR_2	0.03	0.64	1.54	0.79	1.84	0.91	1.13	92.39	0.64	0.09	7.61
SMR_3	0.19	2.29	0.04	0.49	1.56	2.23	1.26	0.49	85.54	5.91	14.46
SMR_4	0.05	3.05	0.19	2.01	1.17	3.96	1.41	0.45	3.52	84.19	15.81
Contr. to others	1.31	29.51	19.09	39.24	22.53	15.69	9.31	6.07	9.77	11.56	
Contr. incl. own	80.5	116.6	103.8	110.8	103.7	105.3	89.7	98.5	95.3	95.8	TC
NDC	-19.5	16.6	3.8	10.8	3.7	5.3	-10.3	-1.5	-4.7	-4.2	**16.41**

ESP lag = 1

To (i) \ From (j)	SSS	ADS	ODS_1	ODS_2	ODS_3	ODS_4	SMR_1	SMR_2	SMR_3	SMR_4	From Others
SSS	70.50	4.88	3.05	0.88	1.65	4.94	2.54	3.27	7.89	0.38	29.50
ADS	0.01	88.12	0.34	8.92	1.12	0.01	0.17	1.21	0.08	0.03	11.88
ODS_1	0.11	0.74	83.72	8.71	3.03	0.39	1.51	0.55	0.45	0.78	16.28
ODS_2	0.05	8.03	7.49	70.66	9.70	0.95	1.47	0.66	0.11	0.88	29.34
ODS_3	0.07	2.90	1.07	11.39	80.31	1.10	0.22	0.64	1.27	1.03	19.69
ODS_4	0.86	0.61	0.13	2.02	1.22	92.19	1.33	0.20	1.39	0.05	7.81
SMR_1	0.12	0.30	2.86	2.19	3.65	1.72	84.99	1.50	1.58	1.08	15.01
SMR_2	0.58	5.27	1.06	2.28	2.08	1.11	0.34	84.36	1.32	1.60	15.64
SMR_3	0.78	0.15	0.31	0.77	1.50	2.47	3.68	1.20	87.46	1.68	12.54
SMR_4	0.14	1.97	3.50	6.20	2.53	0.87	3.85	0.05	1.64	79.23	20.77
Contr. to others	2.72	24.86	19.82	43.36	26.47	13.57	15.12	9.28	15.75	7.50	
Contr. incl. own	73.2	113.0	103.5	114.0	106.8	105.8	100.1	93.6	103.2	86.7	TC
NDC	-26.8	13.0	3.5	14.0	6.8	5.8	0.1	-6.4	3.2	-13.3	**17.85**

FRA lag = 1

To (i) \ From (j)	SSS	ADS	ODS_1	ODS_2	ODS_3	ODS_4	SMR_1	SMR_2	SMR_3	SMR_4	From Others
SSS	73.10	4.94	3.05	0.91	1.70	4.98	2.02	2.55	6.52	0.24	26.90
ADS	0.01	87.42	0.40	9.18	1.20	0.02	0.89	0.76	0.08	0.04	12.58
ODS_1	0.11	0.64	82.39	8.43	3.05	0.41	2.81	0.94	0.59	0.64	17.61
ODS_2	0.05	8.25	7.27	69.81	9.25	1.01	2.52	0.50	0.09	1.25	30.19
ODS_3	0.07	2.92	1.12	11.01	80.56	1.01	0.36	0.73	1.34	0.87	19.44
ODS_4	0.86	0.59	0.20	2.16	1.11	90.96	1.28	0.33	2.33	0.18	9.04
SMR_1	0.11	0.90	6.13	5.44	3.15	1.99	78.37	1.51	1.93	0.46	21.63
SMR_2	0.44	3.41	2.30	1.65	4.12	0.83	2.49	80.30	2.86	1.61	19.70
SMR_3	0.62	0.04	0.56	0.18	3.86	3.10	3.76	1.45	83.46	2.96	16.54
SMR_4	0.34	1.48	5.01	6.14	3.30	1.11	5.17	0.87	3.16	73.41	26.59
Contr. to others	2.60	23.16	26.04	45.11	30.73	14.46	21.30	9.65	18.91	8.25	
Contr. incl. own	75.7	110.6	108.4	114.9	111.3	105.4	99.7	89.9	102.4	81.7	TC
NDC	-24.3	10.6	8.4	14.9	11.3	5.4	-0.3	-10.1	2.4	-18.3	**20.02**

Panel B: Monthly - bi-weekly frequencies

CHI lag = 1

To (i) \ From (j)	SSS	ADS	ODS_1	ODS_2	SMR_1	SMR_2	From Others
SSS	85.02	6.19	1.00	6.27	0.31	1.22	14.98
ADS	0.01	90.92	8.78	0.01	0.13	0.15	9.08
ODS_1	0.06	9.46	89.17	0.94	0.14	0.24	10.83
ODS_2	0.79	0.63	1.72	93.33	0.62	2.91	6.67
SMR_1	0.03	0.45	0.62	0.82	97.99	0.10	2.01
SMR_2	0.06	2.18	2.07	4.65	0.54	90.49	9.51
Contr. to others	0.95	18.91	14.19	12.69	1.73	4.62	
Contr. incl. own	86.0	109.8	103.4	106.0	99.7	95.1	TC
NDC	-14.0	9.8	3.4	6.0	-0.3	-4.9	**8.85**

ESP lag = 1

To (i) \ From (j)	SSS	ADS	ODS_1	ODS_2	SMR_1	SMR_2	From Others
SSS	81.97	5.87	1.01	6.11	4.28	0.75	18.03
ADS	0.01	90.13	8.69	0.00	1.16	0.02	9.87
ODS_1	0.06	9.14	88.01	0.93	0.56	1.30	11.99
ODS_2	0.80	0.67	1.75	96.43	0.23	0.11	3.57
SMR_1	0.62	6.15	2.00	1.30	88.39	1.55	11.61
SMR_2	0.19	2.00	7.59	1.08	0.01	89.13	10.87
Contr. to others	1.67	23.83	21.05	9.42	6.24	3.73	
Contr. incl. own	83.6	114.0	109.1	105.9	94.6	92.9	TC
NDC	-16.4	14.0	9.1	5.9	-5.4	-7.1	**10.99**

FRA lag = 1

To (i) \ From (j)	SSS	ADS	ODS_1	ODS_2	SMR_1	SMR_2	From Others
SSS	83.42	5.91	1.02	6.50	3.04	0.10	16.58
ADS	0.01	90.14	8.85	0.00	0.89	0.11	9.86
ODS_1	0.06	9.21	87.59	0.94	0.40	1.80	12.41
ODS_2	0.79	0.56	1.80	96.20	0.27	0.39	3.80
SMR_1	0.44	5.60	1.26	0.81	90.12	1.78	9.88
SMR_2	0.35	1.13	7.82	1.71	1.15	87.85	12.15
Contr. to others	1.64	22.40	20.74	9.97	5.75	4.18	
Contr. incl. own	85.1	112.5	108.3	106.2	95.9	92.0	TC
NDC	-14.9	12.5	8.3	6.2	-4.1	-8.0	**10.78**

Panel C: Monthly frequencies

CHI lag = 1

To (i) \ From (j)	SSS	ADS	ODS	SMR	From Others
SSS	86.23	6.84	3.31	3.61	13.77
ADS	0.02	88.85	10.25	0.88	11.15
ODS	0.02	0.71	98.78	0.49	1.22
SMR	0.08	0.31	2.63	96.98	3.02
Contr. to others	0.11	7.87	16.19	4.99	
Contr. incl. own	86.3	96.7	115.0	102.0	TC
NDC	-13.7	-3.3	15.0	2.0	**7.29**

ESP lag = 1

To (i) \ From (j)	SSS	ADS	ODS	SMR	From Others
SSS	86.17	7.22	2.61	3.99	13.83
ADS	0.03	89.98	9.73	0.26	10.02
ODS	0.01	0.87	96.32	2.80	3.68
SMR	0.12	0.15	2.41	97.31	2.69
Contr. to others	0.16	8.25	14.75	7.05	
Contr. incl. own	86.3	98.2	111.1	104.4	TC
NDC	-13.7	-1.8	11.1	4.4	**7.55**

FRA lag = 2

To (i) \ From (j)	SSS	ADS	ODS	SMR	From Others
SSS	73.97	6.42	12.31	7.30	26.03
ADS	0.06	75.86	22.77	1.32	24.14
ODS	0.02	0.90	93.24	5.84	6.76
SMR	0.36	0.38	7.77	91.49	8.51
Contr. to others	0.43	7.71	42.85	14.46	
Contr. incl. own	74.4	83.6	136.1	106.0	TC
NDC	-25.6	-16.4	36.1	6.0	**16.36**

Panel A: Monthly - weekly frequencies

GER lag = 1

To (i)	SSS	ADS	ODS_1	ODS_2	ODS_3	ODS_4	SMR_1	SMR_2	SMR_3	SMR_4	From Others
	From (j)										
SSS	70.29	4.56	2.85	0.87	1.62	4.52	1.76	2.02	10.11	1.38	29.71
ADS	0.00	86.72	0.44	9.26	1.11	0.02	1.37	0.83	0.02	0.24	13.28
ODS_1	0.11	0.69	83.18	8.52	3.01	0.40	1.94	1.05	0.41	0.70	16.82
ODS_2	0.04	7.92	7.32	70.00	9.15	1.03	2.45	0.63	0.04	1.42	30.00
ODS_3	0.07	2.36	1.26	10.96	80.83	1.05	0.85	1.32	0.27	1.04	19.17
ODS_4	0.81	0.51	0.18	2.17	1.13	90.33	1.27	1.09	1.65	0.87	9.67
SMR_1	0.06	1.44	4.83	5.67	2.24	1.53	77.67	0.59	4.11	1.85	22.33
SMR_2	0.32	2.52	2.07	1.48	4.04	1.81	0.37	83.06	3.85	0.48	16.94
SMR_3	0.71	0.30	0.44	0.23	0.59	1.66	5.59	2.85	83.86	3.77	16.14
SMR_4	0.13	0.90	2.94	5.72	3.33	1.77	4.37	0.45	3.71	76.69	23.31
Contr. to others	2.26	21.20	22.32	44.87	26.23	13.78	19.97	10.82	24.18	11.74	
Contr. incl. own	72.6	107.9	105.5	114.9	107.1	104.1	97.6	93.9	108.0	88.4	TC
NDC	-27.4	7.9	5.5	14.9	7.1	4.1	-2.4	-6.1	8.0	-11.6	**19.74**

ITA lag = 1

To (i)	SSS	ADS	ODS_1	ODS_2	ODS_3	ODS_4	SMR_1	SMR_2	SMR_3	SMR_4	From Others
	From (j)										
SSS	69.38	4.58	3.06	0.89	1.50	5.03	0.67	4.91	8.66	1.32	30.62
ADS	0.00	88.38	0.37	9.11	1.15	0.01	0.21	0.65	0.06	0.06	11.62
ODS_1	0.11	0.68	82.75	8.55	3.02	0.39	3.14	0.53	0.59	0.26	17.25
ODS_2	0.05	8.55	7.46	70.08	9.47	1.00	2.55	0.63	0.12	0.09	29.92
ODS_3	0.07	2.99	1.13	11.04	79.50	1.20	0.40	1.10	1.95	0.60	20.50
ODS_4	0.80	0.59	0.11	2.04	1.26	89.53	1.12	0.92	3.27	0.36	10.47
SMR_1	0.10	0.26	4.85	4.00	2.86	1.54	78.35	2.24	2.94	2.87	21.65
SMR_2	0.56	2.40	0.96	1.63	4.15	1.56	0.65	82.14	4.93	1.01	17.86
SMR_3	0.63	1.51	0.60	0.19	3.98	4.81	2.18	3.51	81.03	1.56	18.97
SMR_4	0.59	2.62	1.79	1.78	1.62	2.00	8.57	0.59	2.78	77.66	22.34
Contr. to others	2.92	24.18	20.32	39.23	29.01	17.53	19.50	15.07	25.30	8.14	
Contr. incl. own	72.3	112.6	103.1	109.3	108.5	107.1	97.8	97.2	106.3	85.8	TC
NDC	-27.7	12.6	3.1	9.3	8.5	7.1	-2.2	-2.8	6.3	-14.2	**20.12**

JAP lag = 1

To (i)	SSS	ADS	ODS_1	ODS_2	ODS_3	ODS_4	SMR_1	SMR_2	SMR_3	SMR_4	From Others
	From (j)										
SSS	70.15	5.08	1.59	1.06	1.49	4.88	3.20	7.80	4.22	0.53	29.85
ADS	0.01	87.05	0.41	9.28	1.35	0.03	0.80	0.75	0.04	0.29	12.95
ODS_1	0.07	0.48	81.81	8.05	3.23	0.36	4.99	0.60	0.32	0.10	18.19
ODS_2	0.05	8.28	6.84	68.14	9.53	1.03	2.90	1.28	1.22	0.74	31.86
ODS_3	0.06	3.04	1.34	11.29	80.65	1.34	0.03	0.65	1.39	0.20	19.35
ODS_4	0.76	0.63	0.21	2.27	1.51	93.29	0.22	0.24	0.82	0.05	6.71
SMR_1	0.16	0.14	10.03	6.31	4.56	3.41	70.57	0.52	1.82	2.47	29.43
SMR_2	0.25	5.63	1.27	3.27	2.75	0.38	1.07	84.44	0.13	0.81	15.56
SMR_3	0.33	2.36	0.57	3.60	2.69	1.25	2.27	0.55	85.92	0.47	14.08
SMR_4	0.09	3.97	1.36	3.86	4.01	0.13	5.62	1.04	0.29	79.64	20.36
Contr. to others	1.78	29.61	23.62	48.98	31.12	12.82	21.08	13.43	10.24	5.66	
Contr. incl. own	71.9	116.7	105.4	117.1	111.8	106.1	91.7	97.9	96.2	85.3	TC
NDC	-28.1	16.7	5.4	17.1	11.8	6.1	-8.3	-2.1	-3.8	-14.7	**19.83**

Panel B: Monthly - bi-weekly frequencies

GER lag = 1

To (i)	SSS	ADS	ODS_1	ODS_2	SMR_1	SMR_2	From Others
	From (j)						
SSS	82.74	5.60	1.13	6.66	2.87	1.00	17.26
ADS	0.00	89.56	9.08	0.00	0.96	0.40	10.44
ODS_1	0.06	9.00	87.27	0.95	0.53	2.19	12.73
ODS_2	0.78	0.53	1.78	94.82	0.76	1.33	5.18
SMR_1	0.33	4.27	1.11	1.46	92.58	0.26	7.42
SMR_2	0.11	0.85	7.38	2.73	0.30	88.62	11.38
Contr. to others	1.28	20.24	20.48	11.81	5.43	5.18	
Contr. incl. own	84.0	109.8	107.7	106.6	98.0	93.8	TC
NDC	-16.0	9.8	7.7	6.6	-2.0	-6.2	**10.74**

ITA lag = 1

To (i)	SSS	ADS	ODS_1	ODS_2	SMR_1	SMR_2	From Others
	From (j)						
SSS	79.20	5.57	0.98	6.14	6.21	1.89	20.80
ADS	0.01	90.44	8.84	0.00	0.68	0.04	9.56
ODS_1	0.06	9.50	88.78	0.94	0.46	0.26	11.22
ODS_2	0.79	0.60	1.76	95.40	0.68	0.77	4.60
SMR_1	0.63	3.54	1.10	1.32	92.62	0.79	7.38
SMR_2	0.65	2.87	2.31	2.89	0.26	91.03	8.97
Contr. to others	2.13	22.08	14.98	11.30	8.29	3.75	
Contr. incl. own	81.3	112.5	103.8	106.7	100.9	94.8	TC
NDC	-18.7	12.5	3.8	6.7	0.9	-5.2	**10.42**

JAP lag = 1

To (i)	SSS	ADS	ODS_1	ODS_2	SMR_1	SMR_2	From Others
	From (j)						
SSS	77.77	6.17	1.08	5.72	8.97	0.29	22.23
ADS	0.00	89.80	8.97	0.00	0.82	0.39	10.20
ODS_1	0.05	9.33	86.95	1.06	1.39	1.22	13.05
ODS_2	0.78	0.63	1.96	96.36	0.24	0.04	3.64
SMR_1	0.25	6.84	2.77	0.48	88.79	0.86	11.21
SMR_2	0.07	4.33	4.98	0.01	1.26	89.35	10.65
Contr. to others	1.15	27.30	19.77	7.28	12.68	2.80	
Contr. incl. own	78.9	117.1	106.7	103.6	101.5	92.1	TC
NDC	-21.1	17.1	6.7	3.6	1.5	-7.9	**11.83**

Panel C: Monthly frequencies

GER lag = 1

To (i)	SSS	ADS	ODS	SMR	From Others
	From (j)				
SSS	88.12	7.43	2.81	1.63	11.88
ADS	0.03	89.96	9.76	0.25	10.04
ODS	0.02	0.90	96.24	2.84	3.76
SMR	0.04	0.26	1.96	97.74	2.26
Contr. to others	0.08	8.60	14.53	4.73	
Contr. incl. own	88.2	98.6	110.8	102.5	TC
NDC	-11.8	-1.4	10.8	2.5	**6.99**

ITA lag = 1

To (i)	SSS	ADS	ODS	SMR	From Others
	From (j)				
SSS	87.94	7.36	2.89	1.82	12.06
ADS	0.03	89.82	10.07	0.08	10.18
ODS	0.02	0.90	93.58	5.50	6.42
SMR	0.12	0.03	7.02	92.84	7.16
Contr. to others	0.16	8.28	19.98	7.40	
Contr. incl. own	88.1	98.1	113.6	100.2	TC
NDC	-11.9	-1.9	13.6	0.2	**8.96**

JAP lag = 1

To (i)	SSS	ADS	ODS	SMR	From Others
	From (j)				
SSS	87.38	7.31	3.39	1.93	12.62
ADS	0.02	89.70	9.59	0.68	10.30
ODS	0.02	0.73	95.65	3.60	4.35
SMR	0.03	0.22	5.30	94.45	5.55
Contr. to others	0.08	8.25	18.28	6.21	
Contr. incl. own	87.5	98.0	113.9	100.7	TC
NDC	-12.5	-2.0	13.9	0.7	**8.21**

Panel A: Monthly - weekly frequencies

UK	lag = 1										
	From (j)										
To (i)	SSS	ADS	ODS_1	ODS_2	ODS_3	ODS_4	SMR_1	SMR_2	SMR_3	SMR_4	From Others
SSS	73.43	5.16	3.30	0.92	2.25	5.21	0.56	2.43	6.68	0.07	26.57
ADS	0.01	86.47	0.51	9.40	1.18	0.03	1.17	0.56	0.27	0.40	13.53
ODS_1	0.12	0.49	82.66	8.43	3.17	0.44	2.72	0.65	0.82	0.51	17.34
ODS_2	0.05	8.57	7.10	68.67	9.10	1.22	3.44	0.66	0.13	1.06	31.33
ODS_3	0.08	2.44	1.44	10.86	81.17	1.03	1.04	0.77	0.46	0.71	18.83
ODS_4	0.89	0.71	0.33	2.46	1.11	90.69	1.31	0.57	1.68	0.25	9.31
SMR_1	0.07	1.23	8.70	8.74	2.08	2.78	69.50	0.23	2.81	3.87	30.50
SMR_2	0.70	7.51	2.44	2.99	6.23	1.81	1.57	72.03	2.78	1.94	27.97
SMR_3	0.83	1.50	1.13	0.58	3.39	3.66	6.40	0.37	76.60	5.54	23.40
SMR_4	0.13	0.51	5.74	8.13	3.88	0.66	13.86	0.94	4.63	61.52	38.48
Contr. to others	2.89	28.10	30.69	52.52	32.38	16.84	32.07	7.18	20.24	14.35	
Contr. incl. own	76.3	114.6	113.4	121.2	113.6	107.5	101.6	79.2	96.8	75.9	TC
NDC	-23.7	14.6	13.4	21.2	13.6	7.5	1.6	-20.8	-3.2	-24.1	**23.73**

US	lag = 1										
	From (j)										
To (i)	SSS	ADS	ODS_1	ODS_2	ODS_3	ODS_4	SMR_1	SMR_2	SMR_3	SMR_4	From Others
SSS	73.42	5.78	2.15	0.86	2.38	4.88	2.07	2.04	5.78	0.65	26.58
ADS	0.01	87.59	0.39	9.56	1.28	0.02	0.26	0.69	0.00	0.20	12.41
ODS_1	0.09	0.66	84.77	8.69	3.13	0.43	1.07	0.17	0.38	0.61	15.23
ODS_2	0.04	8.11	7.18	69.57	9.25	0.93	1.88	1.02	0.03	1.99	30.43
ODS_3	0.09	2.67	1.17	11.18	81.72	1.09	0.62	0.17	0.69	0.61	18.28
ODS_4	0.84	0.64	0.24	2.04	1.23	90.99	0.48	0.28	2.96	0.29	9.01
SMR_1	0.28	0.66	4.58	7.61	2.65	1.63	74.20	3.42	3.05	1.92	25.80
SMR_2	0.05	4.15	0.29	4.59	1.02	1.67	3.90	80.82	3.24	0.27	19.18
SMR_3	0.67	0.60	0.82	0.15	3.55	6.69	4.44	0.36	79.70	3.03	20.30
SMR_4	0.03	0.37	4.19	10.70	4.55	0.47	4.48	0.04	3.60	71.57	28.43
Contr. to others	2.09	23.64	21.02	55.38	29.05	17.81	19.19	8.20	19.73	9.56	
Contr. incl. own	75.5	111.2	105.8	125.0	110.8	108.8	93.4	89.0	99.4	81.1	TC
NDC	-24.5	11.2	5.8	25.0	10.8	8.8	-6.6	-11.0	-0.6	-18.9	**20.57**

Panel B: Monthly - bi-weekly frequencies

UK	lag = 1						
	From (j)						
To (i)	SSS	ADS	ODS_1	ODS_2	SMR_1	SMR_2	From Others
SSS	84.17	6.09	0.98	6.18	2.55	0.04	15.83
ADS	0.01	89.08	9.49	0.01	0.75	0.67	10.92
ODS_1	0.06	9.57	86.81	0.96	0.73	1.88	13.19
ODS_2	0.81	0.66	1.85	95.58	0.53	0.57	4.42
SMR_1	0.61	10.99	2.67	1.74	81.63	2.37	18.37
SMR_2	0.11	0.51	12.27	1.51	1.58	84.02	15.98
Contr. to others	1.59	27.82	27.25	10.39	6.13	5.52	
Contr. incl. own	85.8	116.9	114.1	106.0	87.8	89.5	TC
NDC	-14.2	16.9	14.1	6.0	-12.2	-10.5	**13.12**

US	lag = 1						
	From (j)						
To (i)	SSS	ADS	ODS_1	ODS_2	SMR_1	SMR_2	From Others
SSS	82.81	6.56	0.94	6.13	2.61	0.96	17.19
ADS	0.01	89.97	8.98	0.01	0.75	0.28	10.03
ODS_1	0.05	9.00	86.21	0.97	1.02	2.75	13.79
ODS_2	0.80	0.59	1.88	96.09	0.15	0.48	3.91
SMR_1	0.02	6.18	3.94	1.26	88.35	0.26	11.65
SMR_2	0.02	0.55	13.25	0.96	0.08	85.14	14.86
Contr. to others	0.91	22.87	28.99	9.33	4.61	4.74	
Contr. incl. own	83.7	112.8	115.2	105.4	93.0	89.9	TC
NDC	-16.3	12.8	15.2	5.4	-7.0	-10.1	**11.91**

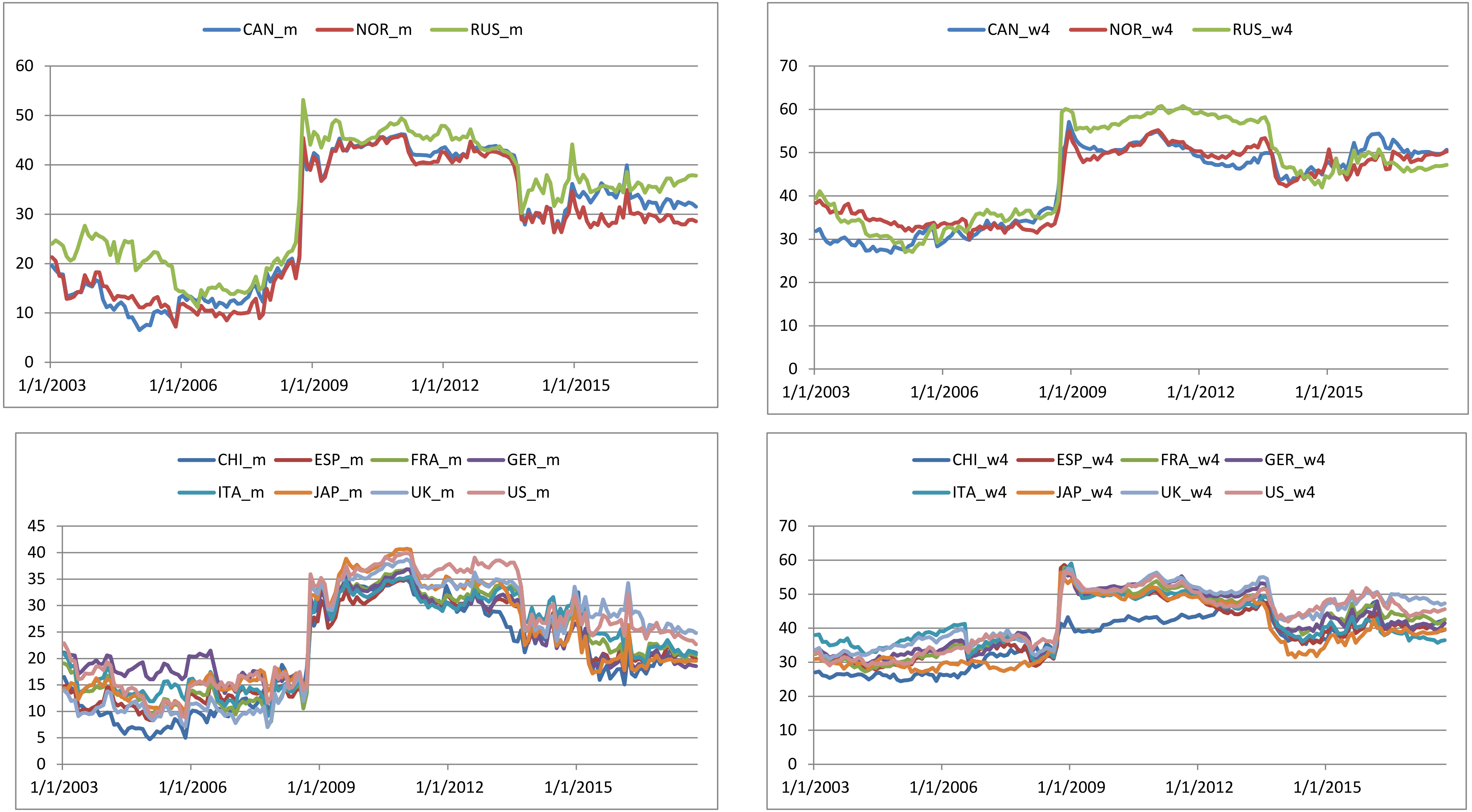
Panel C: Monthly frequencies

UK	lag = 2				
	From (j)				
To (i)	SSS	ADS	ODS	SMR	From Others
SSS	74.36	6.83	12.36	6.45	25.64
ADS	0.09	76.17	21.56	2.19	23.83
ODS	0.02	0.65	93.30	6.03	6.70
SMR	0.47	0.39	9.42	89.72	10.28
Contr. to others	0.57	7.87	43.34	14.67	
Contr. incl. own	74.9	84.0	136.6	104.4	TC
NDC	-25.1	-16.0	36.6	4.4	**16.61**

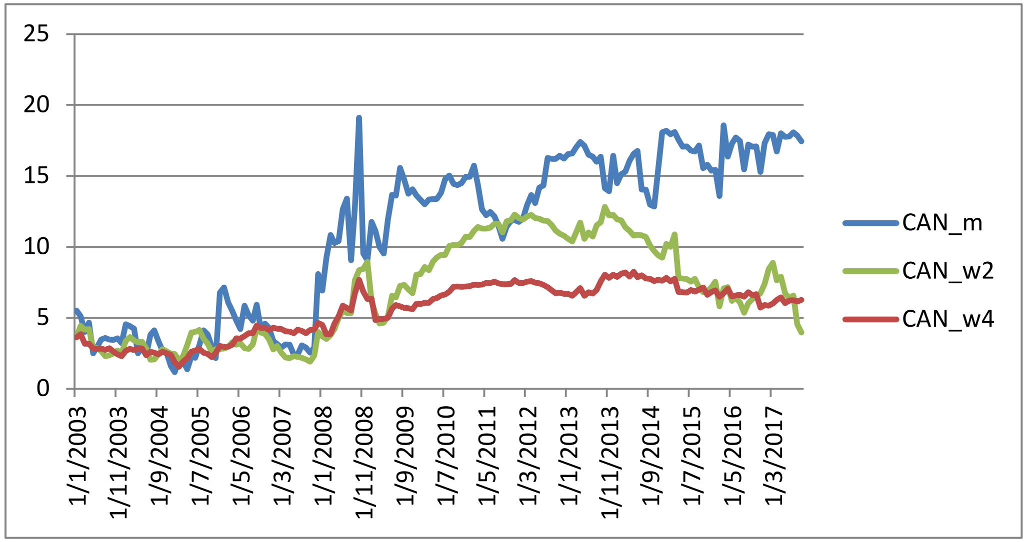
US	lag = 2				
	From (j)				
To (i)	SSS	ADS	ODS	SMR	From Others
SSS	72.60	7.75	11.90	7.74	27.40
ADS	0.09	75.33	21.66	2.92	24.67
ODS	0.02	0.54	93.93	5.51	6.07
SMR	0.38	3.06	11.98	84.58	15.42
Contr. to others	0.49	11.36	45.55	16.17	
Contr. incl. own	73.1	86.7	139.5	100.7	TC
NDC	-26.9	-13.3	39.5	0.7	**18.39**

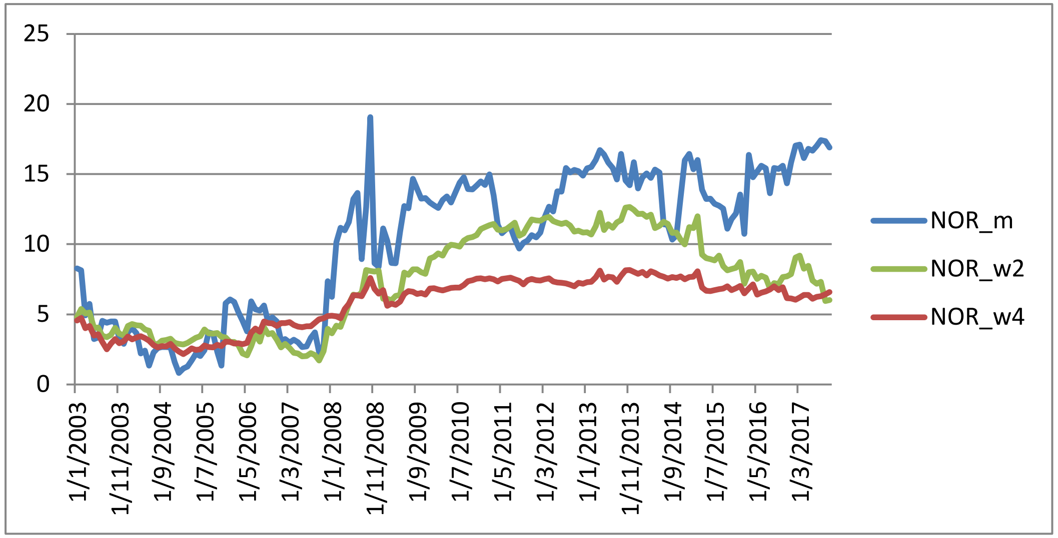
Table 2: Estimation results of the MIDAS-SVAR connectedness measures, calculated from variance decompositions based on 12 step ahead forecasts, for a number of (net) oil-importing and (net) oil-exporting countries in our sample period (January 1998 to September 2017) using either monthly only (right table panel C), monthly-biweekly (center table panel B) or monthly-weekly (left table panel A) data frequencies.

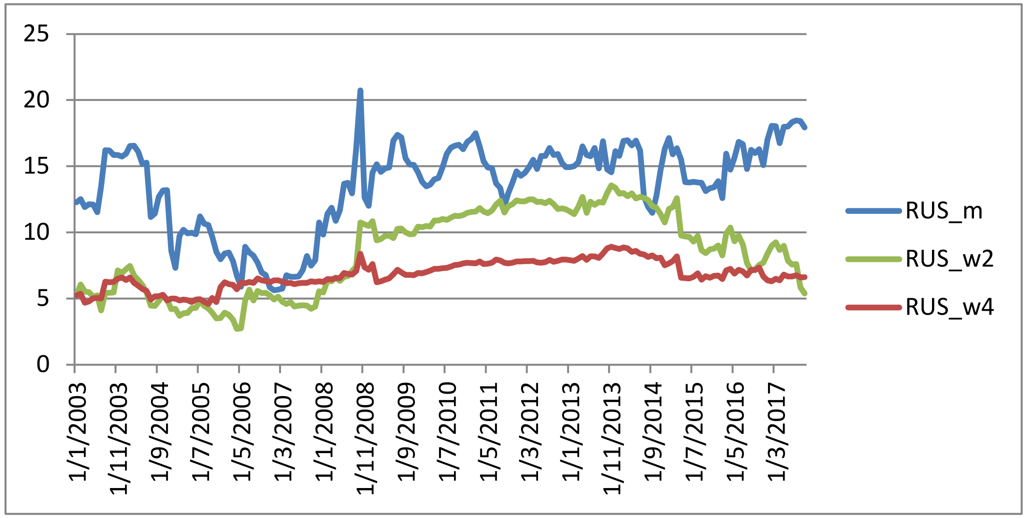
Rolling window Total Connectedness

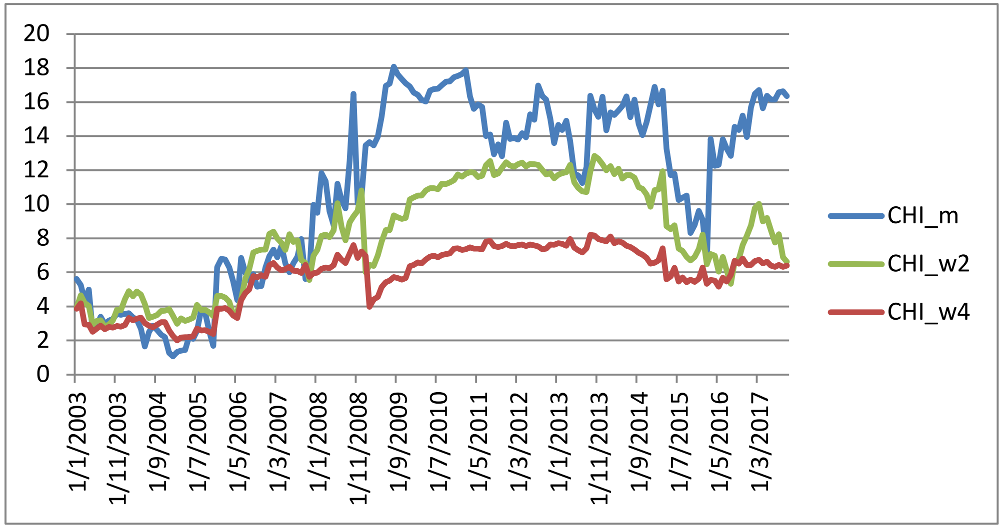


Rolling window Net Directional Connectedness SSS (oil production)





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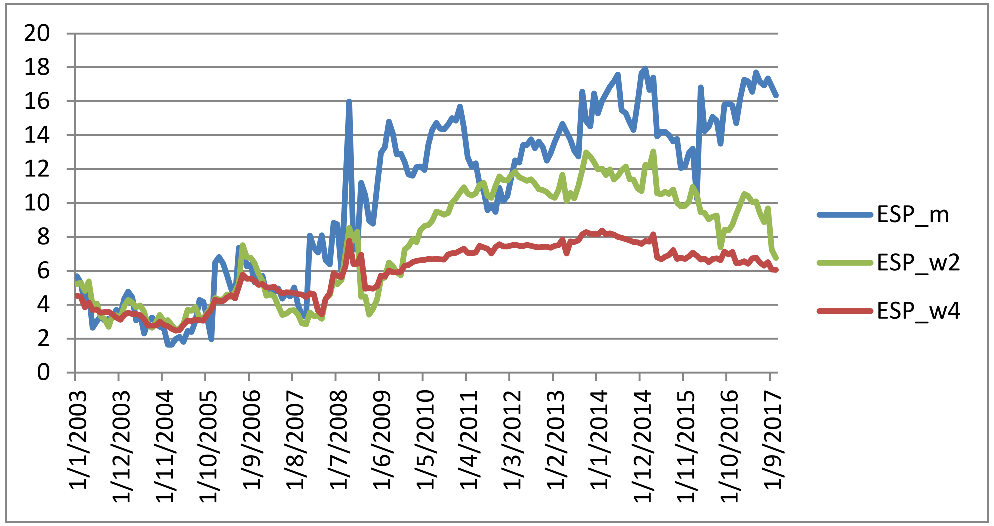
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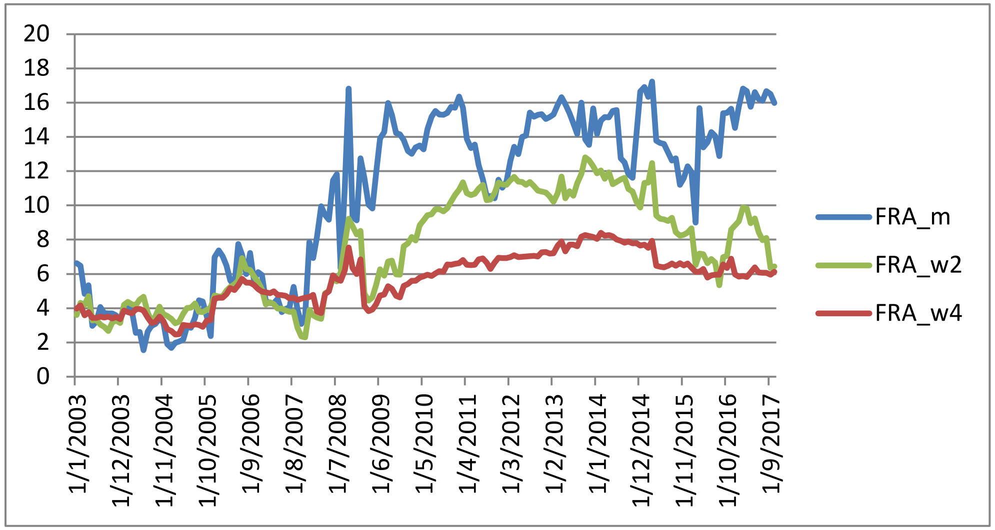
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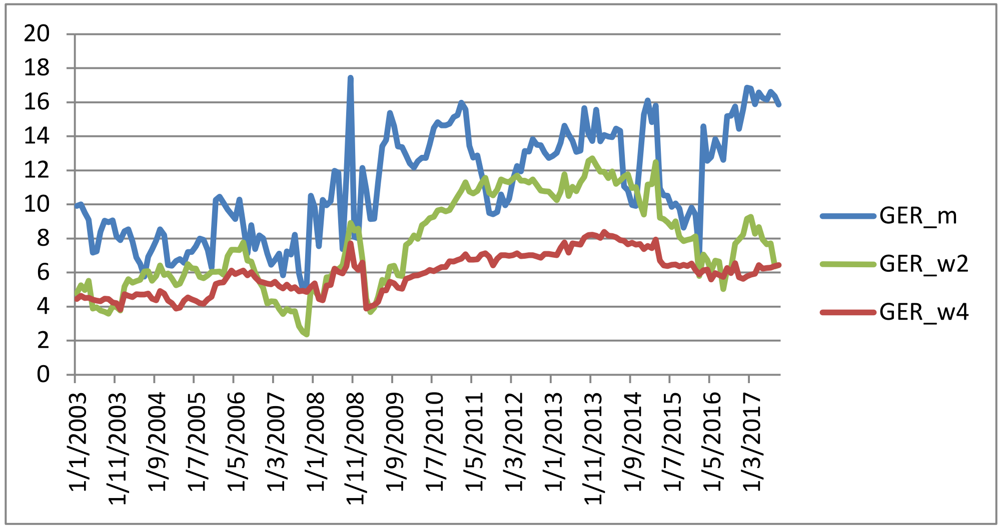
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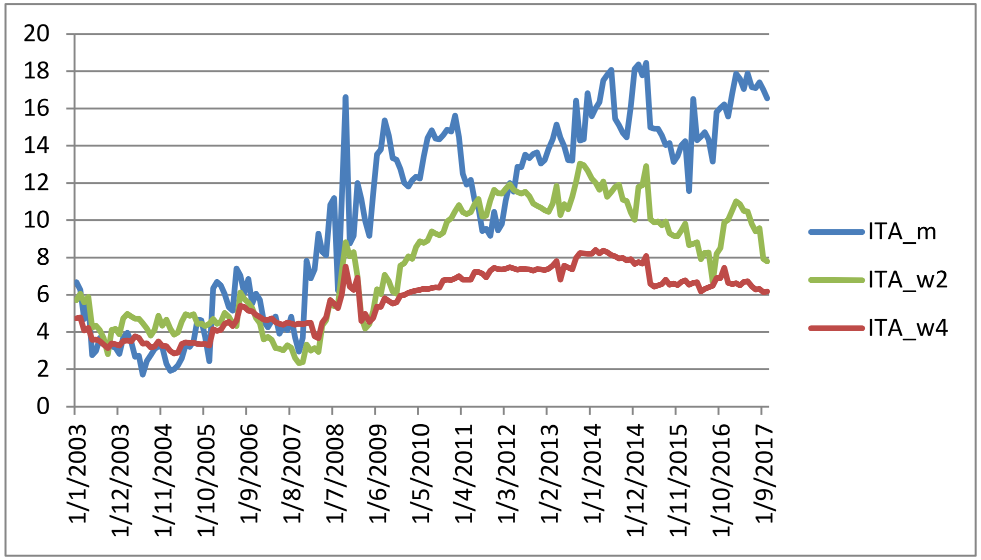

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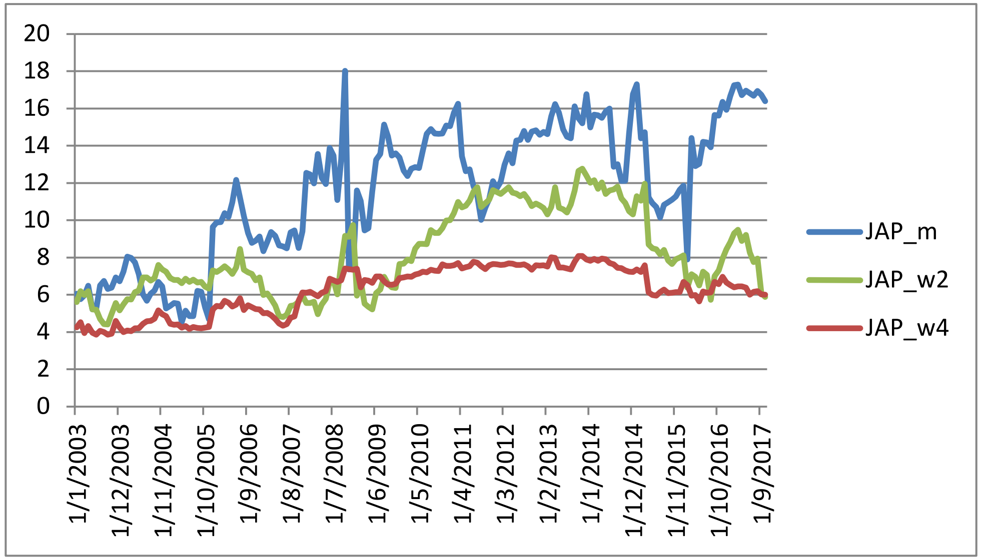

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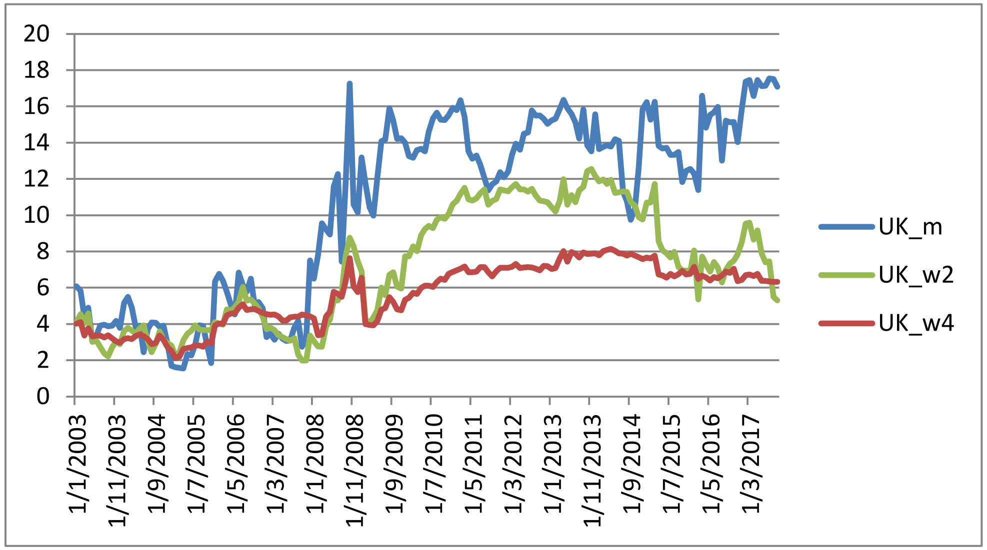

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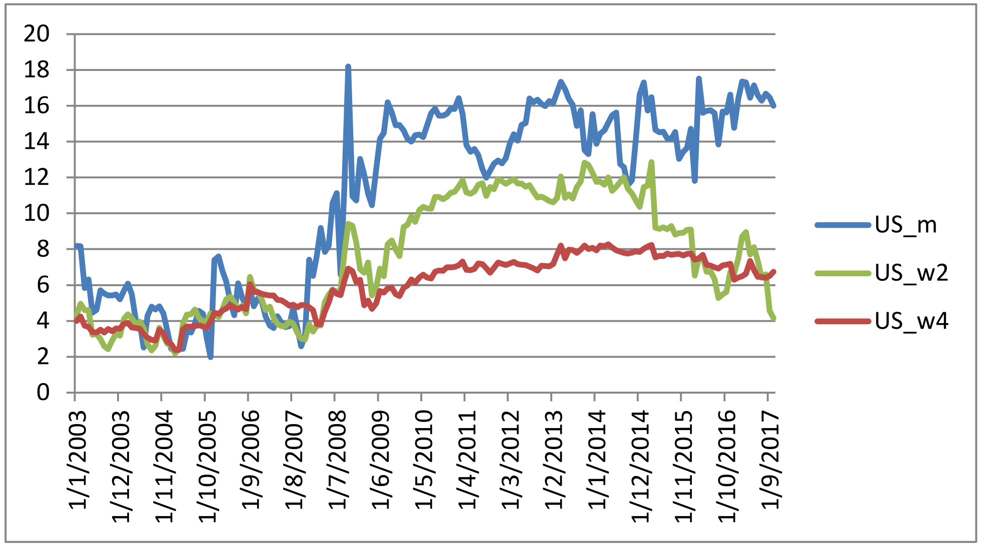

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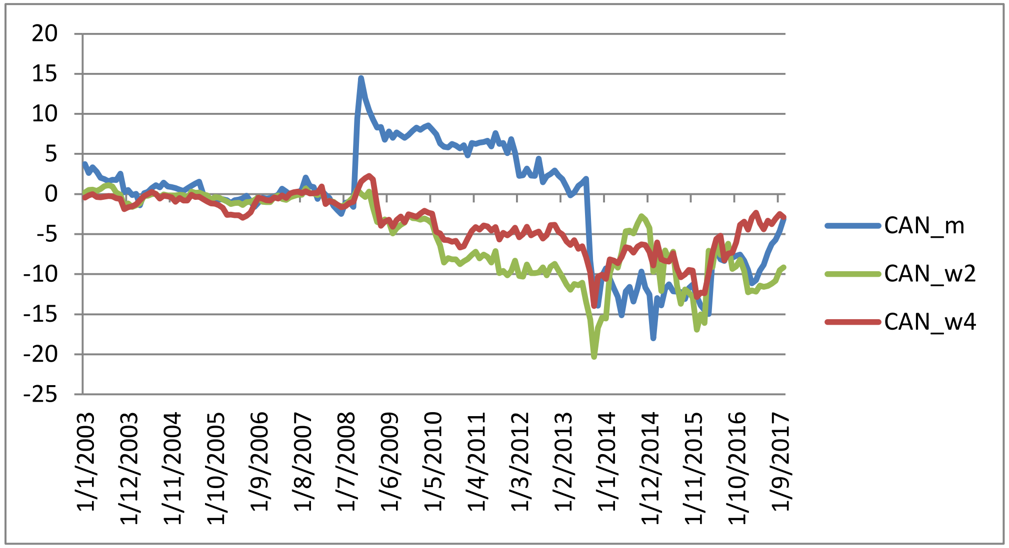
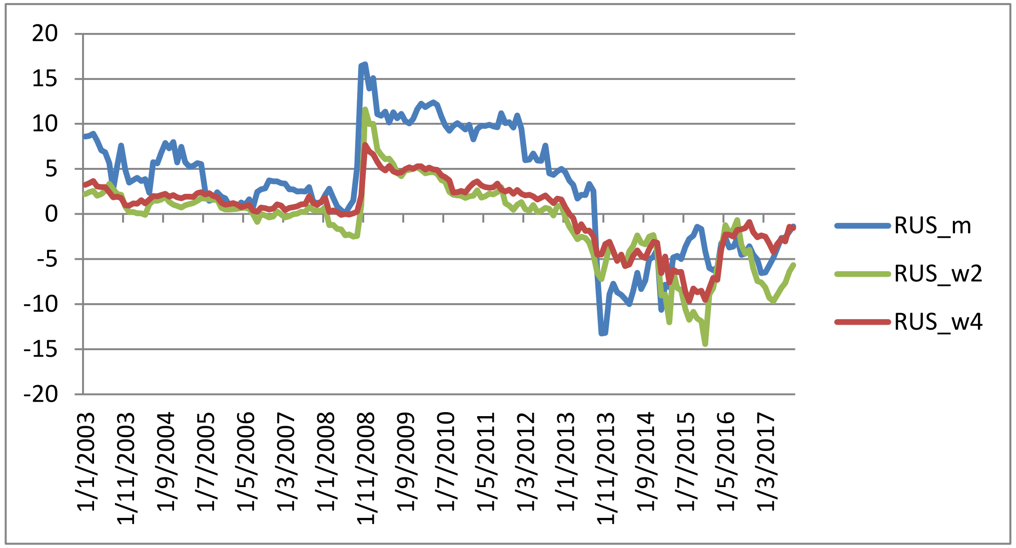
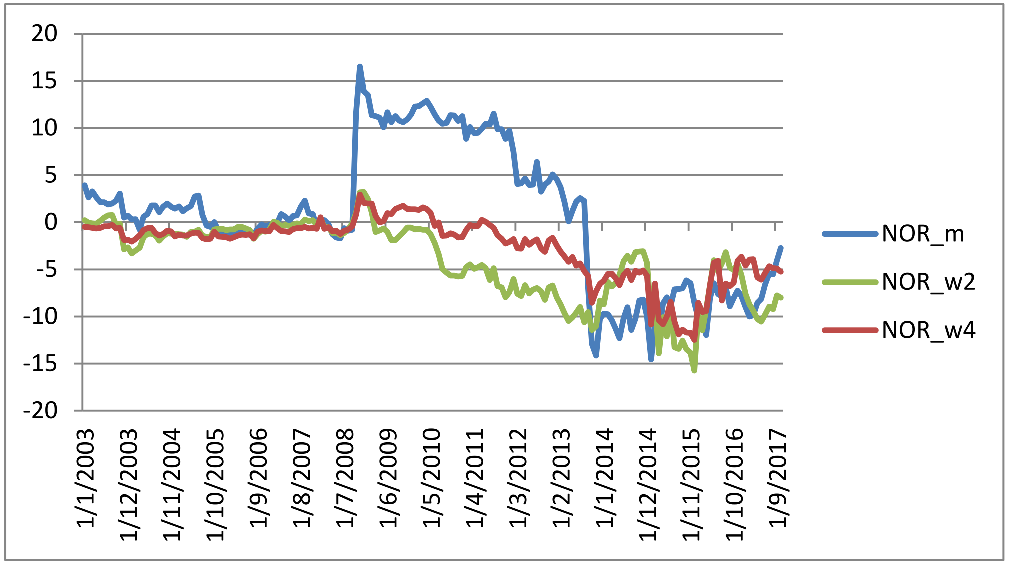
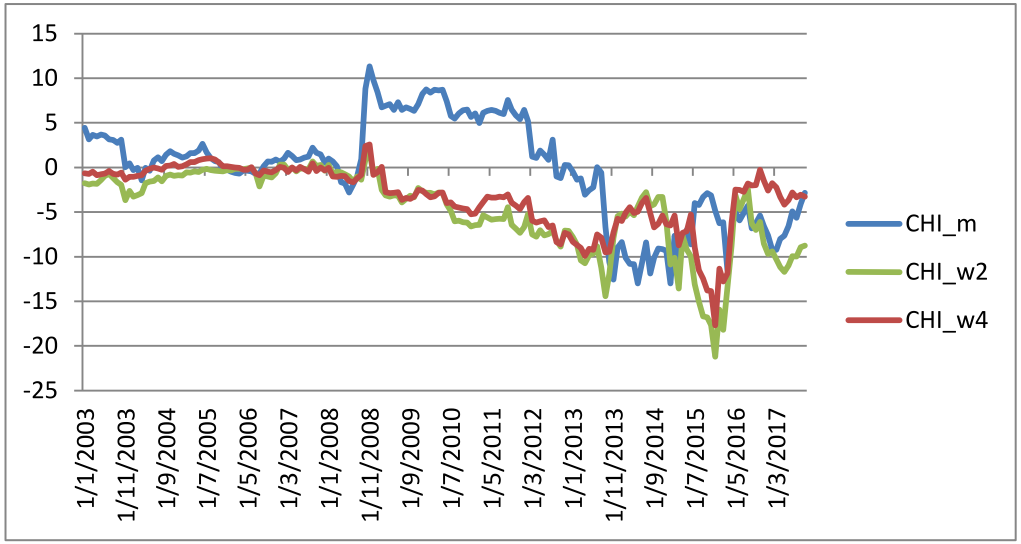
Rolling window Net Directional Connectedness   ADS (global economic activity)





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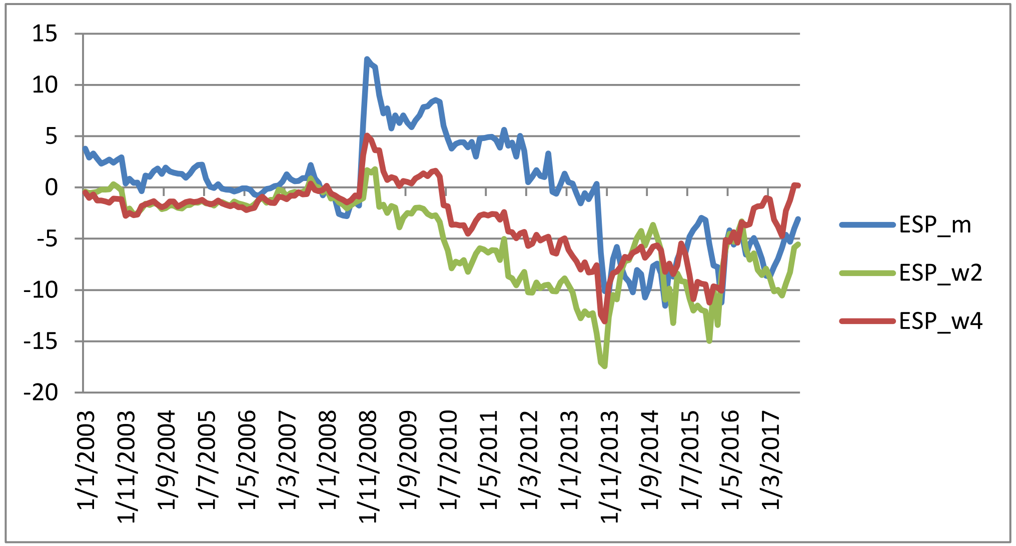
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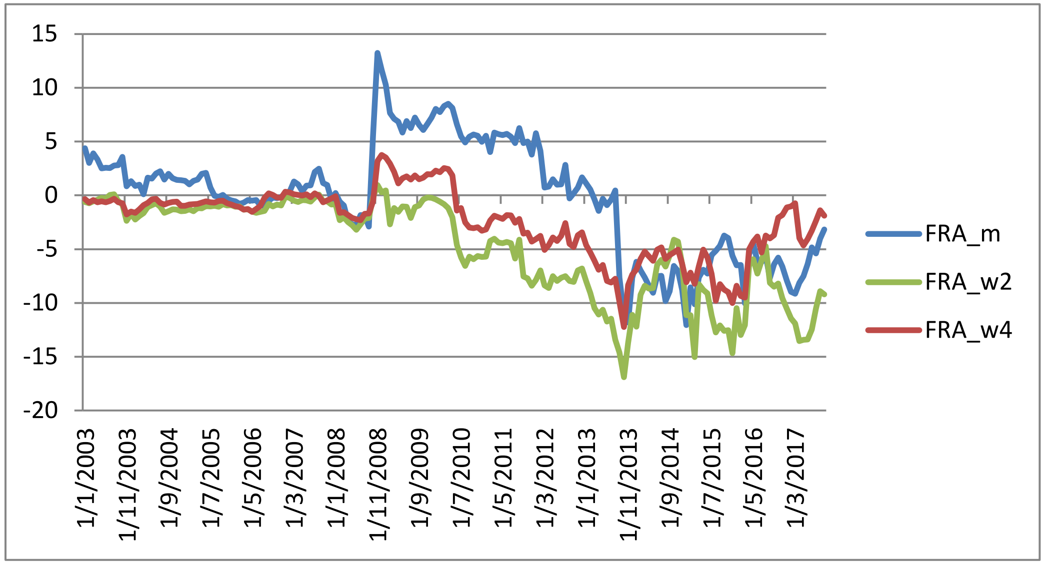
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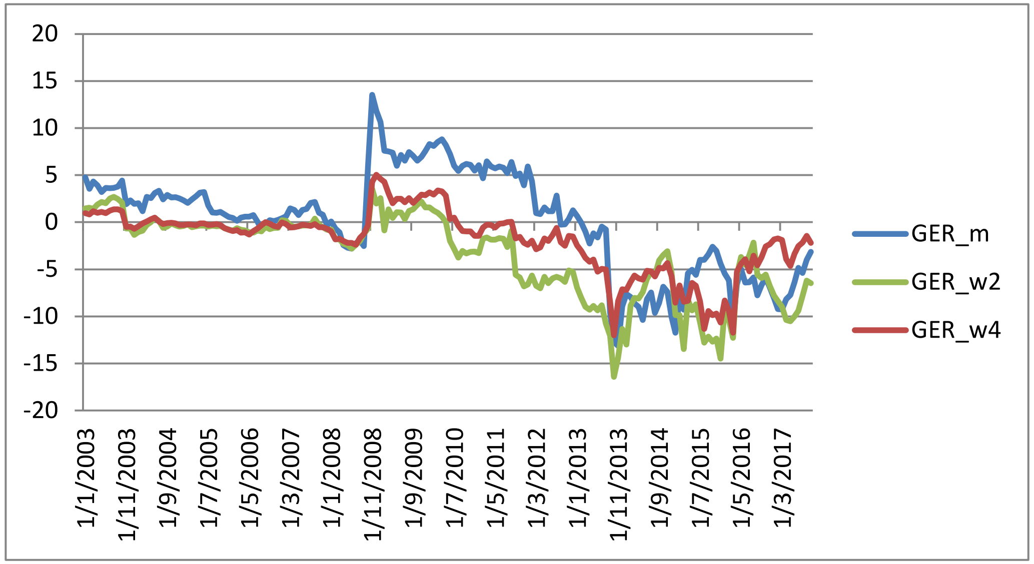
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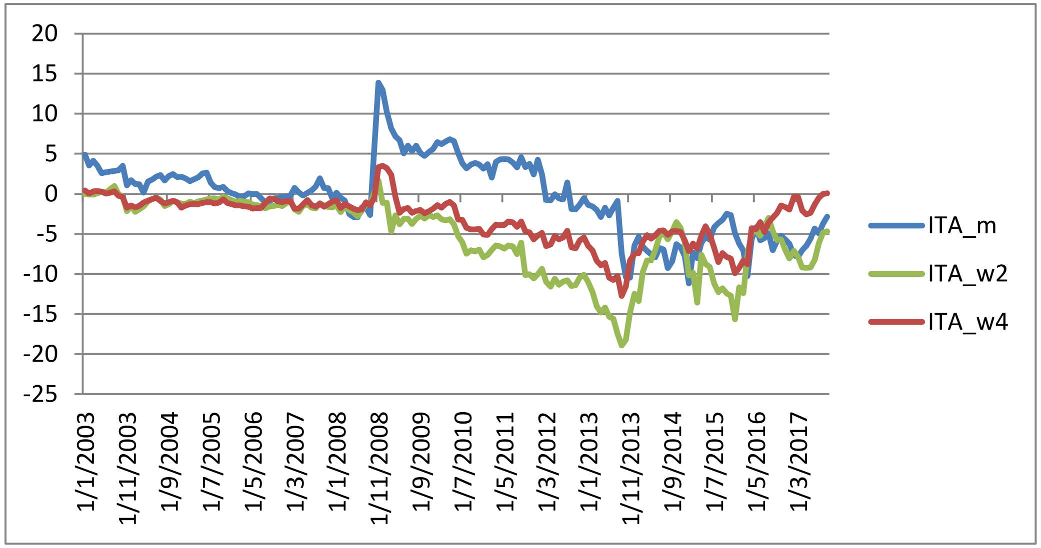
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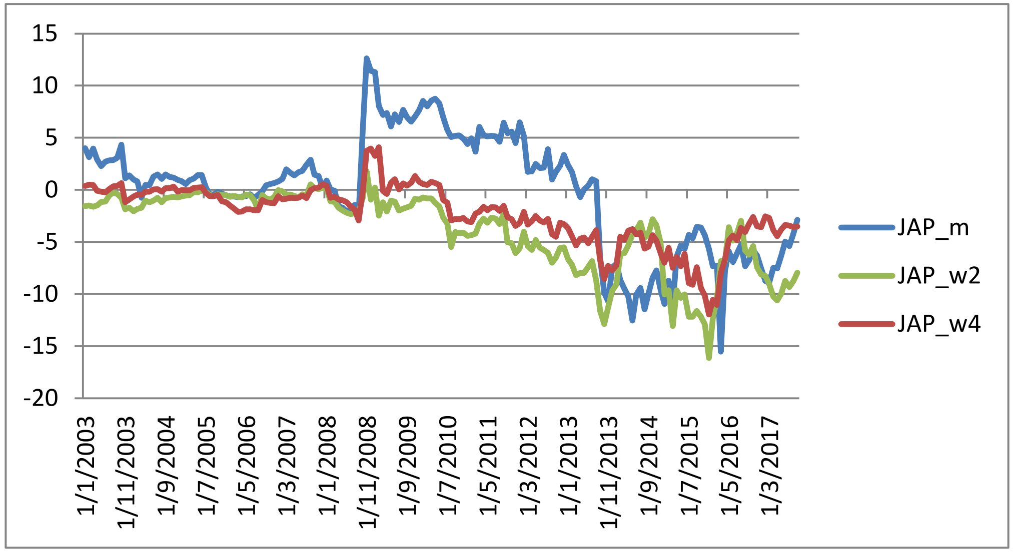
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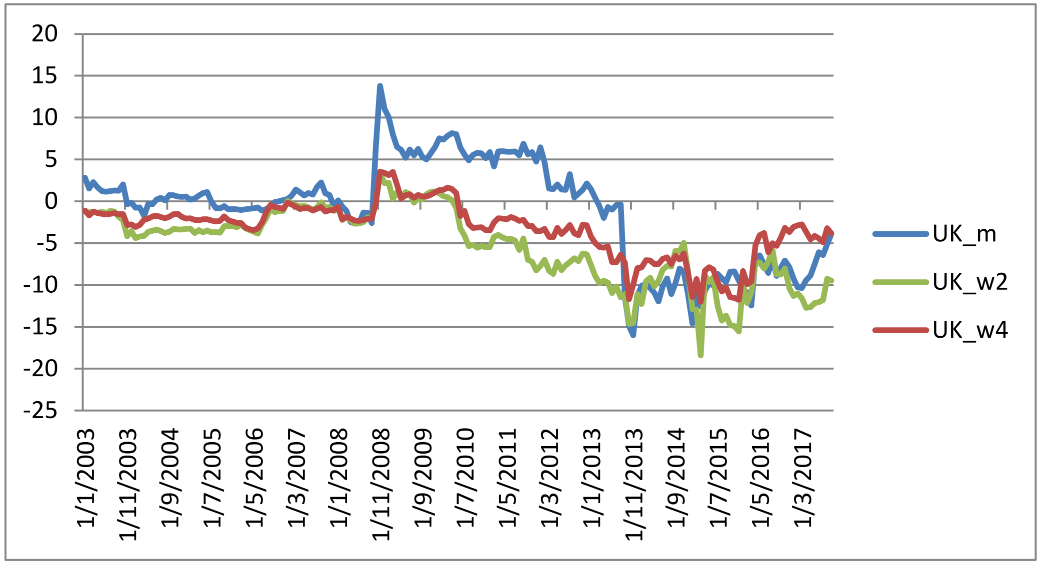
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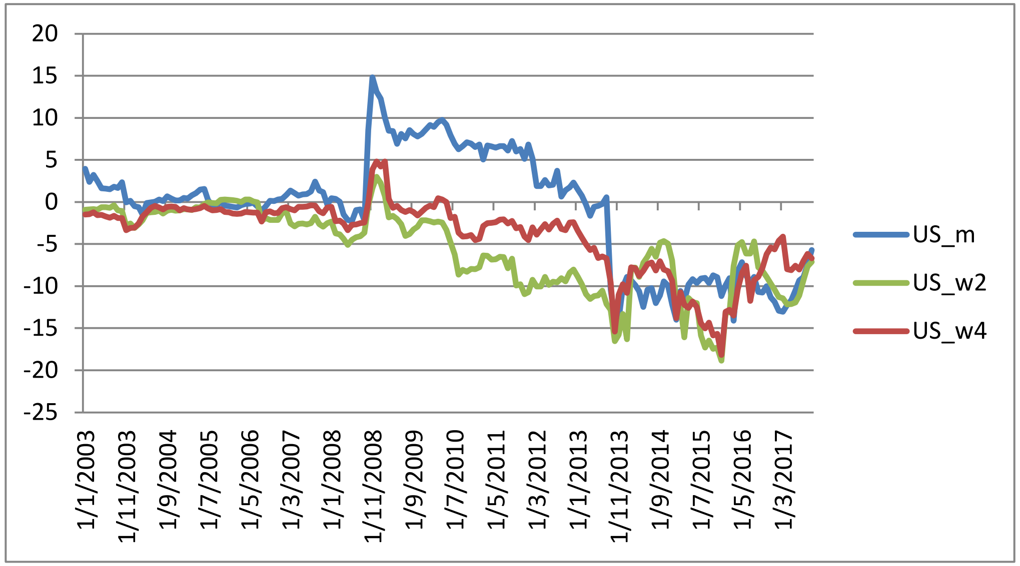
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References

Acharya, V. V., L. H. Pedersen, T. Philippon, and M. Richardson (2017). Measuring systemic risk, *Review of Financial Studies*, 30(1), 2–47.

Adrian, T. and M. K. Brunnermeier (2016), Covar, *American Economic Review*, 106 (7), 1705–1741.

Alter, A. and Beyer, A. (2014), The dynamics of spillover effects during the European sovereign debt turmoil, *Journal of Banking and Finance*, 42, 134–153.

Amisano, G., and Giannini, C. (1997): Topics in structural VAR econometrics. Second edition, Springer Verlag, New York.

Andreou, E., Ghysels, E. and Kourtellos, A. (2011), Forecasting with mixed-frequency data, *Oxford Handbook of Economic Forecasting*, 225–245.

Antonakakis, N. (2012), Exchange return co-movements and volatility spillovers before and after the introduction of Euro, *Journal of International Financial Markets, Institutions and Money*, 22(5), 1091–1109.

Antonakakis, N., Chatziantoniou, I. and Filis, G. (2017). Oil shocks and stock markets: Dynamic connectedness under the prism of recent geopolitical and economic unrest, *International Review of Financial Analysis*, 50, 1-26.

Baruník, J., Kočenda, E. and Vácha, L. (2016), Asymmetric connectedness on the U.S. stock market: Bad and good volatility spillovers, *Journal of Financial Markets*, 27(C), 55–78.

Bjornland, H. C. (2009). Oil price shocks and stock market booms in an oil exporting country. *Scottish Journal of Political Economy*, 56(2), 232–254.

Broadstock, D. and Filis, G. (2014), Oil price shocks and stock market returns: New evidence from the United States and China, *Journal of International Financial Markets, Institutions and Money*, 33, 417–433.

Claeys, P. and Vašíček, B. (2014), Measuring bilateral spillover and testing contagion on sovereign bond markets in Europe, *Journal of Banking and Finance*, 46, 151–165.

Demirer, M., Diebold, F. X., Liu, L. and Yilmaz, K. (2018), Estimating global bank network connectedness, *Journal of Applied Econometrics*, 33(1), 1–15.

Diebold, F. X. and Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *Economic Journal*, 119(534), 158–171.

Diebold, F. X. and Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1), 57–66.

Diebold, F. X. and Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182(1), 119–134.

Favero, C. A., (2000). Applied Macroeconometrics. Oxford University Press, Oxford.

Filis, G., Degiannakis, S. and Floros, C. (2011), Dynamic correlation between stock market and oil prices: The case of oil-importing and oil-exporting countries, *International Review of Financial Analysis*, 20(3), 152–164.

Forbes, K. J. and Rigobon, R. (2002), No contagion, only interdependence: Measuring stock market comovements, *Journal of Finance*, 57(5), 2223-2261.

Foroni, C., E. Ghysels, and M. Marcellino (2014), Mixed-frequency Vector Autoregressive Models, *Advances in Econometrics,* 32, 247–272.

Foroni, C., and M. Marcellino (2014), Mixed-Frequency structural models: Identification, estimation, and policy analysis, *Journal of Applied Econometrics*, 29(7), 1118–1144.

Foroni, C., M. Marcellino, and C. Schumacher (2014), Unrestricted mixed data sampling (UMIDAS): MIDAS regressions with unrestricted lag polynomials, *Journal of the Royal Statistical Society A*, 178(1), 57–82.

Geweke, J. (1978), Temporal aggregation in the multiple regression model. *Econometrica*, 46(3), 643–661.

Ghysels, E. (2016): Macroeconomics and the Reality of Mixed Frequency Data, *Journal of Econometrics*, 193(2), 294–314.

Ghysels, E., Santa-Clara, P. and Valkanov, R. (2004), The MIDAS touch: Mixed data sampling regression models, Working paper.

Ghysels, E., Santa-Clara, P. and Valkanov, R. (2005), There is a risk-return trade-off after all, *Journal of Financial Economics*, 76(3), 509-548.

Giglio, S., Kelly, B. and Pruitt, S. (2016), Systemic risk and the macroeconomy: An empirical evaluation, *Journal of Financial Economics*, 119(3), 457–471.

Jiang, G. J., Konstantinidi, E. and Skiadopoulos, G. (2012), Volatility spillovers and the effect of news announcements, *Journal of Banking and Finance*, 36(8), 2260–2273.

Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review*, 99(3), 1053–1069.

Lütkepohl, H. (ed.) (2006): New Introduction to Multiple Time Series. Springer.

Mohanty, S. K., Nandha, M., Turkistani, A. Q., and Alaitani, M. Y. (2011). Oil price movements and stock market returns: Evidence from Gulf Cooperation Council (GCC) countries. *Global Finance Journal*, 22(1), 42–55.

Sadorsky, P. (2012), Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies, *Energy Economics*, 34(1), 248–255.

Sims, C. A. (1971). Discrete approximations to continuous time distributed lags in econometrics. *Econometrica*, 39(3), 545–563.

Wang, Y., Wu, C. and Yang, L. (2013). Oil price shocks and stock market activities: Evidence from oil-importing and oil-exporting countries. *Journal of Comparative Economics*, 41(4), 1220–1239.