Spillovers beyond the variance: exploring the natural gas and oil higher order risk linkages with the global financial markets

Abstract

We explore the higher order linkages between energy commodity markets and global financial markets. Our focus is on spillovers of realized good and bad volatilities, realized signed jump variation, realized skewness and realized kurtosis. Our results show that the measurement of risk spillovers is sensitive to the definition of risk used in their construction. Asymmetries between good and bad volatility transmission matter, and results when jumps and higher order risk measures are considered are substantially different from those obtained when traditional volatility measures are used. We provide empirical support for theoretical asset pricing models that conduct the optimization required for portfolio balancing in the mean-variance-skewness space by showing that risk diversification opportunities vary greatly when one considers variance or skewness as the fundamental proxy for risk.

Keywords: Energy commodity markets; Risk spillover; Higher order risk measures; LASSO methods.

JEL codes: E44; F31; G01; G12; G15

1. Introduction

International financial market integration has increased rapidly over the last two decades. In a more financially integrated world, policies and events taking place in a market may have important cross-border and cross-market effects. Financial spillovers take place when fluctuations in the price of an asset trigger price variations of other assets. They are not necessarily bad as they reflect both the incorporation of news into prices and the transmission of excess risk due to financial frictions. Financial integration offers many benefits, as increasing opportunities for risk sharing. However, over the past two decades crises have propagated more rapidly than in the past and have proven to be more persistent and disruptive.

The recent Global Financial Crisis has reawakened the interest in studying financial contagion and risk transmission among financial markets. An important strand of this literature follows the seminal contributions of Diebold and Yilmaz (2009, 2012, 2014) and studies volatility spillovers based on forecast error variance decompositions from vector autoregressions (VAR). Many of the most recent studies have focused on the transmission of financial shocks across equity, foreign exchange and sovereign bond markets. And, motivated by the commodity financialization hypothesis, a growing number of them study spillovers between commodity and traditional financial markets (e.g., Lee, Yang and Huang, 2012; Ding, Kim and Park, 2016; Zhang, 2017; Gomez-Gonzalez, Hirs-Garzon and Uribe, 2020.). Moreover, investment in commodity-fuels has become a major mean to foster financial diversification in traditional stock, bond, precious metals, and foreign exchange dominated portfolios, especially during episodes of financial turmoil (Geman and Kharoubi, 2008; Wen et al., 2012; Singleton, 2014). Despite this, and even tough it is currently understood that traditional financial markets and fuel markets are significantly co-dependent, the nature of this integration and the transmission channels through which shocks dissipate are still not fully understood.

One reason for such a lack of understanding is that most of the existing studies focus on first and second moment spillovers. The implicit assumption behind these studies is that the variance is a sufficient measure of financial risk. However, as the literature on decision making has shown, if decision makers are risk averse, higher order risk attitudes such as prudence and temperance determine the effects on economic behavior caused by changes in the risk properties to which they are exposed (Trautmann and van de Kuilen, 2018). The experimental literature on higher order risk measures has shown the importance and strength of prudence, closely linked with the skewness of the distribution of returns[1] (Harvey and Sidique, 2000; de Roon and Karehnke, 2018). For instance, downside risk and tail risk matter. Studying risk propagation among exchange rates, Chuliá, Fernández and Uribe (2018) find important risk propagation asymmetries that become evident when comparing volatility-based and quantile-based spillover measures.

[1] A decision maker with preferences exhibiting prudence shows preference for payoffs distributions with right kurtosis. A decision maker with preferences exhibiting temperance dislikes distributions with high kurtosis.

Alongside the same lines, Baruník et al. (2017) document dominating asymmetries in spillovers, which are due to bad rather than good volatility. They also show that negative spillovers in the stock markets seen to be tied to sovereign debt concerns, while positive spillovers have been mainly associated with the global financial crisis. The results in the two cases imply that studying risk spillovers beyond the variance may provide valuable information on the effects of spillover transmissions among financial markets.

Some specific questions that have not been tackled by the extant literature are: i) how is the transmission of *higher order* risks (i.e. skewness, kurtosis, jumps) between the main financial markets and energy commodities? That is, how risk beyond the variance propagates to/ from the fuel markets? ii) Are natural gas and oil markets net producers or receivers of shocks in the tail or other fragments of the return distribution? iii) What kind of asymmetries (if any) underlay the propagation of shocks between energy commodities and FX, stock or other commodity markets? iv)Has the level of integration between energy commodities and the main financial markets changed during the last decades when we look at different definitions of risk? And in particular when we go beyond the risk embedded by the second moment of the series returns?

Here we answered these questions. We study risk spillover transmission beyond the variance between two important commodity markets (oil and natural gas) and traditional financial (stock, exchange rate and precious metals) markets. Our methodological approach differs from the previous literature in two important ways: First, we estimate connectedness statistics and networks in the vein of Diebold and Yilmaz (2012, 2014) between different (realized) moments of the markets series returns. We consider on top of volatility and semivariances (see Wan and Wu, 2018), a measure of signed jump variation, skewness and kurtosis. It is our contention that each statistic reflects a different dimension of risk, and therefore the study of risk propagation should not be confined only to the first two moments of the series returns. For instance, skewness is related to the probability of market crashes, as it is fully recognized in the literature about momentum trading (Daniel and Moskowitz, 2016), while kurtosis reflects the probability of an extreme realization, which can be either positive or negative as long as it is sizable and relatively unlikely. On its side, jumps and co-jumps are importantly related to price discontinuities and price discovery of the market information (Lahaye et al., 2011). Second, we work with monthly-realized moments (and stand upon a daily frequency to estimate them) seeking to identify relatively persistent shocks to the market and to reduce the noise that features intraday data. Moreover we are able to take into account the main global financial markets in our set up (9 stock markets, 6 FX markets and 4 commodities including gas and oil). We carried out our estimations by means of a recent proposal by Demirer et al. (2018). Our methods combine a traditional vector autoregression set up with selection and shrinkage of the parameter space by LASSO (Least Absolute Shrinkage and Selection Operator). By so doing, we are also able to construct dynamic spillover statistics that would be unfeasible in a traditional regression framework due to the *curse of dimensionality*. Working with this relatively large number of markets is important to understand the increasingly close financial linkages of stock prices, FX variations and commodity prices. Such an analysis requires a complete and comprehensive modeling of the main transmission channels, and the exclusion of some of these markets is potentially costly in terms of the model specification.

Studying spillovers using the measures presented herein, most of which are based on the realized semivariance estimator proposed by Barndorff-Nielsen, Kinnebrock, and Shephard (2010), offers several additional advantages with respect to the more traditional approach. For instance, they admit checking whether the spillover contribution of jumps is different from the contribution of continuous changes in asset prices. They also allow us to assess whether the spillover contributions of past negative returns are different than those of positive returns. All in all, we seek to provide a general framework that allows for a direct comparison of cross-market spillovers occurring at different parts of the asset return distributions. This in turn corresponds to estimate cross-market spillovers according to different notions of risk and hence, allow us to provide more information than the traditional approach, in terms of risk management and portfolio diversification. Our contribution is therefore important for international investors seeking to diversify risk, regulators aiming to preserve financial stability and energy firms' managers interested in maximizing the firm's value.

Our study also contributes to the asset pricing and portfolio construction literatures. Indeed, the definition of risk and in particular, the enhancement of the notion of risk as to consider moments and asymmetries beyond the traditional mean-variance framework also has been a lively line of research. While some studies warn about the wealth losses that may derived from ignoring higher order moments of the return distribution and hence, overinvesting in risky assets (Cvitanić, Polimenis, and Zapatero, 2008), others has attempted to augment the traditional variance-mean portfolio optimization process by incorporating the effect of higher order moments (Mencía and Sentana, 2009; Briec, Kerstens and Jokung, 2007; Briec and Kertens, 2010). Moreover, a third branch of the literature has considered the effect of 'rare' jump shocks, 'disasters', and tail events in the explanation of market crashes (Barro, 2006; Bates, 2012) and of market anomalies such as the equity premium puzzle (Santa-Clara and Yan, 2010; Benzoni, Collin-Dufresne, and Goldstein, 2011; Bollerslev and Todorov, 2011; Gabaix, 2012; Drechsler, 2013; Wachter, 2013).

In summary, our primary contributions to the literature are twofold. First, we estimate tail-spillovers between commodity, stock and exchange rate markets. Unlike previous studies that focus on return co-movements and volatility spillovers, we directly address the issue of asymmetric risk spillovers in the left and right tails of the daily variations in market prices. Second, following the experimental literature that has shown that prudence and temperance matter in decision making, we study risk spillovers using realized skewness and realized kurtosis. To our knowledge, this is the first study exploring higher order risk spillovers between commodity markets and traditional financial markets.

Our results indicate that the measurement of risk spillovers is very sensitive to the definition of risk used in their construction. Asymmetries between good and bad volatility transmission matter, and results when jumps and higher order risk measures are considered are substantially different from those obtained when traditional volatility measures are used. Traditional risk analysis based upon the second moments of the system series implicitly assumes that risk transmission occurs at the same pace whether the shocks hitting the market are positive or negative. Nevertheless, important asymmetries become evident when we go from variances to semivariances. For instance, both natural gas and oil markets gain considerable importance in the transmission of shocks 'to' the system, when good and bad volatility shocks are considered separately, almost doubling the numbers obtained when such asymmetric effects are ignored.

Moreover, when higher order moments are considered in the transmission of financial spillovers, results change dramatically. For instance, when attention is drawn on the transmission of shocks in volatilities or semivolatilities, the oil market seems far more integrated to the rest of the global financial markets than the natural gas market. Indeed, the shocks that the oil market generate 'to' and receive 'from' the other markets (70.3% and 77.5% on volatilities) are larger than those associated to the natural gas market (20.6% and 49.2%). However, when higher order risks such as skewness are measured, the natural gas market becomes one of the largest producers of cross-cumulated shocks to the system (125.3%), well beyond those produced by oil (93.4%). It also exhibits large fragments of cross-variance shares explained by the rest of the system, although still below those of oil (71.2% for natural gas and 92.8% for oil). These results go in line with those of experimental designs that have shown that prudence is a strong, salient feature in financial decision making. In other words, asymmetries in the distribution of financial returns matter and have important implications in risk spillover transmission.

On the other hand, results regarding kurtosis spillovers are significantly different. In this case, shocks to the system coming from oil sum-up to 10.9% and from natural gas to 7.2% only. The transmission of this tail-symmetric risk is far below the one related to volatilities, jumps and skewness (38.7% total cross spillovers). This result coincides with experimental findings reporting that temperance (associated with kurtosis) is by far weaker than prudence.

Our results also indicate that risk spillovers vary importantly over time. The global financial risk profile is remarkably dissimilar depending on the moment of the series under analysis. Realized volatility spillovers (both total and semivolatilities) increase, as expected, during the Global Financial Crisis (GFC) of 2007-2008. Bad volatility is more persistent than good volatility. Interestingly, skewness spillovers are higher around 2012 and 2013 than during the GFC. This result may obey to the behavior of oil and natural gas prices over those two years. Consistent with our static results, kurtosis spillovers are considerably lower although they have been increasing since July 2015. According to our different measures, global risk profile is currently lower than in the aftermath of the GFC. Moreover, according to the systemic risk statistic based on the skewness and jump variations it is even lower than before the crisis and, indeed, it has reached a historical minimum since the beginning of our estimates in April 2005.

Overall, our results highlight the importance of considering alternative risk measures for computing spillovers in financial markets. As shown in the most recent decision theory literature, higher order risks matter, as risk-averse decision makers go beyond the variance when comparing the risk profile of risky projects. Given volatility transmission results vary considerably depending on the definition of risk itself, different measures such as downside risk, tail risk, skewness and kurtosis are worthy of being considered in studies of risk transmission and contagion.

The remainder of the paper is structured as follows: Section 2 introduces the econometric methods used in this paper. Section 3 presents the data. Section 4 describes our main empirical results, and finally, the last section concludes.

2. Methodology

We estimate connectedness statistics as proposed by Diebold and Yilmaz (2012, 2014), but given the frequency of our measures and the number of cross sectional units we resort to the recent proposal by Demirer et al. (2018) to reduce the parameter space dimension of the original VAR system, as to make estimation feasible. Unlike the previous literature our VAR system is used to describe the relationship not only across (realized) volatilities, but also between realized semivariances (good and bad), realized skewness, signed jump variations, realized kurtosis and skewness.

2.1 Spillovers statistics

The spillover indices are built upon a VAR with *N* variables that comprises series of stock, FX and commodity markets. These statistics are constructed by means of the associated forecast error variance decomposition (FEVD). The errors are estimated from the moving average representation of the VAR following equations 1 and 2:

$$X_t = \Theta(L)\varepsilon_t, \tag{1}$$

$$X_t = \sum_{t=0}^{\infty} A_i \varepsilon_{t-i}, \tag{2}$$

where X_t is a matriz $T \times N$, $\Theta(L) = (I - \phi(L))^{-1}$, ε_t is a vector of independently and identically distributed disturbances with zero mean, and Σ covariance matrix, $A_i = \phi A_{i-1} + \phi A_{i-2} + \cdots + \phi A_{i-p}$ is the parameters' matrix, *p* is the number of lags in the estimation, and *T* is the number of time periods. To estimate the FEVD from the h-step ahead forecast, first we f need to identify the structural perturbations to the VAR system. This can be achieved by imposing restrictions on the MA parameters. Following Diebold and Yilmaz's (2012) suggestion, we use the proposal of Koop et al. (1996) and Pesaran and Shin (1998), namely the generalized VAR for the construction of the FEVD.

The errors in the FEVD can be divided into *own variance* shares and *cross variance* shares. The former are the fractions of the errors that are associated to a shock to x_i on itself, while the latter are the portion of the shocks on x_i related to the rest of the variables in the system. Thus, the h-step ahead FEVD can be defined as:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i{}' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i{}' A_h \Sigma A_h{}' e_i)}, \tag{3}$$

where σ_{jj} is the standard deviation of the *j*-th equation, e_i is a selection vector, with ones in the *i*-th element and zero otherwise, and Σ is the variance matrix of ε_t. To guarantee that the sum of each row is 1, $\sum_{j=1}^{N} \tilde{\theta}_{ij}(H) = 1$, each entry of the variance decomposition must be normalized as follows:

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N} \theta_{ij}(H)}. \tag{4}$$

where $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H) = N$.

With the normalized variance decomposition, a total spillover index can be calculated as:

$$C(H) = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\theta}_{ij}(H)}{N} \times 100. \tag{5}$$

This index measures the percentage of the forecasted variance series that can be explained by cross-spillovers. It can be extended to a *directional spillover* index, in which the effect of a shock from all other variables j on the variable x_i is given by:

$$C_{i \leftarrow j}(H) = \frac{\sum_{j=1, i \neq j}^{N} \tilde{\theta}_{ij}(H)}{N} \times 100, \tag{6}$$

conversely, the effect of a shock from x_i on all other markets j is given by:

$$C_{i \rightarrow j}(H) = \frac{\sum_{j=1, i \neq j}^{N} \tilde{\theta}_{ji}(H)}{N} \times 100, \tag{7}$$

with the two directional spillover indices one constructs a *net spillover* index, given by:

$$C_i(H) = C_{i \to j}(H) - C_{i \leftarrow j}(H). \quad (8)$$

The net spillover index is a measure of the effect related to a shock in the variable x_i on the rest of the system. Therefore, each variable will act either as a *net receiver* or as a *net transmitter* of shocks in each *t*. It is also possible to construct a *net pairwise spillover* statistic, which accounts for the net spillover effect of variable x_i on x_j, where $i \neq j$. The net pairwise index is defined as follows:

$$C_{ij}(H) = \frac{\tilde{\theta}_{ji}(H) - \tilde{\theta}_{ij}(H)}{N} \times 100. \quad (9)$$

It is also possible to present the information contained in the variance of the forecasted error by networks. Nodes and edges constitute network graphs. In the results section the placement of nodes in the network is determined by the Force Atlas2 algorithm developed by Jacomy et al. (2014). This algorithm encounters a steady-state balance between forces of transmission and reception. Color intensity represents the degree of connectedness between the corresponding markets. Darker color segments correspond to more connected markets.

2.1.1 Least Absolute Shrinkage and Selection Operator (LASSO)

LASSO was proposed by Demirer et al. (2018) in the context of VAR systems for financial connectivity. These authors highlight that in applications that study connectivity across numerous markets or asset classes the VAR system requires estimation on a large dimensional space, without losing excessive degrees of freedom (to the point of making the estimation unfeasible). By using shrinkage or through model comparison and selection (using traditional AIC or BIC criteria) this can be achieved. LASSO blends the two approaches.

Consider an ordinary regression by least squares:

$$\hat{\beta} = \underset{\beta}{\arg min} \sum_{t=1}^{T} (y_t - \sum_{i}^{N} \beta_i x_{it})^2, \quad (10)$$

subject to the restriction

$$\sum_{i=1}^{K} |\beta_i|^q \leq c \,, \quad (11)$$

which can be also presented as a penalized estimation problem as follows:

$$\hat{\beta} = \underset{\beta}{\arg min} [\sum_{t=1}^{T} (y_t - \sum_{i}^{N} \beta_i x_{it})^2 + \lambda \sum_{i=1}^{K} |\beta_i|^q], \quad (12)$$

Concave penalty functions non-differentiable at the origin produce selection, whereas smooth convex penalties generate shrinkage. Thus, penalized estimation blend selection and shrinkage. The LASSO solves the penalized regression problem with q = 1. Hence it shrinks and selects. In addition, it requires only one minimization, and it uses the smallest q for which the minimization problem is convex.

The Adaptive elastic net is an extension of LASSO due to Zou and Zhang (2009), which does on top of shrinking and selecting, presents the 'oracle property'. In the implementation of the adaptive elastic net in this proposal, following Demirer et al. (2018) is necessary to solve

$$\hat{\beta}_{AEnet} = \arg min_{\beta} \left[\sum_{t=1}^{T} (y_t - \sum_{i}^{N} \beta_i x_{it})^2 + \lambda \sum_{i=1}^{K} w_i \left(\frac{1}{2} |\beta_i| + \frac{1}{2} \beta_i^2 \right) \right], \quad (13)$$

where $w_i = 1/|\hat{\beta}_{i,OLS}|$ and λ is selected equation-by-equation by 10-fold cross validation. The adaptive elastic net penalty weights the average by the inverse of OLS parameter estimates, and by so doing it shrinks the smallest OLS coefficients toward zero.

2.2 Realized statistics

The *N* series included in the VAR representation are generally returns or volatilities. In both cases spillovers statistics constructed upon the FEVD of the system refer to second order risks faced by financial investors. We expand this traditional analysis by allowing different moments and statistics to be consider as our work unit. We estimate monthly-realized variances of log asset prices Y (see Andersen et al., 2011) as follows:

$$RV = \sum_{j=1}^{n} \left(Y_{t_j} - Y_{t_{j-1}} \right)^2, \quad (14)$$

where $0 = t_0 < t_1 < \cdots < t_n = 1$ are the times at which prices are available, in our case on a daily frequency. This has been proved to be a useful methodology to estimate and forecast conditional variances for risk management and asset pricing. We also estimate realized-semivariances proposed by Barndorff-Nielsen et al. (2010), as:

$$\begin{aligned} RS^- &= \sum_{j=1}^{n} {r_{t_j}}^2 \, 1_{r_{t_j} \leq 0} \\ RS^+ &= \sum_{j=1}^{n} {r_{t_j}}^2 \, 1_{r_{t_j} > 0} \end{aligned} \quad (15)$$

where $r_{t_j} = Y_{t_j} - Y_{t_{j-1}}$. Using equation 15 is possible to estimate a measure of the realize jump variations as $\mathrm{RJ} = \mathrm{RS}^{+} - \mathrm{RS}^{-}$. (standardized) realized skewness and realized kurtosis in our framework are estimated as:

$$RS = \sum_{j=1}^{n} \frac{\left(r_{t_j}\right)^3}{\sqrt{RV}}, \qquad (16)$$

$$RK = \sum_{j=1}^{n} \frac{\left(r_{t_j}\right)^4}{\sqrt{RV}}, \qquad (17)$$

With these six measures we estimated separate VAR systems and constructed spillovers and connectedness statistics and networks aiming to analyze spillovers at different moments of the return distributions.

3. Data

Our data set consists of daily closing prices from nine financial markets, six foreign exchange markets and four commodity markets from January 4 2000 to March 30 2018. All data is collected from Bloomberg. The following stock markets indices are included in the study: S&P500 (the USA), S&P/TSX (Canada), DAX (Germany), FTSE100 (the UK), SHCOMP (China), INDEXCF (Russia), CAC40 (France), FTSEMIB (Italy), NIKKEI 225 (Japan). The exchange rate markets are represented by six of the most traded currencies per US dollar: Russian Ruble (RUB), Canadian dollar (CAD), Chinese Yuan (CNY), Euro (EUR), the Japanese Yen (JPY) and the Pound sterling (GBP). Finally, the commodity markets used include: oil (WTI), natural gas, gold and copper.

We work with monthly moments (estimated based on daily frequency data) seeking to identify relatively persistent shocks in the market and reduce the noise presented by intraday data. The span period of the data allows us to evaluate the effect of the global financial crisis on the dynamic interactions between different markets.

4. Results

4.1 Univariate summary statistics

Our main results are reported in tables 1-3 and figures 1-4. Table 1 shows the univariate summary statistics for the markets in our sample. The average monthly realized volatility (panel A), positive and negative realized semivariances (B and C), alongside the average realized sign jump variation (panel D), realized skewness (E) and realized kurtosis (F) are shown in Table 1 for two subsamples: The first running from January 2000 to December 2008 and the second from January 2009 to March 2018 (before and after the GFC). Statistics for the total sample are shown jointly.

Table 1

Univariate Summary Statistics

Sample	Stocks									Foreign Exchange						Commodities			
Panel A: Realized Volatility																			
Sample	**USA**	**CAN**	**GER**	**UK**	**CHI**	**RUS**	**FRA**	**ITA**	**JAP**	**RUB**	**CAD**	**CNY**	**EUR**	**JPY**	**GBP**	**WTI**	**COOP**	**GOLD**	**NG**
00-08*	33,54	31,08	55,97	33,52	62,47	148,58	47,88	41,95	51,20	1,37	6,65	0,13	8,52	8,57	6,31	97,56	72,07	27,10	204,49
09-18**	22,58	17,54	35,43	21,68	45,58	90,05	36,89	56,12	40,23	24,02	7,42	0,44	8,26	8,76	8,28	96,09	53,61	24,31	138,18
Total	28,70	24,99	45,90	27,76	54,09	119,44	42,88	49,68	45,83	13,02	7,10	0,29	8,53	8,74	7,49	98,59	63,56	26,02	171,04
Panel B: Realized Bad Volatility																			
	USA	**CAN**	**GER**	**UK**	**CHI**	**RUS**	**FRA**	**ITA**	**JAP**	**RUB**	**CAD**	**CNY**	**EUR**	**JPY**	**GBP**	**WTI**	**COOP**	**GOLD**	**NG**
00-08*	18,34	17,31	30,72	18,06	29,34	82,90	25,41	22,93	28,89	0,52	3,41	0,10	4,18	4,38	2,92	50,84	37,73	12,58	108,20
09-18**	10,88	8,45	17,60	10,70	24,62	45,25	19,00	30,81	20,44	10,29	3,67	0,23	3,68	4,08	3,63	49,17	24,43	12,69	71,11
Total	14,99	13,35	24,19	14,43	27,13	64,06	22,42	27,23	24,68	5,50	3,59	0,17	4,06	4,29	3,32	51,29	31,63	12,78	89,28
Panel C: Realized Good Volatility																			
	USA	**CAN**	**GER**	**UK**	**CHI**	**RUS**	**FRA**	**ITA**	**JAP**	**RUB**	**CAD**	**CNY**	**EUR**	**JPY**	**GBP**	**WTI**	**COOP**	**GOLD**	**NG**
00-08*	15,21	13,76	25,25	15,47	33,13	65,69	22,47	19,03	22,31	0,86	3,24	0,02	4,33	4,19	3,40	46,72	34,34	14,52	96,29
09-18**	11,69	9,10	17,83	10,97	20,97	44,80	17,90	25,31	19,78	13,73	3,75	0,21	4,57	4,67	4,64	46,92	29,18	11,62	67,07
Total	13,71	11,64	21,71	13,33	26,96	55,39	20,46	22,45	21,15	7,52	3,51	0,12	4,47	4,45	4,17	47,30	31,93	13,24	81,76
Panel D: Realized Singed Jump Variation																			
	USA	**CAN**	**GER**	**UK**	**CHI**	**RUS**	**FRA**	**ITA**	**JAP**	**RUB**	**CAD**	**CNY**	**EUR**	**JPY**	**GBP**	**WTI**	**COOP**	**GOLD**	**NG**
00-08*	-3,13	-3,55	-5,47	-2,59	3,79	-17,21	-2,95	-3,90	-6,59	0,34	-0,17	-0,08	0,15	-0,19	0,48	-4,12	-3,39	1,94	-11,91
09-18**	0,81	0,65	0,22	0,27	-3,65	-0,44	-1,10	-5,50	-0,66	3,44	0,07	-0,02	0,89	0,59	1,01	-2,25	4,75	-1,08	-4,04
Total	-1,27	-1,71	-2,48	-1,11	-0,17	-8,67	-1,96	-4,77	-3,54	2,01	-0,07	-0,05	0,41	0,17	0,85	-4,00	0,30	0,47	-7,52
Panel E: Realized Skewness (std)																			
	USA	**CAN**	**GER**	**UK**	**CHI**	**RUS**	**FRA**	**ITA**	**JAP**	**RUB**	**CAD**	**CNY**	**EUR**	**JPY**	**GBP**	**WTI**	**COOP**	**GOLD**	**NG**
00-08*	0,514	3,297	0,698	1,198	1,636	4,174	1,35	-1,35	0,014	3,56	-3,34	-6,83	-1,81	0,718	1,509	2,61	3,438	3,307	-0,08
09-18**	5,391	0,93	6,756	2,066	1,109	3,729	4,169	0,878	4,107	0,303	1,517	-8,67	2,179	2,203	-1,51	-1,46	1,022	-0,19	-2,54
Total	2,899	1,957	3,819	1,656	1,239	3,952	2,818	-0,22	2,057	2,111	-0,94	-7,53	0,118	1,408	0,09	0,48	2,147	1,525	-1,17
Panel F: Realized Kurtosis (std)																			
	USA	**CAN**	**GER**	**UK**	**CHI**	**RUS**	**FRA**	**ITA**	**JAP**	**RUB**	**CAD**	**CNY**	**EUR**	**JPY**	**GBP**	**WTI**	**COOP**	**GOLD**	**NG**
00-08*	18,41	19,25	17,72	16,79	21,53	19,81	17,52	19,11	18,41	25,52	19,05	21,33	19,85	20,44	19,73	19,78	20,31	21,42	20,48
09-18**	20,08	18,67	19,92	20,12	22,98	20,31	19,35	18,83	20,25	20,03	18,3	24,17	19,95	23,58	20,27	20,57	22	22,77	19,60
Total	19,29	18,98	18,87	18,53	22,29	20,08	18,47	18,98	19,39	22,76	18,67	22,88	19,88	22,02	20	20,15	21,16	22,09	20,10

The table shows the average of the statistics for the periods: Jan 2000 -Dec 2008, Jan 2009-Mar 2018 and for the total sample. The realized skewness and kurtosis were standardized and multiplied by 100.

Columns 16 and 19 correspond to the average statistics of oil and natural gas prices that we seek to emphasize (shadowed columns). In terms of volatilities and semivariances, energy commodities display a significantly larger variation than stock and a foreign exchange markets (except for the Russian stock market that depicts a larger variation than the oil market). Volatility is higher for natural gas prices than for oil, especially in the subsample that houses the GFC (2000-2008). In the two cases, 'bad' volatility is higher than 'good' volatility. Consistently, a negative sign is identified for the two commodities in signed jump variation. These jumps are also by general rule larger for energy commodities than for the rest of the financial assets in our sample, and we can observe that natural gas was especially prone to jumps during the first part of the sample.

In terms of realized skewness, natural gas returns present a negative sign in both subsamples and in the total sample, while the oil returns display a positive skewness before the global financial crisis and a negative sign thenceforth. In general, while stocks display a positive skewness (except for Italy before the crisis), FX average skewness is more balanced between positive and negative values. Remarkably, the absolute value of the skewness for energy commodities is relatively small compared to the rest of the assets, and particularly to stocks. The panorama is more even across asset classes when it regards to realized kurtosis. In all cases the values of these statistics suggest and non-Gaussian behavior and with heavy tail distributions. Energy commodities display a larger kurtosis than the mature stock markets, and similar values than other stock markets and FX markets. These univariate results are appealing by themselves when it comes to informing risk analysis. Nevertheless, they are silent regarding risk transmission and risk diversification opportunities. In what follows we emphasize risk transmission 'from' the two major energy markets to the rest of the system and from the major financial markets 'to' natural gas and oil markets.

4.2 Static spillovers

Table 2 presents the spillovers across the realized variances of the markets in our sample in panel A and across the realized semivariances, positive and negative, in panels B and C respectively. The percentage of the variation of the forecast error (1 month ahead) explained by each market in the sample is reported in rows. Each row's entries add-up to 1. When looking at panel A, that contains the realized variance spillovers, the first shadowed column corresponds to the variation of each series explained by a shock to the series of oil returns. Hence, we can observe that oil explains between a minimum value of 1.6% and a maximum of 6.4% of Japan and Russia stock market variations respectively, while it explains between a minimum of 1.3% and a maximum of 6.5% of the forecasted variation of the Chinese Yuan and the Euro. In the two cases, it is evident the sensitivity of the Russian market to the WTI price variations, housing the largest amount of variance explained by oil shocks on stocks and the second largest in the case of the FX market (namely 6.0%). This result is not surprising, given the importance of Russia as a producer of energy commodities.

Numbers are considerably lower in the case of natural gas and stock markets (between 0.02% and 2% for the US and Russian stock markets). In the case of natural gas and exchange rate markets, numbers range between 0.72% and 6.8% for the British Pound and the Chinese Yuan, respectively. In fact, this latter impact is considerably high, highlighting the important magnitude of spillovers from gas to the Chinese FX market. All in all, the Chinese Yuan is the most vulnerable currency to natural gas shocks and the least to oil shocks. A measure of the cross-volatility-spillovers that oil and natural markets transmit to the other markets in the system is reported in the last row of panel A. This corresponds the sum of the column entries minus the entry in which the own variance share is reported. The greater integration of the oil market compared to the natural gas market with traditional FX and stock markets, measured as the cross-spillovers across these markets becomes evident when we compare these figures, namely 29.7% in the case of oil and 14.0% for natural gas.

Table 2

Variance Decomposition of the total, good and bad realized volatilities in the global economy

Panel A: Realized Volatility

	Stocks									Foreign Exchange						Commodities					
	USA	**CAN**	**GER**	**UK**	**CHI**	**RUS**	**FRA**	**ITA**	**JAP**	**RUB**	**CAD**	**CNY**	**EUR**	**JPY**	**GBP**	**WTI**	**COOP**	**GOLD**	**NG**	FROM	NET
USA	17,8	11,2	9,1	11,9	2,8	4,2	10,9	8,8	4,0	1,0	3,0	0,1	2,9	2,3	1,6	3,4	2,5	2,3	0,0	82,2	30,8
CAN	10,5	17,9	7,0	9,0	3,8	6,4	8,3	6,9	3,7	2,2	2,8	0,2	5,0	2,0	2,5	4,8	3,6	3,1	0,3	82,1	31,1
GER	9,9	7,6	17,0	11,9	1,6	4,1	15,0	11,2	4,0	1,1	2,8	0,1	2,0	2,2	1,9	2,4	3,1	2,0	0,1	83,0	16,0
UK	11,3	9,5	10,8	17,0	3,2	3,6	13,9	9,6	3,9	0,9	2,8	0,2	2,3	2,2	1,9	2,2	2,5	2,3	0,0	83,0	31,2
CHI	2,7	1,5	2,1	2,4	60,4	3,6	2,4	2,1	3,1	2,8	2,5	0,0	1,6	0,8	0,4	3,3	5,4	1,6	1,2	39,6	12,4
RUS	5,7	7,7	5,6	5,3	5,1	20,1	5,3	3,9	2,8	6,1	3,4	0,1	5,9	1,8	2,3	6,4	4,7	5,7	2,0	79,9	6,5
FRA	10,2	8,3	13,3	13,3	2,2	3,6	16,2	11,8	3,5	1,0	3,2	0,1	2,5	2,2	2,1	1,9	2,7	1,9	0,1	83,8	29,3
ITA	9,7	7,6	11,5	10,2	1,6	3,3	13,2	18,0	3,5	1,2	4,8	0,1	2,5	3,6	2,2	1,7	3,7	1,4	0,2	82,0	6,0
JAP	7,8	6,9	6,1	7,5	4,3	4,4	6,6	5,1	16,4	1,5	2,6	0,1	4,3	9,9	6,3	1,6	1,9	5,1	1,6	83,6	-26,9
RUB	2,2	3,8	2,5	2,3	2,2	10,3	2,6	2,1	2,1	34,6	7,2	0,4	2,7	4,0	2,9	6,0	5,3	4,3	2,3	65,4	-18,0
CAD	5,0	4,8	3,3	4,9	1,4	6,3	4,2	3,3	2,2	4,1	34,1	0,8	5,6	0,8	4,8	3,5	7,0	3,2	0,7	65,9	19,1
CNY	0,8	1,3	0,4	1,1	0,4	0,9	0,4	0,3	0,4	1,0	1,9	76,3	1,8	0,6	1,3	1,3	2,0	1,0	6,8	23,7	-18,7
EUR	7,2	7,4	3,7	5,6	2,1	5,5	4,8	3,7	2,1	2,9	5,1	0,5	23,0	3,7	8,1	6,5	4,0	3,8	0,4	77,0	-5,2
JPY	5,5	5,4	3,3	5,2	3,0	3,1	4,3	3,6	5,6	2,8	5,8	0,3	7,1	23,3	8,8	4,0	4,0	4,0	0,9	76,7	-27,2
GBP	5,2	6,1	3,7	5,3	1,5	4,8	4,7	3,3	2,9	3,5	14,3	0,6	8,9	3,5	16,6	5,7	5,3	3,4	0,7	83,4	-21,7
WTI	7,2	8,1	5,8	5,9	3,9	5,8	5,8	4,7	3,1	4,3	4,0	0,2	5,6	1,9	3,8	22,5	5,1	1,5	0,9	77,5	-7,2
COOP	4,6	5,6	4,0	4,9	4,5	6,5	4,7	3,3	3,4	4,2	10,2	0,6	5,0	2,4	5,4	5,4	19,6	4,8	1,0	80,4	-10,1
GOLD	5,1	5,5	4,2	5,3	4,8	5,9	4,1	2,7	3,7	4,2	6,5	0,3	4,2	3,5	4,0	3,3	5,0	26,6	1,3	73,4	-18,8
NG	2,5	5,0	2,5	2,2	3,4	4,3	2,0	1,6	2,7	2,6	1,9	0,4	2,0	2,1	1,3	6,8	2,7	3,1	50,8	49,2	-28,6
TO	113,1	113,2	99,0	114,2	52,0	86,4	113,2	88,0	56,7	47,3	85,0	5,0	71,9	49,5	61,7	**70,3**	70,3	54,6	**20,6**	TOTAL	72,2

Panel B: Realized Good Volatility

	Stocks									Foreign Exchange						Commodities					
	USA	**CAN**	**GER**	**UK**	**CHI**	**RUS**	**FRA**	**ITA**	**JAP**	**RUB**	**CAD**	**CNY**	**EUR**	**JPY**	**GBP**	**WTI**	**COOP**	**GOLD**	**NG**	FROM	NET
USA	23,1	13,1	8,6	13,5	1,6	3,9	13,5	9,0	2,5	0,2	2,3	0,0	1,4	0,8	0,3	1,3	1,7	2,9	0,3	76,9	33,0
CAN	11,7	26,5	6,1	11,0	4,1	5,3	9,9	6,1	1,9	0,8	3,5	0,1	3,5	1,4	1,1	1,3	3,1	1,9	0,6	73,5	43,0
GER	10,7	7,1	21,7	13,2	0,9	4,3	18,7	12,7	2,8	0,3	0,9	0,1	1,5	0,9	0,4	0,8	1,1	2,1	0,1	78,3	20,7
UK	12,1	10,4	10,3	21,9	2,4	3,1	16,0	9,7	2,3	0,2	2,5	0,0	1,2	1,2	0,7	1,7	1,6	2,7	0,2	78,1	51,5
CHI	2,4	5,5	2,3	3,3	59,4	4,7	2,6	2,0	1,8	0,2	0,7	0,0	1,2	0,4	0,7	2,3	6,9	2,3	1,5	40,6	-4,7
RUS	6,9	9,8	8,0	7,2	4,4	30,4	8,2	5,5	2,3	1,1	1,4	0,2	2,2	1,1	1,4	3,2	3,5	2,7	0,4	69,6	-10,4
FRA	11,6	9,0	13,7	14,9	1,2	3,6	20,4	12,0	2,1	0,5	2,1	0,1	2,1	0,9	0,8	1,0	0,7	3,4	0,1	79,6	53,2
ITA	9,7	7,0	14,2	12,5	0,6	3,8	17,1	26,1	2,7	0,5	1,0	0,1	1,3	1,1	0,2	0,5	0,4	1,1	0,1	73,9	16,1
JAP	7,3	6,3	8,4	8,5	1,4	3,6	8,6	7,6	33,3	0,3	0,8	0,0	0,7	5,9	0,6	1,6	2,5	1,9	0,7	66,7	-27,1
RUB	0,1	1,0	0,4	0,1	0,1	1,1	0,8	0,3	0,1	65,8	9,8	2,8	11,5	1,3	4,1	0,1	0,4	0,1	0,4	34,2	-7,0
CAD	4,6	5,6	2,6	5,4	1,7	2,9	5,0	2,2	0,5	6,7	39,4	1,6	8,3	0,7	7,4	1,6	1,7	1,6	0,4	60,6	-1,0
CNY	2,5	2,5	2,5	2,4	0,8	1,9	2,5	2,2	0,9	2,9	2,5	65,5	2,7	0,7	1,7	1,1	0,7	1,1	2,8	34,5	-25,4
EUR	3,8	4,9	2,4	3,5	0,7	2,4	4,4	2,6	0,3	7,0	8,6	1,5	39,5	2,7	12,5	1,0	0,4	0,3	1,5	60,5	-0,6
JPY	3,2	5,5	2,8	5,4	1,6	1,9	3,8	4,5	9,0	1,3	1,8	0,4	3,2	48,3	3,3	1,4	1,6	0,7	0,2	51,7	-26,4
GBP	2,9	4,5	1,7	4,9	1,2	1,7	3,4	1,6	0,5	3,6	12,4	1,2	14,0	2,8	39,7	1,8	1,2	0,5	0,7	60,3	-19,9
WTI	5,8	7,9	4,7	7,5	5,2	4,0	6,1	4,2	2,0	0,6	3,9	0,4	2,0	1,7	2,6	34,7	3,4	1,7	1,5	65,3	-35,6
COOP	4,8	7,2	3,0	5,1	4,2	5,6	3,1	1,5	2,5	0,4	2,9	0,1	0,9	1,2	1,9	3,4	46,0	4,9	1,1	54,0	-16,6
GOLD	7,1	6,4	2,7	8,2	2,0	3,7	5,0	3,0	3,3	0,3	2,1	0,2	0,4	0,6	0,3	2,2	5,3	45,6	1,6	54,4	-19,6
NG	2,7	2,8	4,7	3,1	1,8	1,8	4,0	3,1	2,2	0,3	0,5	0,1	1,9	0,3	0,2	3,2	1,5	3,1	62,9	37,1	-23,2
TO	109,9	116,5	99,0	129,6	35,9	59,2	132,8	89,9	39,6	27,2	59,6	9,0	59,9	25,3	40,4	**29,7**	37,4	34,8	**14,0**	TOTAL	60,5

Panel C: Realized Bad Volatility

	Stocks									Foreign Exchange						Commodities					
	USA	**CAN**	**GER**	**UK**	**CHI**	**RUS**	**FRA**	**ITA**	**JAP**	**RUB**	**CAD**	**CNY**	**EUR**	**JPY**	**GBP**	**WTI**	**COOP**	**GOLD**	**NG**	FROM	NET
USA	21,2	12,3	10,3	10,5	2,6	4,0	12,1	8,9	7,9	0,1	0,0	0,0	0,9	2,2	0,3	2,7	2,8	1,0	0,1	78,8	31,1
CAN	12,1	22,7	8,8	9,5	1,6	5,5	11,3	8,9	6,0	0,1	0,1	0,0	0,6	1,3	0,6	4,0	4,7	1,8	0,4	77,3	39,2
GER	9,5	8,2	20,3	11,9	2,1	4,4	15,2	11,6	7,8	0,3	0,1	0,1	0,9	2,6	0,6	2,3	1,0	0,5	0,7	79,7	19,3
UK	10,3	9,8	12,3	20,9	2,6	4,3	12,7	10,7	5,7	0,2	0,6	0,1	0,9	2,4	1,0	2,7	1,6	0,4	1,0	79,1	50,5
CHI	4,2	3,8	4,8	5,3	51,6	4,3	4,0	3,6	3,3	1,2	0,2	0,1	0,9	1,7	0,2	3,3	6,1	1,1	0,5	48,4	-12,6
RUS	6,3	8,1	7,3	7,0	2,7	33,6	8,0	5,9	5,5	0,6	0,0	0,1	0,6	0,9	0,3	4,7	5,6	2,4	0,2	66,4	-7,2
FRA	10,9	9,8	14,1	11,6	1,4	4,4	19,4	13,9	7,1	0,1	0,0	0,0	0,4	2,3	0,3	1,8	1,8	0,4	0,3	80,6	52,3
ITA	9,2	8,9	12,6	10,8	1,5	3,8	16,1	22,7	6,6	0,2	0,0	0,1	0,2	2,4	0,3	2,4	1,3	0,1	1,0	77,3	12,6
JAP	10,2	7,4	10,9	7,7	1,7	4,6	10,2	8,0	25,5	0,3	0,0	0,0	0,8	7,7	0,8	1,5	1,4	0,7	0,6	74,5	-34,9
RUB	0,2	0,2	0,8	0,2	1,6	1,4	0,2	0,4	0,9	63,1	7,2	1,5	4,9	2,7	5,9	5,3	0,8	0,2	2,5	36,9	-9,7
CAD	1,7	1,8	2,1	2,1	2,9	1,7	1,7	1,8	2,1	5,4	54,9	1,7	4,7	4,5	3,4	3,1	3,2	0,6	0,8	45,1	14,5
CNY	0,8	0,9	1,2	1,2	0,2	0,8	1,0	0,9	0,9	2,0	2,3	76,7	2,2	2,2	4,5	1,0	0,5	0,2	0,5	23,3	-14,3
EUR	3,1	3,7	3,0	2,7	1,4	1,8	2,9	2,2	2,6	3,5	2,5	0,1	39,9	6,0	14,5	5,6	2,1	0,8	1,5	60,1	-0,2
JPY	4,0	2,4	5,8	4,7	1,8	1,2	5,0	4,3	10,8	0,8	0,9	0,8	5,7	42,7	2,9	1,0	0,7	0,7	3,8	57,3	-32,0
GBP	2,2	3,0	2,8	3,1	0,9	1,9	2,4	2,3	3,2	3,5	3,5	0,3	15,3	6,0	38,0	6,0	2,1	1,2	2,4	62,0	-21,6
WTI	5,6	8,3	5,2	5,2	2,6	6,8	4,9	5,4	3,1	0,7	0,0	0,1	0,1	0,5	0,0	41,1	6,7	2,1	1,5	58,9	-29,2
COOP	5,0	8,4	2,6	3,5	4,6	7,3	4,4	3,1	2,6	0,6	1,4	0,2	1,0	1,7	1,3	6,6	37,9	6,7	1,0	62,1	-24,6
GOLD	3,2	5,4	1,7	1,8	2,7	5,2	1,8	0,8	0,7	0,4	0,2	0,0	1,7	0,6	1,2	3,6	10,5	56,8	1,6	43,2	-8,4
NG	1,4	2,4	1,0	1,0	0,2	2,1	1,1	0,8	1,0	2,7	0,0	0,1	0,3	3,4	2,4	4,8	2,6	3,6	69,0	31,0	-17,0
TO	99,7	104,6	107,4	99,9	35,1	65,2	115,2	93,5	77,6	22,6	19,3	5,4	42,2	51,2	40,4	**62,3**	55,6	24,6	**20,3**	TOTAL	60,1

We estimate the forecast error variance decomposition for the system. Shadowed columns correspond to WTI and Natural Gas series.

The rows in Table 2 depict the share of the forecasted volatility of oil and natural gas returns explained by other markets in the system. In the case of oil, the largest shocks explaining its dynamics come from the stock market, notably from Canada (8.1%) and the US (7.2%) and to a lesser extent from other Western European markets and Russia. The impact of the FX markets is relatively lower, and the highest one is asserted by the Euro (5.6%). In other commodities we see that variations in copper prices explain more of the oil expected variance than variations in natural gas (5.1% versus 0.9%). In total, 77.5% of the total variability of oil's realized volatility is explained by shocks arising in other markets in the system. This value is notably lower for natural gas (49.2%), which in opposition to oil is very sensitive to the other energy commodity in the sample (oil explains 6.8% of the natural gas variations in terms of realized volatility). The influence of the Canadian stock market in the natural gas market is also remarkable (5.0%).

A different landscape arises when looking to the results reported in Table 3. This table shows higher order risk spillovers. Specifically, in terms of jumps (panel A), skewness (panel B) and kurtosis (panel C). Note that the natural gas market becomes a major producer of shocks to the rest of the systems (81.1% in terms of jumps and 125.3% regarding skewness, overcoming the role of oil (76.3% and 93.4% respectively). Natural gas jump shocks affect particularly the oil market (13.1%), the Euro (9.0%), the Russian Rubble (8.3%) and to a lesser extent, although still of significant magnitude, the Chinese stock market (7.3%). In terms of realized skewness, interestingly natural gas price shocks have an important impact on all the stock markets in the sample (except Japan), and to a considerably lesser extent on the WTI market. Regarding oil shocks in jumps their importance is mainly detected on the French stock market and, in terms of skewness, on the Canadian, French and Italian stock markets, and on the Euro.

Interestingly, the two energy commodities in our sample are more sensitive to shocks originating in the rest of the system when looking at panels A and B of Table 3, than when looking at Table 1 (variances and semivariances). Additionally, and in concordance to what we documented with univariate statistics, in terms of kurtosis neither the oil nor the natural gas markets are important producers of shocks to the rest of the system (10.9% and 7.2% respectively). However, while the natural gas market is relatively unaffected by shocks to the kurtosis in the rest of the system (10.4 %), the oil market is highly affected by these shocks (99.3%).

The results described above show that risk transmission across different financial markets is highly depended on the definition of *risk* itself. In other words, traditional risk analysis based uniquely upon the second moments of the system series implicitly assumes that risk transmission occurs at the same pace whether the shocks hitting the market are positive or negative. Nevertheless, important asymmetries become evident when we go from variances to semivariances (from panel A to panels B and C of Table 1). For example, both natural gas and oil markets gain considerable importance in the transmission of shocks 'to' the system, when are good and bad volatility shocks' transmission is accounted for, almost doubling the figures in the last column of Table 1.

Table 3

Variance decomposition of the realized jumps, skewness and kurtosis a in the global economy

Panel A: Realized Singed Jump Variation

	Stocks									Foreign Exchange						Commodities				
	USA	**CAN**	**GER**	**UK**	**CHI**	**RUS**	**FRA**	**ITA**	**JAP**	**RUB**	**CAD**	**CNY**	**EUR**	**JPY**	**GBP**	**WTI**	**COOP**	**GOLD**	**NG**	FROM	NET
USA	23,7	10,0	9,1	6,7	1,2	5,2	8,4	6,2	6,9	2,2	2,9	0,7	1,8	1,5	2,7	4,0	2,8	1,5	2,7	76,3	33,5
CAN	8,6	20,5	6,9	8,0	2,7	4,4	7,2	7,1	3,6	3,9	2,9	1,2	1,1	2,1	2,1	3,2	4,4	4,8	5,2	79,5	37,0
GER	7,0	5,2	14,7	6,1	1,9	4,9	10,6	7,6	5,5	3,6	2,5	0,9	3,9	2,1	4,1	6,4	3,0	5,8	4,2	85,3	13,6
UK	4,9	5,8	5,5	13,0	2,3	5,3	8,0	7,4	4,2	5,2	3,4	0,5	7,1	1,8	6,9	7,3	2,4	3,5	5,4	87,0	42,6
CHI	3,5	3,8	2,9	3,2	25,9	4,7	2,5	3,6	3,7	5,5	2,1	3,3	2,8	7,2	5,4	7,2	3,0	2,5	7,3	74,1	-38,3
RUS	6,1	5,4	4,1	5,0	3,1	36,8	5,1	5,5	4,8	6,5	6,5	0,8	1,9	0,0	1,4	2,0	3,7	1,0	0,2	63,2	-4,0
FRA	4,6	3,6	9,7	5,5	3,5	3,8	12,7	7,6	4,0	4,7	2,1	0,9	7,4	1,7	5,6	10,5	1,9	5,8	4,4	87,3	45,5
ITA	5,3	5,0	9,5	7,4	2,1	4,9	12,5	18,7	4,4	3,3	2,4	0,3	4,6	1,8	4,1	4,2	1,2	3,4	4,9	81,3	8,6
JAP	7,8	5,5	6,5	3,6	2,5	5,0	5,8	4,2	19,0	4,5	3,9	2,9	3,0	4,4	2,3	5,3	5,1	5,0	3,6	81,0	-41,4
RUB	3,1	7,6	3,0	5,6	5,2	5,6	5,5	9,2	1,7	16,4	4,6	1,5	4,2	3,5	3,1	3,6	4,3	3,9	8,6	83,6	-56,4
CAD	9,3	5,6	3,2	3,5	1,6	6,9	3,7	3,6	2,8	4,2	32,5	1,0	6,0	1,1	2,8	2,3	4,7	3,5	1,4	67,5	-7,9
CNY	2,1	0,5	0,2	0,4	0,7	1,8	0,3	0,1	1,7	2,9	2,1	81,5	1,7	0,1	0,5	0,0	2,9	0,5	0,0	18,5	-9,5
EUR	1,4	1,9	0,4	0,7	0,9	3,5	0,6	1,0	0,7	7,4	6,6	0,9	35,6	3,9	13,4	3,1	2,8	6,2	9,0	64,4	-4,5
JPY	0,8	0,1	4,4	1,4	0,6	0,0	1,6	1,3	8,0	1,4	1,5	0,0	6,0	60,3	1,4	0,7	0,6	10,0	0,0	39,7	-14,4
GBP	3,3	5,3	2,2	1,6	1,8	3,8	2,1	1,9	2,6	3,1	3,6	2,1	12,2	5,8	25,8	4,9	3,0	5,5	9,3	74,2	-33,9
WTI	1,5	3,2	2,3	3,3	3,5	6,1	1,8	2,8	4,8	6,2	4,3	0,7	5,3	5,4	5,5	18,1	5,2	7,1	13,1	81,9	-52,3
COOP	3,7	7,1	0,3	2,3	2,8	5,0	1,4	0,5	0,6	5,3	6,4	1,8	3,3	0,5	2,0	2,0	49,8	5,1	0,4	50,2	-12,8
GOLD	0,0	2,7	1,0	0,0	0,1	1,4	0,1	0,2	1,3	3,5	5,6	0,4	8,2	9,1	3,5	0,9	5,6	55,0	1,4	45,0	-10,2
NG	2,0	5,8	2,0	2,6	2,4	8,2	2,5	2,4	2,5	4,6	3,5	1,1	6,3	2,9	2,2	8,7	3,3	5,9	31,1	68,9	-54,9
TO	75,0	84,1	73,2	66,9	38,9	80,5	79,6	72,3	63,7	78,0	67,0	20,9	86,7	54,9	69,1	**76,3**	59,9	81,0	**81,1**	TOTAL	68,9

Panel B: Realized Skewness (std)

	Stocks									Foreign Exchange						Commodities				
	USA	**CAN**	**GER**	**UK**	**CHI**	**RUS**	**FRA**	**ITA**	**JAP**	**RUB**	**CAD**	**CNY**	**EUR**	**JPY**	**GBP**	**WTI**	**COOP**	**GOLD**	**NG**	FROM	NET
USA	34,4	13,6	8,9	7,0	0,6	4,7	9,2	6,5	6,7	1,5	1,2	0,4	0,7	0,4	2,4	0,1	1,5	0,0	0,0	65,6	44,3
CAN	5,0	10,5	5,0	4,5	3,9	5,1	7,6	8,9	4,2	2,4	2,4	2,9	1,7	1,0	4,2	11,4	2,4	4,3	12,7	89,5	27,1
GER	2,9	4,4	5,8	5,3	3,6	8,4	5,5	5,9	3,7	5,4	5,0	2,9	3,0	1,1	7,6	7,2	6,2	5,1	11,0	94,2	4,8
UK	3,0	5,7	3,3	9,2	0,8	5,2	5,6	7,7	4,3	6,7	6,5	1,2	5,1	2,1	9,2	5,6	6,4	4,2	8,2	90,8	38,9
CHI	2,2	3,5	3,0	4,7	8,7	2,5	4,7	11,0	4,5	9,0	5,4	4,2	3,3	3,3	5,1	5,6	3,2	3,7	12,4	91,3	-55,5
RUS	2,8	3,9	6,2	3,0	5,8	5,9	9,2	14,7	5,9	1,3	2,4	1,9	1,1	1,7	5,0	6,1	2,2	6,4	14,8	94,1	-34,9
FRA	1,8	4,7	5,4	2,0	6,7	1,1	9,4	9,7	5,7	2,0	1,6	2,3	2,6	0,5	4,4	12,0	3,0	10,9	14,0	90,6	42,3
ITA	2,4	5,5	3,8	3,2	4,6	2,5	6,6	10,6	3,7	4,6	3,8	1,4	2,8	0,8	8,0	11,5	4,6	10,8	8,8	89,4	0,6
JAP	8,6	7,1	7,9	5,9	0,9	3,9	6,5	5,5	44,2	0,4	0,9	1,0	0,3	4,4	0,0	0,7	0,1	1,2	0,4	55,8	-16,2
RUB	3,4	5,8	3,4	4,7	3,0	2,9	5,0	17,6	3,2	17,0	4,5	1,7	5,8	1,3	2,2	3,6	3,3	2,3	9,1	83,0	-55,8
CAD	20,4	10,1	5,4	5,1	0,9	5,1	6,0	4,6	4,3	2,4	25,0	0,4	2,8	0,6	1,9	0,7	2,0	1,6	0,6	75,0	-15,5
CNY	1,1	0,7	0,2	0,1	0,7	0,7	0,4	0,1	2,0	2,0	0,7	87,9	0,4	0,1	1,0	0,1	1,3	0,0	0,4	12,1	-3,1
EUR	2,1	3,4	5,0	4,8	4,0	4,3	9,4	11,3	2,8	3,7	3,9	2,8	4,3	1,0	5,8	10,5	3,0	4,1	13,6	95,7	-35,8
JPY	0,8	0,2	4,9	2,3	0,5	0,0	3,2	2,4	6,4	0,3	1,0	0,1	5,0	64,6	1,0	0,5	0,1	6,8	0,0	35,4	-10,1
GBP	2,3	3,8	4,4	6,4	0,7	3,3	6,3	13,3	2,6	4,1	5,6	3,0	5,4	3,2	11,3	7,2	6,1	4,1	7,1	88,7	-48,3
WTI	2,4	6,4	3,9	5,8	1,6	6,6	5,7	12,8	2,1	3,0	4,2	3,0	2,7	2,3	4,6	7,2	5,5	9,6	10,6	92,8	-63,1
COOP	2,6	7,0	0,3	2,1	2,1	3,3	1,1	0,2	0,2	4,5	2,9	0,9	2,0	0,1	2,4	2,9	60,1	4,6	0,7	39,9	-2,5
GOLD	0,1	2,4	0,6	0,0	0,2	2,8	0,0	0,1	1,7	2,0	4,0	0,0	5,8	6,6	4,0	0,6	4,9	63,3	0,8	36,7	-1,9
NG	3,1	4,1	5,3	3,4	1,8	6,2	7,9	9,8	4,3	2,4	3,5	1,3	2,1	1,7	2,0	7,1	2,2	3,2	28,8	71,2	-57,3
TO	67,0	92,3	76,8	70,3	42,4	68,6	100,1	142,1	68,0	57,8	59,6	31,3	52,6	32,4	70,7	**93,4**	57,9	83,0	**125,3**	TOTAL	73,2

Panel C: Realized Kurtosis (std)

	Stocks									Foreign Exchange						Commodities				
	USA	**CAN**	**GER**	**UK**	**CHI**	**RUS**	**FRA**	**ITA**	**JAP**	**RUB**	**CAD**	**CNY**	**EUR**	**JPY**	**GBP**	**WTI**	**COOP**	**GOLD**	**NG**	FROM	NET
USA	76,0	5,6	2,2	4,2	0,1	2,7	4,2	2,4	0,6	0,0	0,0	0,1	1,0	0,0	0,0	0,4	0,0	0,2	0,2	24,0	85,9
CAN	6,1	83,0	0,3	2,8	0,0	0,4	0,9	0,9	1,5	0,0	0,1	0,0	0,9	0,0	0,4	0,3	0,0	2,3	0,2	17,0	99,5
GER	1,4	0,2	47,8	8,2	0,0	0,2	22,6	12,7	0,8	0,0	0,3	0,0	1,8	0,5	2,8	0,1	0,2	0,0	0,4	52,2	46,8
UK	3,2	1,9	10,0	58,0	0,2	0,7	9,9	8,5	1,6	0,0	0,9	1,6	0,8	0,2	0,7	0,1	1,2	0,1	0,4	42,0	87,6
CHI	0,1	0,0	0,0	0,4	88,3	1,1	0,2	0,0	0,2	0,0	0,0	0,0	0,4	0,4	0,0	2,0	5,6	1,1	0,1	11,7	24,2
RUS	10,1	2,1	2,5	13,9	0,2	1,0	3,2	3,5	1,4	57,9	0,2	0,4	0,6	0,4	0,4	0,1	1,8	0,0	0,2	99,0	-39,8
FRA	2,4	0,5	21,0	7,6	0,1	0,2	44,4	16,7	1,0	0,0	1,8	0,0	0,6	2,5	1,0	0,0	0,0	0,0	0,2	55,6	77,3
ITA	1,7	0,6	13,8	7,6	0,0	0,0	19,5	52,0	1,3	0,0	0,9	0,1	0,6	1,3	0,5	0,0	0,1	0,0	0,0	48,0	41,9
JAP	0,7	1,5	1,3	2,3	0,2	0,3	1,8	2,0	82,3	0,1	0,3	0,9	0,4	1,3	0,4	2,9	1,4	0,0	0,0	17,7	21,9
RUB	0,8	0,3	1,4	13,7	0,0	1,8	1,8	2,2	0,6	74,9	0,2	0,4	0,2	0,6	0,0	0,4	0,2	0,0	0,4	25,1	2,1
CAD	0,0	0,1	0,5	1,4	0,0	0,4	3,5	1,6	0,3	0,0	88,6	0,7	0,8	0,8	0,2	0,6	0,0	0,5	0,0	11,4	48,2
CNY	0,1	0,1	0,0	2,6	0,0	0,2	0,0	0,1	1,0	0,0	0,7	93,1	0,0	0,3	0,5	0,0	0,0	1,0	0,2	6,9	2,1
EUR	1,1	0,7	10,4	2,2	0,3	0,1	4,6	2,8	0,4	0,7	0,6	0,0	63,0	0,2	10,1	1,0	0,2	0,4	1,1	37,0	22,9
JPY	9,4	0,5	1,0	0,4	0,2	0,0	2,8	1,4	0,9	0,6	20,7	0,7	0,1	58,5	1,8	0,1	0,0	0,8	0,0	41,5	-16,2
GBP	0,0	0,3	4,1	0,9	0,0	0,2	1,6	0,6	0,3	0,0	0,2	0,4	10,8	2,0	70,6	0,5	0,5	5,0	1,9	29,4	10,9
WTI	30,0	4,9	3,5	11,5	0,5	0,5	4,3	4,5	2,1	26,8	0,2	0,4	3,8	0,1	0,9	0,7	3,9	0,0	1,5	99,3	-69,6
COOP	69,4	5,1	2,1	4,0	0,5	2,7	3,8	2,2	0,7	0,0	0,0	0,1	0,9	0,0	0,1	0,4	7,3	0,2	0,5	92,7	-55,3
GOLD	0,3	2,4	0,0	0,1	1,0	0,3	0,0	0,0	0,0	0,0	0,5	0,9	0,6	1,0	6,1	1,8	0,2	84,8	0,1	15,2	19,6
NG	0,3	0,2	0,7	0,6	0,1	0,4	0,4	0,0	0,0	0,2	0,0	0,2	1,5	0,0	2,4	0,2	3,2	0,1	89,6	10,4	3,6
TO	137,0	26,9	74,9	84,3	3,5	12,3	85,2	62,1	14,8	86,4	27,6	6,9	25,8	11,6	28,3	**10,9**	18,5	11,9	**7,2**	TOTAL	38,7

We estimate the forecast error variance decomposition for the system. Shadowed columns correspond to WTI and Natural Gas series

However, asymmetries go even further than those generated by the sign (positive or negative) of the shock. This sign asymmetry is captured also when asymmetric GARCH models are used. However, more economically significant asymmetries appear when higher order moments are considered for risk definition purposes. For instance, when skewness (prudence) and kurtosis (temperance) are considered, spillover transmissions significantly change. For instance, when the focus is on the transmission of shocks in volatilities or semivolatilities, the oil market seems far more integrated to the rest of the global financial markets than the natural gas market. Indeed, the shocks that the oil market generate 'to' and receive 'from' the other markets (70.3% and 77.5% on volatilities) are way larger than those associated to the natural gas market (20.6% and 49.2%). However, when higher order risks are considered, the natural gas market appears producing one of the largest cross-cumulated shocks to the system (125.3%), well beyond those produced by oil (93.4%). It also exhibits large fragments of cross-variance shares explained by the rest of the system, although still below those of oil (71.2% for natural gas and 92.8% for oil).

The relative magnitude of the shocks that both WTI and NG produce to the system in terms of an even higher (but symmetric) moment, namely the kurtosis, are remarkably lower. In this case, shocks to the system coming from oil are of only 10.9% and from natural gas of 7.2%. In general, the transmission of this tail-symmetric risk is far below those related to volatilities, jumps and skewness (38.7% total cross spillovers).

4.3 Network analysis

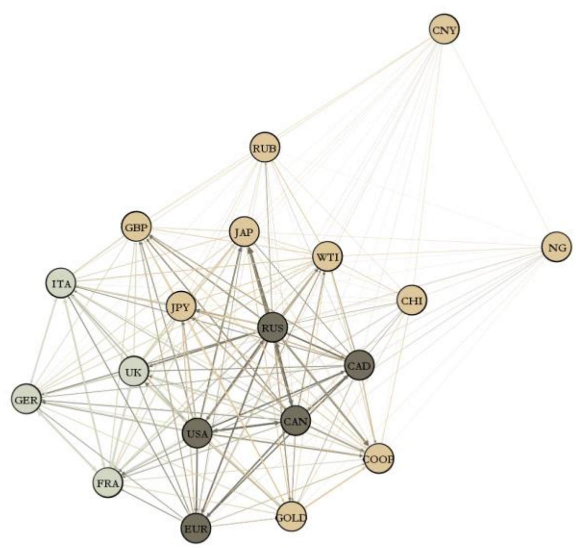
Different moments measure distinct faces of risk which ideally should be addressed from an integrated perspective by portfolio managers and energy firms. However, such asymmetries are overlooked by traditional risk analysis based solely on the analysis of volatility. For instance, while variances and kurtosis are related to symmetric risks, skewness speaks about the probability of market crashes, which is asymmetric by its very nature. The kind of asymmetries that we seek to emphasize are better explained graphically, using networks. We use the algorithm developed by Jacomy et al. (2014) to represent our findings regarding the propagation of risk beyond the variance. In panel A of Figure 1 we show the risk clusters that corresponds to volatilities and in panel B to kurtosis. The first panel presents a larger density while in the second the relationship across the global markets is sparser. In both cases, the predominant role of WTI is illustrated by its central position in the network, while the natural gas market seems much more isolated, mainly interacting with the rest of the system through its direct relation with the oil market (and some FX markets in the case of skewness).

In panel B the change in the position of natural gas in the network is evident. Natural gas becomes by all measures a central market in the cluster regarding the transmission and reception of shocks, thus acting as an amplifier for the observed skewness and jump shocks to the global financial markets. For the sake of comparison, notice that in all cases China FX market seems relatively isolated from the rest of the system, so this change in the position when moving from symmetric to asymmetric risks in the case of natural gas is not granted, and constitutes a feature of this specific financial asset.

Figure 1 Network representation of the global financial markets

Panel A: Symmetric statistics: volatility and kurtosis

Volatility



Kurtosis

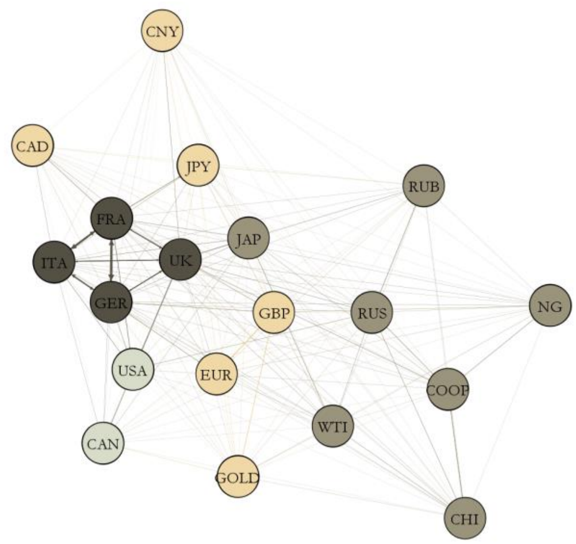
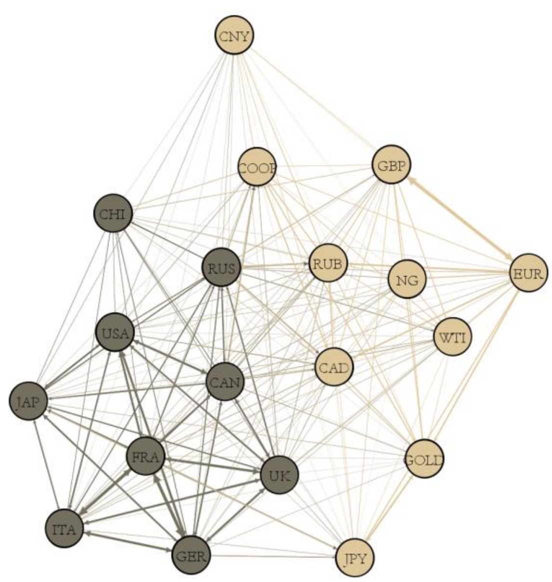


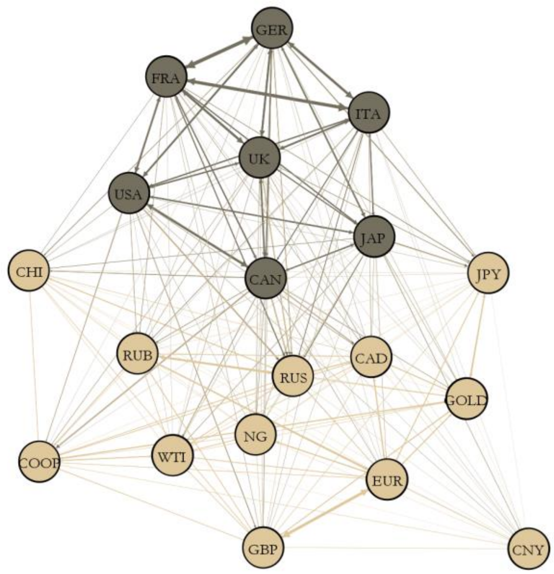
Figure 1 Network representation of the global financial markets

Panel B: Asymmetric statistics: jump variations and skewness

Jumps



Skewness

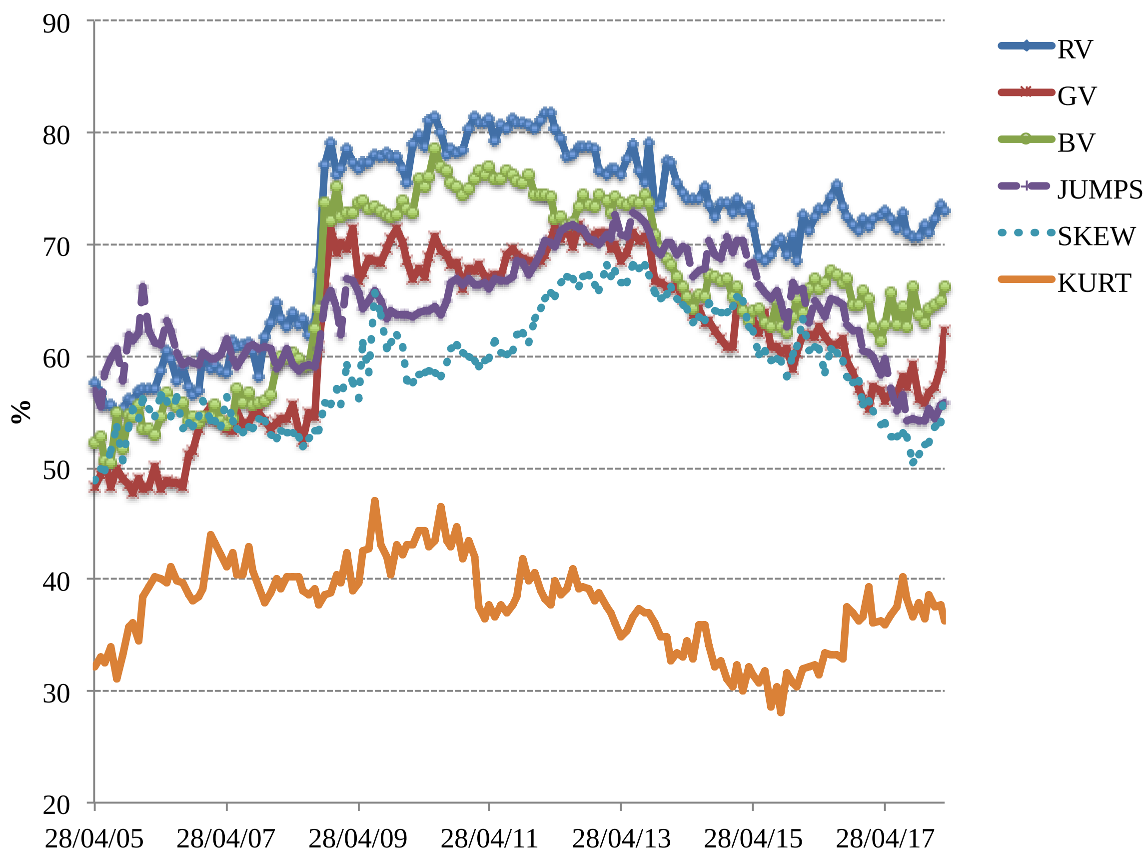


4.4 *Dynamic spillovers*

It is also interesting to check the change in risk spillovers when they are measured at different moments of the return distributions. Figure 2 shows several total dynamic spillover indices of the system constructed with the risk measures explained above. Notice that the global financial risk profile is remarkably dissimilar whether we focus on volatility, skewness, or other moments of the series under analysis. Realized volatility spillovers, both total and semivolatilities, display the expected increase after the beginning of the GFC. Bad volatility presents more persistence than good volatility. Note the incremental trend in terms of the realized jump variation, which peaks around June 2013, significantly later than the recorded peak dates in good (mid-2012) and bad (mid-2010) volatilities. Skewness dynamics depict a close relationship with the evolution of jump variation spillovers, also peaking around mid-2013, with a clear positive trend before that date and a clear negative trend afterwards. Consistent with our previous results, the spillovers in kurtosis are considerably lower although they have been increasing since July 2015. According to the different measures, global risk profile is currently lower than in the aftermath of the global financial crisis. Moreover, according to the systemic risk statistic based on the skewness and jump variations, it is even lower than before the crisis and, reaching a historical minimum since the beginning of our estimates in April 2005.

Figure 2

Total Dynamic Spillover Indices



In figure 3 we report our results regarding the net spillovers to the system originated in the oil market (panel A) and the natural gas market (panel B). The estimations were carried out using a rolling window of 60[2]. As in the static case, results regarding spillover transmission are heavily dependent on the measure of risk that is adopted. In the case of oil, we can observe that in terms of volatility oil changed from being a net receptor of shocks from other markets between 2005 and 2013, to be a net transmitter from 2013 onwards. A similar pattern is documented regarding bad volatility spillovers. This change in the net position coincides with the beginning of the drop in oil prices in world markets. Meanwhile, oil presents mainly a net receiver position in terms of good volatility, signed jumps and skewness. All together these results indicate that shocks from oil markets to traditional financial markets transmit basically during hard times for the oil market. Interestingly, the magnitude of net skewness spillovers to the oil market increased importantly in the last part of the sample period. This result may be indicative of the increasing important of prudence in the behavior of investors in financial markets.

Regarding spillovers from the natural gas market, different results are encountered. Firstly, except for a very brief period in 2014, this market has been a net receiver of volatility spillovers. This result is identical when only bad volatility is considered. Some peaks of good volatility transmission to the rest of the system are observed between 2011 and 2013. Volatility in the natural gas markets can be linked to large temperature variability over the United States in recent winters. Unusually warm temperatures in 2011/12 suppressed demand and drove natural gas prices downward, whereas the reverse happened in 2012/13. This may have increased volatility transmission from the natural gas market to other markets during those years. Note also that spillover transmission to the natural gas market is especially high in terms of jumped sign and skewness, indicating that prudence affects importantly the risk transmission to oil markets. Kurtosis (temperance) does not appear to be very important in risk transmission to and from the natural gas market.

An interesting feature of our results is that the net position of volatility spillover transmission in oil and natural gas markets appears to be the contrary, at least during the last part of our sample

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[2] The results are robust to the specification of different window lengths.

period. This result indicates that these two markets offer hedging possibilities to volatility transmission in financial markets.

Figure 3

Net spillover statistics

A: oil

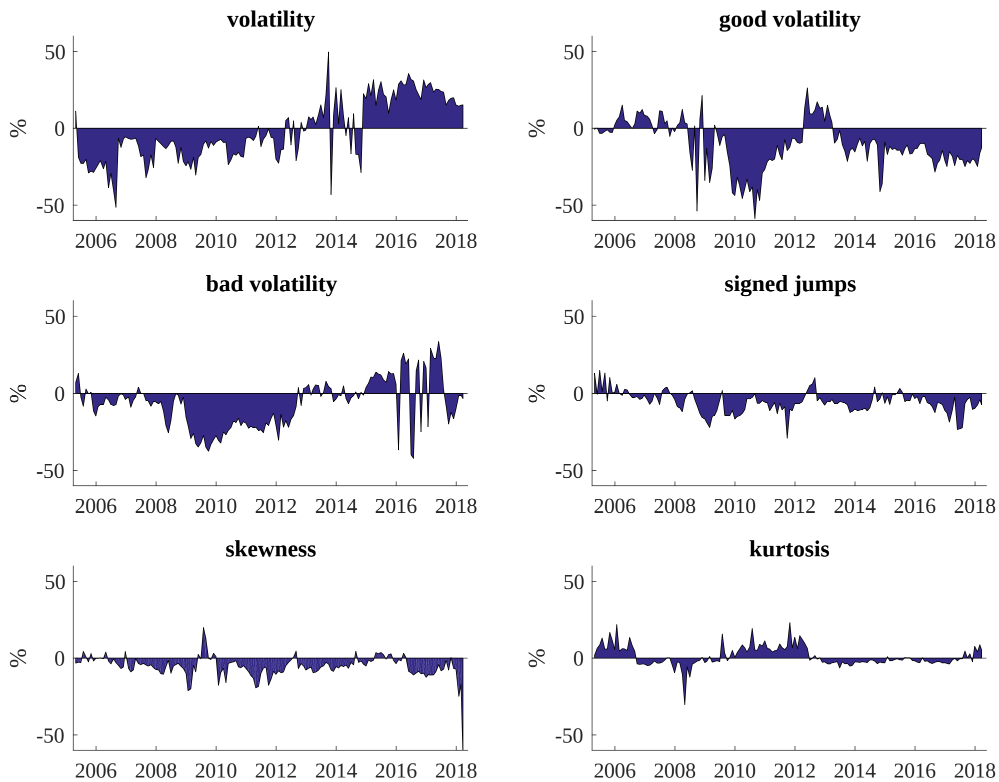
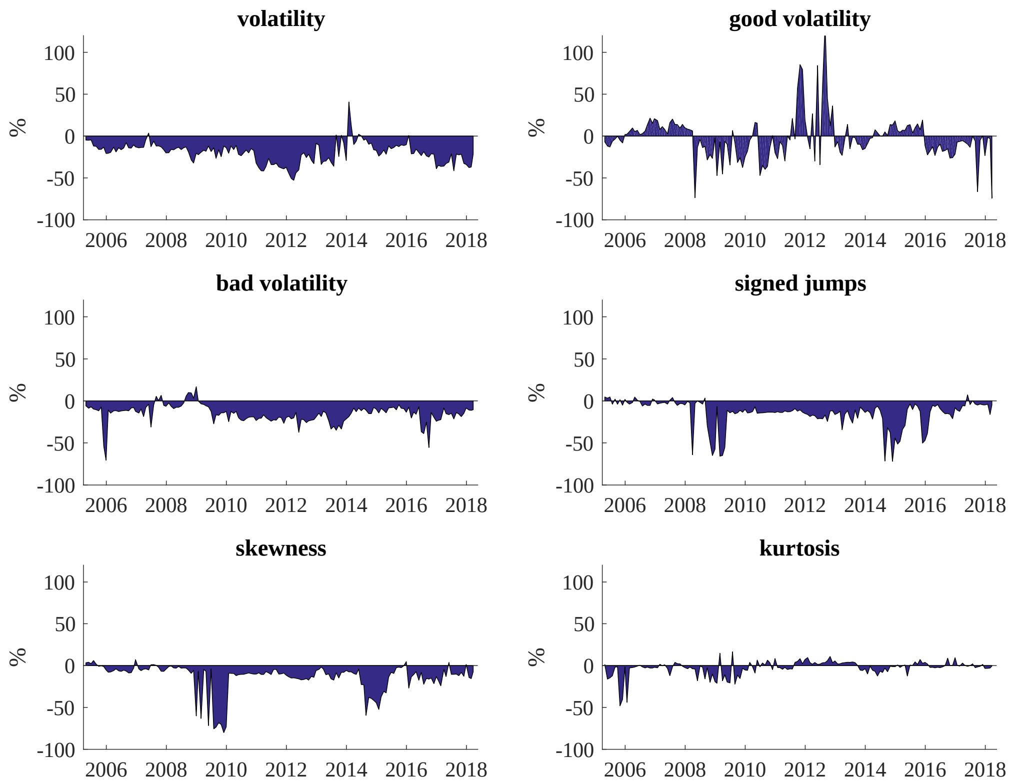


Figure 3

Net spillover statistics

B: Natural gas



5. Conclusions

This paper studies the higher order linkages between energy commodity markets (oil and natural gas) with the global financial markets. Focus is set on spillovers of realized good and bad volatilities, realized signed jump variation, realized skewness and realized kurtosis. Higher order risks have received important attention in the recent literature on decision making, as experimental evidence has shown that risk averse individuals show strong evidence of prudence (preference for right-skewed distributions) as well as some evidence of temperance (dislike for fat-tailed lotteries) when choosing between risky alternatives. Risk spillovers are likely to be sensitive to higher order risk attitudes of decision makers as well, and their intensities may vary as risk perceptions evolve over time.

We make two main contributions to the growing body of literature on financial market spillovers. On the one hand, we estimate good and bad volatility spillovers between commodity, stock and exchange rate markets. Unlike previous studies that focus on return co-movements and volatility spillovers, we directly address the issue of asymmetric risk spillovers in the left and right tails of the daily variations in market prices. On the other hand, we study risk spillovers using realized skewness and realized kurtosis, and therefore we can check whether the measures of spillovers are affected by the definition of risk used to construct it. To our knowledge, this is the first study exploring higher order risk spillovers between commodity markets and traditional financial markets.

Our results indicate that the measurement of risk spillovers is very sensitive to the definition of risk used in their construction. Asymmetries between good and bad volatility transmission matter, and results when jumps and higher order risk measures are considered are substantially different from those obtained when traditional volatility measures are used. Traditional risk analysis based upon the second moments of the system series implicitly assumes that risk transmission occurs at the same pace whether the shocks hitting the market are positive or negative. Nevertheless, important asymmetries become evident when we go beyond the variance. Interestingly, when higher order moments are considered in the transmission of financial spillovers, results change dramatically. Generally speaking, skewness spillovers are more significant than kurtosis spillovers, result that goes in line with experiments showing evidence of strong prudence and light temperance of decision makers.

Our results also provide empirical support for theoretical asset pricing models that conduct the optimization required for portfolio balancing in the mean-variance-skewness space (instead of the traditional mean-variance or the mean-variance-kurtosis spaces) by showing that risk diversification opportunities vary greatly when one considers variance or skewness as the fundamental proxy for risk, but also by showing that kurtosis does not propagate as much as skewness, and therefore the latter merits a more significant consideration in risk analysis than the former.

Our results also indicate that risk spillovers vary importantly over time. The global financial risk profile is remarkably dissimilar depending on the moment of the series under analysis. Realized volatility spillovers increase, as expected, during the GFC. Bad volatility is more persistent than good volatility. Interestingly, skewness spillovers are higher around 2012 and 2013 than during the GFC. This result probably responds to the behavior of oil and natural gas prices over those two years. Consistent with our static results, kurtosis spillovers are considerably lower although they have been increasing since July 2015.

Overall, our results highlight the importance of considering alternative risk measures for computing spillovers in financial markets. Higher order risks matter, as risk-averse decision makers go beyond the variance when comparing the risk profile of risky projects. Given volatility transmission results vary considerably depending on the definition of risk itself, different measures such as downside risk, tail risk, skewness and kurtosis are worthy of being considered in studies of risk transmission and contagion.

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