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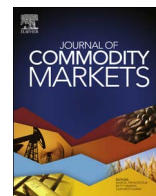
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# The connectedness between crude oil and financial markets: Evidence from implied volatility indices



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## ABSTRACT

In this paper we exploit newly introduced implied volatility indexes to investigate the directional risk transfer from oil to US equities, Euro/Dollar exchange rates, precious metals and agricultural commodities. We find significant volatility transmission from oil to equities but little transmission to agricultural commodities. The total pairwise directional connectedness to equities is around 20.4%, while it is only 1.6%, 1.0% and 2.0% to wheat, corn, and soybeans respectively. The risk spillover from oil to precious metals and Euro/Dollar foreign exchange rates is moderate. For instance, the oil market uncertainty spills 11.0%, 11.1% and 8.9% to gold, silver and Euro/Dollar exchange rate respectively. The volatility crossover from all of these markets to oil is tiny, implying that oil is the main driver of its association with these markets. Finally, we provide evidence that the transmission from oil to other markets has increased since the collapse of oil prices in July 2014.

## 1. Introduction

Recently, a number of papers have studied the co-movement of oil with equities, agricultural commodities and precious metals. Prior studies provide evidence on the connectedness between oil and one or more markets. However, the bulk of these studies have so far focused on price connectedness. Little research has been dedicated to volatility association. Like prices, volatilities are important driving factors of options markets. This raises an interesting question: how are oil and other related markets associated in terms volatilities? The main aim of this paper is to provide an answer to such a question.

Most of the existing studies on oil connectedness have investigated the relation between the oil market and other markets on a one-to-one basis.<sup>1</sup> In contrast, this study looks into the oil association using all relevant markets. Specifically, we study the influence of oil on the US equity market, the Euro/Dollar exchange rate market, the gold market, the silver market, the wheat market, the corn market and the soybeans market.

One notable exception is Sari et al. (2010) who studied oil association with more than one market. However, we take a more inclusive approach as we consider a broader set of markets in the analysis. Our choice of markets represents a universe of financial assets that cover a wide range of investment strategies. The cash and derivative markets associated with these assets are global, large and liquid and therefore the risk transfer between oil and these markets is an important piece of information for investors.

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<sup>1</sup> For research with equities see Kilian (2008), Nandha and Faff (2008), Cong et al. (2008), Chen (2010), Arouri and Rault (2012), Apergis and Miller (2009), Driesprong et al. (2008), Park and Ratti (2008); and with commodities see Baffes (2007), Alom et al. (2011), Soytaş et al. (2009); and with foreign exchange see Sari et al. (2010) and Antonakakis and Kizys (2015).

Many hedge funds have their strategies and asset classes defined within the context of these markets. For instance, global macro funds take opportunities in cash and derivatives markets that include equities, currencies and commodities. Similarly, managed futures funds invest in futures and options that are written on the commodities traded in these markets. The exposure to these markets is usually assumed indirectly through derivatives and hence, the study of risk connectedness between oil and other commodity markets is important to understand diversification in derivatives portfolios that contain commodities, foreign exchange and equity options.

The weak association between oil, commodities and equities has been challenged by recent research (Zhang and Wei, 2010; Alom et al., 2011; Chang and Su, 2010; Du et al., 2011; Harri and Hudson, 2009). These studies show that shocks in the oil market are transmitted to other markets through the rebalancing activities in the paper commodity markets. Hence, an interesting question is whether commodities and equities are strongly or weakly associated in terms of volatility. This is important as most of commodity exposures in the paper markets are established by derivatives rather than through buying commodities outright in the cash market.

Our sample spans an interesting period. Since 2012 the shale oil production industry consolidated its position as a major player in the oil market. This period has also witnessed the collapse of cooperation among OPEC members, the slowdown of the biofuel industry, the start of the global recovery and the slowdown of China. These events provide a unique opportunity to study risk transfer among markets.

During this period, the oil and other markets have also witnessed a growing activity by speculators, arbitrageurs, and convergence traders. These traders are highly leveraged and their trading is occasionally based on sentiment and risk aversion and hence their presence has intensified co-volatility association across markets.

Most of the existing research on oil risk transfer employs statistical models to estimate volatilities that are poor approximations of true volatilities. An alternative to model-based statistical volatility is option price implied volatility. Implied volatility has been found to be more accurate than model-based volatilities in predicting latent volatility (Christensen and Prabhala, 1998; Fleming, 1998; Jorion, 1995; Blair et al., 2001). As connectedness is a function of volatility, an accurate measurement of this latter becomes essential for an accurate measurement of interdependence. Thus, the results provided by previous studies are potentially misleading. In this paper we avoid this potential pitfall and use implied rather than historical volatilities in estimating interdependence.

Using implied volatility in this context is important as they are derived from market option prices and, hence, represent the market consensus on the expected future uncertainty. The implied volatility indexes are considered as gauges for fear and in that sense the inferred implied volatility connectedness reflects the fear connectedness that is expressed by traders and market participants. As a result, implied volatilities are a better means to capturing volatility crossovers that are related to market sentiment. They are also more suitable for capturing cross market fluctuations that are related to portfolio rebalancing and speculative activities that have increased recently in the paper commodity markets.<sup>2</sup>

This paper employs a set of connectedness measures proposed by Diebold and Yilmaz (2016).<sup>3</sup> These measures are dynamic and directional, which makes it possible to determine the relative importance of markets in the information transmission across time. To our knowledge, we are the first to apply the Diebold-Yilmaz methodology on a large set of financial markets.

The results of our analysis show that the oil market is a dominant source of transmission and risk transfer to equities, the Euro/Dollar exchange rate, precious metals and agricultural commodities. This highlights the important contribution of the oil market in the cross-market association relative to commodities. Relative to oil, volatility transmission is highest with equities and lowest with agricultural products. The pairwise directional connectedness observed from oil to equities is around 20.4%, while it is 1.6%, 1.0% and 2.0% to wheat, corn and soybeans respectively. We further find that directional linkages from oil to gold and silver are significantly higher than agricultural commodities, but still much lower than equities. The pairwise directional connectedness from oil to gold and silver is around 11.0% for both precious metals. Finally, the risk transfer from oil to the Euro/Dollar exchange rate is slightly lower, with a pairwise directional connectedness of around 8.9%.

The dynamic analysis shows that there was an increase in total and directional connectedness from oil to other markets between July 2014 and March 2015. This period saw an increased uncertainty about the future of crude oil due to excess supply, shale production and weak global economies. The barrel of oil which traded above \$100 around the end of July 2014 collapsed to \$44 by March 2015. The uncertainty regarding the future price of crude oil was translated into increased risk transfers from oil to other markets. In the analysis of the total pairwise connectedness we found increased transmissions to equities, gold, silver and wheat.

The rest of the paper is organized as follows. The next section includes a brief review of the related literature. In Section 3 we describe the methodology used to construct the implied volatility indexes and we provide some preliminary statistics of the sample. Section 4 summarizes the directional connectedness measures proposed by Diebold and Yilmaz (2016). In Section 5 we perform a full sample analysis in which we characterize the connectedness among oil and other markets' volatilities. We also perform a rolling sample analysis to check the dynamics of connectedness across time. Robustness checks are offered in Section 6. In this section we present results from two different measures of volatility. The final Section 7 contains some concluding remarks.

## 2. Literature review

The literature on the association of oil with other commodities is vast.<sup>4</sup> One of the earliest works is Pindyck and Rotemberg

<sup>2</sup> For more information on this structural change and its impact on markets linkages see (Kyle and Xiong, 2001; Kodres and Pritsker, 2002; Broner et al., 2006; Pavlova and Rigobon, 2008; and Büyüksahin and Robe, 2014).

<sup>3</sup> These measures are developed by Diebold and Yilmaz in a series of papers (Diebold and Yilmaz, 2009, 2012, 2014) and then unified in Diebold and Yilmaz (2016).

<sup>4</sup> Table 1 shows chronological summary of the studies that have addressed volatility connectedness.

(1990) who find excess co-movement between unrelated commodities such as cocoa and crude oil. They attributed their results to the herding behavior in commodity markets. However, these initial results did not find much support by later studies, such as Deb et al. (1996) recording weak excess co-movement in commodity markets.

More recently the results of Pindyck and Rotemberg found some support from Baffes (2007) and Reboredo (2013). Baffes (2007) finds that oil price increases passes through to other commodities particularly to gold and silver. These strong responses of precious metals are attributed to the use of oil in the production of both gold and silver. Reboredo (2013) finds significant dependence between gold and oil. Nevertheless, he indicates that the tail dependence is weak and that gold volatility is not weakly linked to oil volatility in extreme market conditions and hence, gold can be used as a safe haven to hedge oil in stressful markets.

The surge in oil and grains prices in the last decade has motivated many studies to focus on the co-movement of crude oil and agricultural commodities. A number of studies blame increasing food prices in the last decade on the rise of biofuel market and high oil prices (see, for example, Abbott et al., 2009; Baffes, 2007; Chang and Su, 2010; Collins, 2008; Mitchell, 2008; Rosegrant et al., 2008; and Yang et al., 2008). For instance, Chang and Su use an EGARCH model to study the volatility transmission between crude oil, corn and soybeans and find significant volatility spillovers across these markets.

Zhang and Wei (2010) study the causality between oil and gold volatility. Their results indicate that the crude oil price changes Granger cause the volatility of gold but not the other way around. Alom et al. (2011) find that the oil price volatility is positively correlated with food price volatility. However, they also find that this relationship varies across countries and time periods. Similarly, Du et al. (2011) investigate the volatility linkages between crude oil, wheat and corn using a bivariate stochastic volatility model. Their results show that oil price shocks trigger sharp increases in agricultural commodity markets. They attributed the increase in connections between oil and food to the recent increase in commodity investments. Similar results on variance dependence between oil and corn is provided by Harri and Hudson (2009).<sup>5</sup>

Some studies have attributed the increase in co-movement between commodities and oil to the emergence of paper commodity markets, which has allowed equity portfolio managers to invest in oil and agricultural commodities for diversification and hedging purposes. For instance, Baffes and Haniotis (2010) find that the role of biofuel in establishing the links between oil and agricultural commodities is much smaller than what is indicated by previous studies. Their results points to the role of speculative activities of index commodity funds in the commodity paper market. Similar results on the weak association especially in the long run have been reported by Sari et al. (2012).

Most globally traded commodities, such as oil and gold, are denominated in US dollar. A rise in the value of the dollar can increase the price of these commodities in domestic currencies and, hence, demand can fall. It is thus possible that the value of the dollar may also drive both oil and the other commodities simultaneously. Following this line of enquiry, Sari et al., (2010) looked into the dynamics of oil, precious metals and Euro/Dollar exchange rate. They found little evidence of long run equilibrium relation between exchange rates and oil. Moreover, oil is found to be uninformative of foreign exchange movements in the short run. In contrast, metals are found to provide useful information on exchange rate changes.

### 3. Data description and preliminary statistics

#### 3.1. Implied volatility indexes

The implied volatility index, known as the VIX index, is constructed and published by the Chicago Board of Options Exchange (CBOE). Before September 22, 2003, the CBOE used the Black and Scholes model to compute the index. However, the index was criticized for the bias of the underlying Black and Scholes option valuation model (see for instance, Fleming, 1998; and Simon, 2002). Currently many practitioners and academics prefer computing implied volatilities from options based on the concept of fair value of future volatility. Following this concept the CBOE directly computes the VIX indexes from the market prices of out-of-the-money calls and puts and without the use of any pricing models. The indexes are calculated using the following formula:

$$\sigma^2 = \frac{2}{T} \sum_i \frac{\Delta K_i}{K_i^2} e^{RT} Q(K_i) - \frac{1}{T} \left[ \frac{F}{K_0} - 1 \right]^2 \quad (1)$$

where  $\sigma$  is defined as the VIX/100 and hence, the VIX =  $\sigma \times 100$ ,  $T$  is the time to maturity of the set of options,  $F$  is the forward price level derived from the lowest call-put option premium difference,  $R$  is the risk free interest rate,  $\Delta K_i = \frac{K_{i+1} - K_{i-1}}{2}$  is a measure of the average interval of the two strike prices adjacent to the strike price of option  $i$ ,  $K_0$  is the first strike price below the forward price level  $F$ . Finally  $Q(K_i)$  denotes the option premium computed as the mid- point of the bid ask spread of each option with strike  $K_i$ .

The inclusion criteria into these indexes is designed such that it includes all out of the money puts and calls that are centered around an at the money strike,  $K_0$ . However, if there are no bids for an out of the money option at a certain strike, then this option and all other options at higher (or lower in the case of puts) strikes are excluded from the computation of the index. Note that in high volatility markets demand for out of the money options is strong and more options are included in the construction of the index.

Each option entering the VIX computation is given a weight proportional to its premium and to the average distance of the strike of option with adjacent strikes that have non-zero bids. The option weight is also inversely proportional to the square of the option's strike.

To construct the index, the CBOE computes implied volatility using Eq. (1) for two sets of options: the near term options and the

<sup>5</sup> Gilbert (2010) points out that oil-food linkages are related to the general demand growth and that the influence of the biofuel industry growth is marginal.

next near term options. Both sets have between 23 and 37 days to expiration. For instance, suppose that in any one day the two sets of options expire in 24 and 31 days respectively. Then we compute Eq. (1) twice: once for the near term options with 24 days to maturity and another for the next near term options with 31 days to expiration. The VIX index which represents the 30 d volatility implied by option prices is interpolated from these two implied volatilities.<sup>6</sup>

The VIX index is computed without any option valuation model and in that sense the index is model free. The index is directly related to the market values of calls and puts and, hence, reflects what the option traders think of future market volatility. The forward looking nature of option prices is the most important distinguishing feature of the index. These implied volatility indexes have been shown to be more informative than historical volatility in volatility measurement and prediction.<sup>7</sup>

### 3.2. Preliminary statistics

Our data consists of implied-volatility indexes of crude oil, US equity, Euro/Dollar exchange rate and five commodities. The connectedness with precious metals is inferred by combining the implied volatility indexes of gold and silver. The association with agricultural products is based on the implied volatility indexes of wheat, corn and soybeans.

The indexes for silver, wheat, corn, and soybeans are calculated from the mid-2012. Our sample is therefore restricted to the period between the 27th of July 2012 and the 3rd of June 2015 for a total of 744 observations. This limitation is dictated by the availability of the data on the VIX series. All indexes are obtained from Datastream.

Panel A and Panel B of Fig. 1 plot the time series of the levels and the log differences of the implied volatility indexes respectively. The figure shows that the crude oil and the Euro/Dollar implied volatilities share similar patterns. The big jump in oil volatility after July 2014 is matched by increases in the volatility of the Euro/Dollar, equity, gold and silver.<sup>8</sup> No similar increase in the volatility of agricultural products was observed during the same period. Despite the common trends shared by agricultural products, the volatilities of these products seem to be less integrated with oil volatility over the sample period.

To compare the statistical properties of the crude oil implied volatility index with other indexes, we compute a variety of summary statistics. Table 2, Panels A and B report summary statistics for level and log level changes in implied volatility indexes. Panel A displays the mean, standard error, minimum, maximum, skewness, and excess kurtosis. It also shows the Jarque-Bera statistic which tests the null hypothesis that implied volatility is normally distributed. The mean level of the indexes in the table shows that the least volatile market is the Euro/Dollar followed by the US equity market. As can be seen, crude oil is slightly more volatile than equities and other commodities.

Panel A of Table 2 also shows that none of the implied volatility series are normally distributed. Their empirical distribution is characterized by positive skewness and slight excess kurtosis, and hence the null hypothesis of normality is rejected by the Jarque-Bera statistic for all indexes. The Ljung-Box statistic shows significant serial correlation for all indexes.

The unit root tests for the indexes are reported in the last two rows of Panel A, Table 2. These are based on two specifications of the implied volatility process and a standard Augmented Dickey Fuller (ADF) test. The tests show that the implied volatilities of all commodities except oil are stationary at conventional levels. The US equities are found also to be covariance stationary but the test fails to reject the null of unit root in the Euro/Dollar implied volatility.

Panel B of Table 2 reports the same summary statistics for the log differences in implied volatility indexes. As can be seen in the ADF tests the log changes of implied volatility are all covariance stationary at conventional levels.

To get an idea on how volatility pricing options are related in the various markets, we compute the correlation matrix of implied volatilities in Table 3. Panel A of the table reports correlations of implied volatilities, while Panel B reports correlations of the log changes. The table clearly shows that oil volatility is more correlated with equities and the Euro/Dollar exchange rate than it is correlated with commodities. Within the commodities, oil is more correlated with precious metals than with agricultural commodities, with the exception of wheat. For instance, the correlation of oil with the Euro/Dollar exchange rate and the US equities is around 0.69 and 0.77, while its correlation with gold, silver, wheat, corn and soybeans is 0.32, 0.29, 0.36, 0.10, 0.09 respectively.<sup>9</sup>

To get more insights on the correlation structure of various markets we compute dynamic conditional correlations between the oil and other markets across time.<sup>10</sup> Fig. 2 plots the dynamic conditional correlations of oil volatility with the implied volatility of each of the markets in the sample. As can be seen in the figure apart from the trio of oil, Euro/Dollar and US equities, the remaining conditional correlations are weak and are less than 0.35. This suggests that there are higher likelihoods of risk transfer between oil, exchange rates and equities, but lower risk of risk transfer with the rest of commodities. Therefore, it is expected that there is substantial diversification benefits from adding commodities to an option portfolio that contain US equities and oil. Given that the commodities themselves are also weakly correlated, the benefits of diversification are expected to be even greater.<sup>11</sup>

<sup>6</sup> More details on the calculation of the implied-volatility indexes can be found in Bozdog et al. (2011).

<sup>7</sup> See for instance Poon and Granger (2003), Whaley (2008), Carr and Wu (2006), Corrado and Miller (2005), Bentes (2015), Kanas (2012), and Gonzalez-Perez (2015).

<sup>8</sup> Oil traded above \$100 per barrel until the end of July 2014. At that point, prices started to collapse falling to approximately \$44 by March 2016. OPEC's announcement on November 27, 2014 to hold crude oil supplies steady at 30 million barrels per day led to 11.2% decline in the price of crude in that day alone. The recent slowdown of the Chinese economy also contributed to weakening the oil market.

<sup>9</sup> Naturally correlations are higher within group. For instance, the correlation between gold and silver is 0.9, and 0.74 between corn and soybeans.

<sup>10</sup> The conditional correlations are computed following Engle (2002). We assume that the underlying volatility follows a GARCH process.

<sup>11</sup> The exception is gold and silver where the correlation between the two is high.

**Table 1**  
Summary of literature review.

Study	Data	Method	Commodity /Assets	Key findings
Deb et al. (1996)	1960–1985 (monthly) 1974–1992 (monthly)	Multi-variate GARCH	oil, copper, cotton, gold, lumber, cocoa, maize, sugar, lead, coffee	In the 60–85 sample the evidence with excess co-movement is weak. There is some evidence of excess co-movement in the 1974–1992 sample.
Harri and Hudson (2009)	2003–2009 (daily)	CCF	oil, wheat, cotton, soybeans, soybeans oil, corn	The variance of crude oil Granger cause the variance of corn prices
Zhang and Wei (2010)	2000–2008 (daily)	cointegration	oil and gold	Oil volatility Granger cause gold volatility but not the other way around
Sari et al. (2010)	1999–2007 (daily)	VAR, variance decomposition	oil, gold, silver, platinum, foreign exchange rate	The long term relation is weak. However, there is strong feedback between oil and these markets in the short term
Chang and Su (2010)	2000–2008 (daily)	EGARCH	Crude oil, corn, soybeans,	There is significant volatility transmission from oil to corn and soybea
Du et al. (2011)	1998–2009 (weekly)	Bi-variate stochastic volatility model	oil, corn, wheat	oil shocks trigger sharp price changes in agricultural commodity prices
Alom et al. (2011)	1995–2010 (daily)	VAR	oil, food price index	The oil price volatility is positively correlated with food price volatility. However, the relationship varies across countries and periods
Reboredo (2012)	2000–2010 (daily)	Couplas	Oil, foreign exchange rates	Oil and exchange rates dependence is weak
Reboredo (2013)	2000–2011 (weekly)	Couplas	gold and oil	Positive and significant average dependence between gold and oil. Tail dependence as well

Notes: VAR stands for vector auto-regression model. CCF stands for conditional correlation functions. ARDL stands for auto regressive dynamic linear models.



**Fig. 1.** A: Time series plot of the implied volatility index in level. Notes: This figure shows the implied volatility index of crude oil, US-stock, Euro/Dollar exchange, gold, silver, wheat, corn and soybeans markets over the sample period 27th July 2012 to 3rd June 2015. B: Time series plot of the implied volatility index in log changes. Notes: This figure shows the implied volatility index in log changes of crude oil, US-stock, Euro/Dollar exchange, gold, silver, wheat, corn and soybeans markets over the sample period 27th July 2012 to 3rd June 2015.



**Table 2**

Descriptive statistics of the implied volatility indexes.

Panel A: Levels								
	Crude Oil	US-Stock	Euro/Dollar	Gold	Silver	Wheat	Corn	Soybeans
Mean	27.822	15.737	8.6063	18.058	30.034	26.582	25.312	21.612
Min	14.500	5.770	4.690	11.970	18.330	9.190	12.310	0.012
Max	63.140	27.842	14.550	34.480	54.920	49.220	45.780	38.130
Std.dev	11.337	2.795	2.114	3.978	5.778	4.743	4.793	3.752
Skewness	1.345	0.734	0.721	0.792	0.294	0.529	0.692	0.182
Kurtosis	0.981	0.736	0.352	0.256	-0.099	3.374	1.641	3.627
Jarque-Bera	254.24***	83.73***	68.38***	79.88***	11.06***	387.80*	143.04*	411.95*
Q (10)	3343.30***	434.32*	592.60***	1298.00***	831.80***	695.79***	664.04***	531.80***
ADF Intercept	-1.614	-4.575***	-1.981	-3.625***	-3.584***	-5.373***	-5.201***	-3.582***
ADF Intercept and trend	-2.024	-5.167***	-2.317	-3.611**	-3.572**	-5.427***	-5.187***	-3.811**
Panel B: Log volatility changes								
Mean	0.0001	-8.09e-7	0.0010	-3.21e-5	-0.00055	-0.00084	-0.00081	-0.00100
Min	-0.114	-1.046	-0.175	-0.160	-0.254	-0.676	-0.593	-0.265
Max	0.278	1.062	0.569	0.480	0.566	0.665	0.653	0.070
Std.dev	0.043	0.080	0.045	0.053	0.054	0.073	0.070	0.049
Skewness	1.293	0.252	0.365	1.819	2.383	-0.360	0.628	0.203
Kurtosis	5.885	75.984	5.1174	11.959	20.321	28.170	29.342	7.358
Jarque-Bera	1276.00***	1.78e+5***	825.02***	4824.30***	13451.00***	24517.00***	26632.00***	1676.70***
Q (10)	26.025	79.471***	25.145	27.985***	32.669**	71.565***	75.620***	20.813
ADF Intercept	-16.941***	-18.784***	-17.285***	-16.838***	-17.252***	-20.423***	-17.982***	-16.690***
ADF Intercept and trend	-16.962***	-18.790***	-17.365***	-16.827***	-17.241***	-20.454***	-17.988***	-16.688***

Notes: This table reports summary statistics of the implied volatility indexes. The number of daily observations is equal to 744 from 27th July 2012 to 3rd June 2015. Panel A reports statistics for the levels, while Panel B reports results for log differences. ADF is the t-statistics for the Augmented Dickey-Fuller test. \*\*\*, \*\* and \* denote significance at the 1%, 5%, and 10% levels, respectively.

**Table 3**

Unconditional correlation among the implied volatility indexes.

	Crude Oil	US-Stock	Euro/Dollar	Gold	Silver	Wheat	Corn	Soybeans
Panel A: Levels								
Crude Oil	1.000							
US-Stock	0.688	1.000						
Euro/Dollar	0.767	0.625	1.000					
Gold	0.320	0.266	0.195	1.000				
Silver	0.287	0.383	0.320	0.919	1.000			
Wheat	0.361	0.396	0.361	0.143	-0.030	1.000		
Corn	0.101	0.169	-0.001	0.321	0.307	0.509	1.000	
Soybeans	0.086	0.157	-0.084	0.170	0.235	0.432	0.744	1.000
Panel B: Log volatility changes								
Crude Oil	1.000							
US-Stock	0.338	1.000						
Euro/Dollar	0.417	0.177	1.000					
Gold	0.327	0.113	0.278	1.000				
Silver	0.301	0.089	0.185	0.735	1.000			
Wheat	0.173	0.071	0.109	0.005	0.118	1.000		
Corn	0.083	0.062	0.081	0.080	0.127	0.517	1.000	
Soybeans	0.095	-0.011	0.110	0.139	0.169	0.223	0.352	1.000

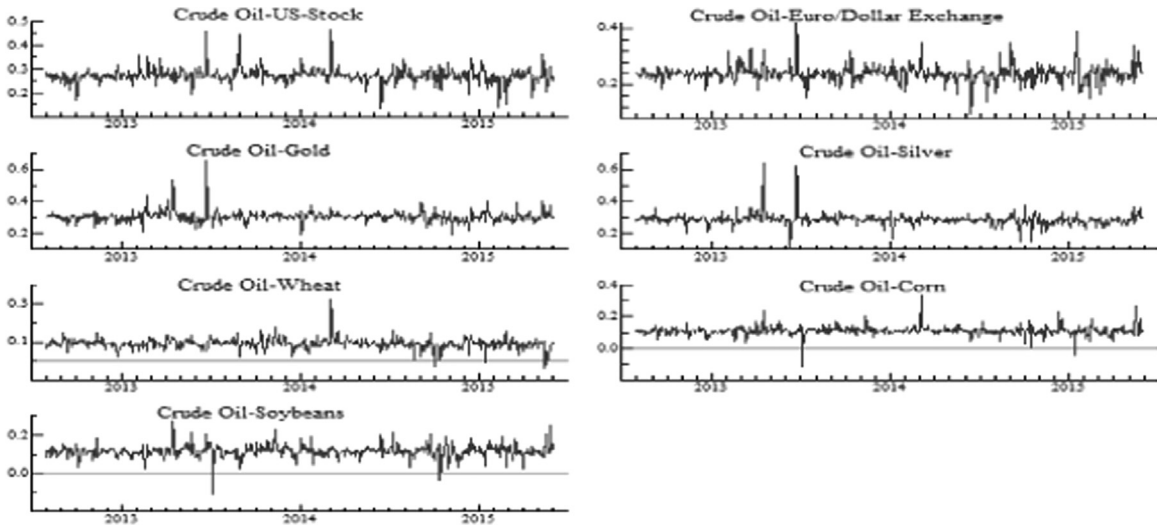
The figure also shows low conditional correlations between oil and agricultural commodities across time. The correlation with wheat, corn and soybeans is weak and hovers around 0.1. There are cases where the correlation is even negative, as is the case with soybeans and corn in July 2013 and with wheat in April 2014.

The correlation of oil with precious metals is relatively higher and fluctuates around 0.3 for both gold and silver. There are spikes in correlations with the two metals in March and June 2013, reaching around 0.6. The correlation is around 0.28 with US equities, and around 0.25 with the Euro/Dollar exchange rate.

Finally, the figure shows that the pattern of correlations is different across the markets. There are similar patterns in the correlations of oil with gold and silver and also oil with corn and wheat. However, the pairwise pattern of correlation is different and oil is associated differently with each market and across time.

#### 4. Empirical method

Our methodology is based on the directional connectedness measures of Diebold and Yilmaz (2012, 2014, 2016).<sup>12</sup> The basic



**Fig. 2.** Dynamic conditional correlations. *Notes:* This figure shows the dynamic conditional correlations between crude oil volatility index and seven market volatility indices during the period 27th July 2012 to 3rd June 2015.

ingredient of these measures is the variance decomposition of forecast errors of  $N$ -variable (market) vector autoregression model (VAR). For instance, the total risk transmission in the system of markets is computed by adding the shares of forecast error variance of all markets that are coming from shocks to other markets. Hence, for each asset  $i$  we simply add the shares of its forecast error variance coming from shocks to asset  $j$ , for all  $i \neq j$ , and then we add across all markets  $i = 1, \dots, N$ .

More formally, assume that the first difference of log implied volatility,  $IV_t$  is modeled as a vector autoregressive process,  $VAR(p)$  that can be written as<sup>13</sup>

$$IV_t = \sum_{i=1}^p \Phi_i IV_{t-i} + \varepsilon_t \tag{2}$$

where  $\Phi$  is a  $N \times N$  matrix of parameters to be estimated. Also assume that the vector of error terms  $\varepsilon_t$  is independently and identically distributed with zero mean, and  $\Sigma$  covariance matrix. If the VAR system above is covariance stationary, then there exists a moving average representation that is given by  $IV_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$ , where the  $N \times N$  coefficient matrices  $A_i$  obey a recursion of the form  $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \dots + \Phi_p A_{i-p}$  with  $A_0$  is the  $N \times N$  identity matrix and  $A_i = 0$  for  $i > 0$ .

The moving average coefficients are important in understanding the dynamics, while the variance decompositions are computed by transforming the coefficients in the moving average representation above. The variance decompositions (or impulse responses) allow us to split the  $H$ -step ahead forecast error of each variable into parts that can be attributable to the various market shocks. The aggregation of these decompositions will be subsequently used to compute the directional connectedness from a particular market to any or to all of the included markets.

The variance decompositions computation is usually done by using orthogonal VAR shocks. The Cholesky identification scheme achieves orthogonality but the computed variance decompositions are then unstable and they are dependent on the ordering of the markets.<sup>14</sup> Thus, Cholesky decomposition is not suitable. A framework that produces invariant decompositions is the generalized VAR that allows for correlated shocks but accounts for them appropriately. The framework, which we denote KPPS, has been first proposed by [Koop et al. \(1996\)](#) and [Pesaran and Shin \(1998\)](#). The KPPS forecast error variance decomposition ( $H$  step ahead) is computed as

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

where  $\Sigma$  is the variance matrix of the vector of errors  $\varepsilon$ , and  $\sigma_{jj}$  is the standard deviation of the error term of the  $j^{th}$  market. Finally,  $e_i$  is a selection vector with one on the  $i^{th}$  element, and zero otherwise. In order to get a unit sum of each row of the variance decomposition, we normalize each entry of the matrix by the row sum as<sup>15</sup>

<sup>12</sup> This procedure has been widely adopted in the literature. See, for example, [McMillan and Speight \(2010\)](#), [Antonakakis \(2012\)](#), [Awartani and Maghyreh \(2013\)](#), [Awartani et al. \(2013\)](#), and [Maghyreh et al. \(2015\)](#).

<sup>13</sup> We adopt a similar notation to [Diebold and Yilmaz \(2012, 2014, 2016\)](#).

<sup>14</sup> Different orderings may result in significantly different spillover estimates ([Klößner and Wagner, 2014](#)).

<sup>15</sup> Although the KPPS approach is robust to ordering, its decompositions do not sum up to one as in the Cholesky factorization. Thus, the normalization of the sum will enable an intuitive computation of the contribution of a particular market, and an intuitive sum of contributions across markets.



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

Note that the sum of decompositions across any particular market and across all markets is  $\sum_{j=1}^N \theta_{ij}^g(H)=1$  and  $\sum_{j=1}^N \tilde{\theta}_{ij}^g(H)=N$  respectively. Therefore,  $\tilde{\theta}_{ij}^g(H)$  can be seen as a natural measure of the pairwise directional connectedness from market  $j$  to market  $i$  at horizon  $H$ . To make (4) more intuitive, we use the notation  $C_{i \leftarrow j}(H)$  to represent this transmission. In the same way, we might also compute the pairwise directional connectedness in the opposite direction as  $C_{j \leftarrow i}(H)$ . The two statistics allows us to compute the net pairwise directional connectedness as

$$C_{ij} = C_{i \leftarrow j}(H) - C_{j \leftarrow i}(H) \tag{5}$$

This is an interesting statistic as it identifies the market that is playing the dominant role in the information transmissions between the two markets.

In order to find how all markets are jointly contributing to a single market, we aggregate partially. The total directional connectedness from all markets to market  $i$  is denoted  $C_{i \leftarrow \bullet}(H)$  and is computed as

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

Using the same logic we are also able to compute how a particular market  $i$  is contributing to the shocks of all other markets by aggregating partially. The total directional connectedness from market  $i$  to all markets is denoted as  $C_{\bullet \leftarrow i}(H)$  and it can be computed as

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

This is also an informative connectedness measure. Together with the previous statistic it may define the role of the market in the whole system of markets as a net giver or receiver of shocks. In particular we are occasionally interested in computing the net total directional connectedness which can be calculated as

$$C_i(H) = C_{\bullet \leftarrow i}(H) - C_{i \leftarrow \bullet}(H) \tag{8}$$

The total aggregation of the variance decompositions across all markets measures the system-wide connectedness. The total connectedness in all markets can be computed as

$$C(H) = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H)} = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\theta}_{ij}^g(H)}{N} \tag{9}$$

This is simply the ratio of the sum of all off diagonal elements in the variance decomposition matrix of all markets to the sum of all elements (off diagonal and own shocks). It measures the total information flow among all markets under consideration.

## 5. Empirical results

### 5.1. Static volatility connectedness analysis

The matrix presented in Table 4 reports the full sample cross market connectedness of the first difference of implied volatilities.<sup>16</sup> The diagonal elements of the matrix represents the own market connectedness and are not particularly interesting in our context. The off diagonal elements (i.e.  $C_{i \leftarrow j}(H)$ ) of the matrix measure the pairwise volatility directional connections. These are particularly important for our study.

As can be seen in the table, the highest oil volatility pairwise connectedness measure observed is from oil to US equities of a round 20.4% (first column, second row). In return, the pairwise connectedness from equities to oil is almost nil (first row, second column). The difference between the two pairwise directional measures implies that the net pairwise connectedness is from oil implied volatility to the implied volatility of the US equities. Similarly, the pairwise directional volatility connectedness from oil to the Euro/Dollar exchange rate is 8.9%, while it is nil in the opposite direction. Thus, we may conclude that the linkages of oil with either US equities or the Euro/Dollar exchange rate is governed more by information transmissions to these markets from the oil market.<sup>17</sup>

<sup>16</sup> All the results in the table are based on vector autoregression of order 2, and generalized variance decompositions of 10d ahead forecast errors. We also use Cholesky-factorizations with alternative orderings. The results (unreported but available from the authors upon request) remain qualitatively similar.

<sup>17</sup> The US dollar volatility causes volatility in the revenues of oil producing countries. Thus, the links between Oil and the Euro/Dollar exchange rate may also be established through hedging the value of the dollar by these countries.

**Table 4**  
Direction of implied volatility spillovers.

To market <i>i</i>	From market <i>j</i>								
	Crude Oil	US-Stock	Euro/Dollar	Gold	Silver	Wheat	Corn	Soybeans	Contribution from others
Crude Oil	98.7	0.3	0.0	0.1	0.2	0.0	0.1	0.6	1
US-Stock	20.4	75.5	1.1	0.4	1.3	0.1	0.1	0.9	24
Euro/Dollar	8.9	1.5	88.8	0.0	0.5	0.1	0.0	0.1	11
Gold	11.1	1.0	5.2	78.5	0.1	0.4	3.5	0.2	22
Silver	11.0	0.6	4.0	59.0	22.1	0.5	2.8	0.0	78
Wheat	1.6	3.6	0.5	0.4	2.8	88.4	1.0	1.7	12
Corn	1.0	1.2	0.2	2.0	0.3	31.6	60.9	2.7	39
Soybeans	2.0	0.2	1.3	1.1	2.8	10.4	15.1	67.2	33
Contribution to others	56	8	12	63	8	43	22	6	220
Contribution including own	155	84	101	141	30	132	83	73	Total spillover Index =27.5%

Notes: The underlying variance decomposition is based on a daily VAR system with two lags. The  $(i, j)$  value is the estimated contribution to the variance of the 10 step ahead implied volatility forecast error of market  $i$  coming from innovations to implied volatility of market  $j$ . The decomposition is generalized, and thus it is robust to the ordering shown in the column heading. The last column (labeled 'Contribution from others') is equal to the row sum excluding the diagonal elements, and gives the total directional spillovers from all others to markets. The row at the bottom is (labeled 'Contributions to others') equal to the column sum excluding the diagonal elements, and reports the total directional spillover from market  $j$  to others. Finally, The lower right corner is expressed in percentage points and reports the total volatility spillover index which equal to the grand off-diagonal column sum relative to the grand column sum including diagonals.

There are many theoretical channels of information transmissions from oil volatility to equity volatility. For instance, high volatility in the oil market can be translated into higher earnings volatility in oil and oil related companies. Oil price volatility may create comparable uncertainties regarding business cost, disposable income and consumer spending on energy using durable goods. Volatile oil markets may also convey information on future global economic uncertainty and hence, can influence global equity markets volatilities. Therefore, we expect high transmissions from oil volatility to equity volatility.

The pairwise directional connectedness observed with commodities is relatively lower compared to either equities or to the Euro/Dollar exchange rate. It is highest with precious metals and miniscule with agricultural commodities. The connectedness from oil to gold and silver is identical, at around 11.0%. However, it is only 1.6%, 1.0%, and 2.0% to wheat, corn and soybeans respectively. The connectedness in the opposite direction from each commodity to oil is negligible and can be ignored. Therefore, we may conclude that there exists some risk transfer from the oil market to the gold and silver markets but not to wheat, corn and soybeans markets.

The oil and precious metals volatilities are connected through various channels. For instance, oil volatility increases inflation uncertainty. To hedge against potential price increases portfolio managers may allocate more funds to precious metals such as gold and silver, therefore increasing their volatility (see, for example, Jaffe, 1989; Hooker, 2002; and Hunt, 2006).<sup>18</sup> Unlike wheat, corn and soybeans, precious metals are storable and correlated with inflation. Hence they are considered to be better inflation hedges by portfolio managers when the oil market is volatile and inflation expectations are uncertain.<sup>19</sup> Furthermore, high oil prices may threaten economic growth and raise the risk of equities, and hence investors may turn to gold and other precious metals for protection (Reboredo, 2010; Baur and McDermott, 2010; and Baur and Lucey, 2010). These mechanisms support the argument that volatility connectedness between oil and precious metals is established by the information transmissions from the oil market and not the other way round.<sup>20</sup>

Like other commodities, wheat, corn and soybeans should also be affected by the fluctuations in the oil market. The risk transfer mechanism with the oil market is expected to be significant with the recent rise of technologies that produce fuel from agricultural commodities (biofuel). For instance, the bioethanol fuel which is produced from corn (or wheat) and the biodiesel fuel which is produced from soybeans are good substitutes for traditional diesel and gasoline (Chang and Su, 2010). Therefore, crude oil, corn, wheat and soybeans markets are found to be more integrated with oil by many researchers.<sup>21</sup>

However, in our sample we find that risk transfer between oil and corn, wheat, and soybeans is weak. The strong volatility linkages between oil and agricultural commodities that were reported by many researchers after the rise of the bio-fuel industry in 2005 cannot be confirmed by our sample. Chang and Su (2010), Zhang and Wei (2010), Alom et al. (2011), and Du et al. (2011) reported significant volatility linkages between oil and agricultural commodities. Nevertheless, our results are consistent with the findings of Gilbert (2010) who shows weak linkages between oil and food.

The evidence that we provide is derived from a more recent sample starting in 2012, eight years after the rise of the bio-fuel industry. The changing fundamentals of energy markets since then may have severely affected production in the biofuel industry and

<sup>18</sup> The relationship between gold and inflation has been widely studied in the literature (Chua and Woodward, 1982; Ghosh et al., 2004; Worthington and Pahlavani, 2007; Tully and Lucey, 2007; Blose, 2010).

<sup>19</sup> Silver is also an industrial metal and is similar to oil in that it is related to economic activity.

<sup>20</sup> The connectedness between oil and precious metals returns can be established by many factors. For instance, when the dollar depreciates in value the price of oil increases, and meanwhile investors switch to precious metals for protection and thus pushing up their prices (Capie et al., 2005; Joy, 2011). Similarly, with the increase in oil prices and oil revenues, oil exporting countries increase their demand for gold to maintain the gold share in their international reserves portfolios and this also increases the price of gold (Melvin and Sultan, 1990).

<sup>21</sup> Substantial linkages between oil and agricultural commodities are found in many studies (Du et al., 2011; Tyner, 2008; Mitchell, 2008; Yang et al., 2008).

consequently reduced the risk transfer between oil and agricultural commodities.<sup>22</sup>

In the system of markets that we have, oil, gold and wheat are found to be net contributors to all others. The total directional net connectedness of oil, gold and wheat with all other markets is 55%, 41% and 31% respectively. Finally, the total connectedness of implied volatilities that is reported in the lower right corner of Table 3 is 27.5%. Thus, around one quarter of the system shocks is due to shocks that emanate from other markets while three quarters are due to own shocks. This is relatively high compared to the total connectedness measures reported by Diebold and Yilmaz (2009).<sup>23</sup>

## 5.2. Dynamic volatility connectedness analysis

Fig. 3 plots the total volatility connectedness using 200 days rolling sample windows. The figure shows that the total connectedness of the markets is time varying over the sample period. However, there is a big increase in total cross transmissions in July 2014, where the measure has increased from 40% to 60%. Later that year, connectedness reverted back to 40%, but increased again at the beginning of 2015 before reverting in March of the same year. This period is characterized by heightened market uncertainty regarding future prices of oil. This uncertainty was caused by the plentiful oil supplies due to shale production and to the excess supplies by oil producers who were trying to maintain their market shares amid a weakening demand following the financial crisis and the slow down of the global economy. As a result, the price of crude oil fell by a round 60% between late July 2014 and March 2015. The barrel traded above \$100 until the end of July 2014 before collapsed to \$44 by March 2015.

Panel a of Fig. 4 presents plots of total directional connectedness of implied volatility originating from the oil market and transmitting to all markets (i.e.  $C_{\bullet-oil}(H)$ ). Panel b of the same figure presents the transmissions of implied volatility in the opposite direction (i.e.  $C_{oil-\bullet}(H)$ ). The net transmissions are presented in Panel c (i.e.  $C_i(H)$ ).

The figure shows that the connectedness is largely dominated by the information transmissions from the crude oil market to the other markets and not the other way round. The crude oil gives to the rest of markets multiples of what it receives as seen in Panels a and b. Hence, there is a positive net spillover of uncertainty from the oil market to other markets. The graph of the net transmissions is presented in Panel c. It shows clearly that for most of the sample period the directional connectedness is established more by the transmissions from the oil market to other markets. The increase in the system transmissions around July 2014 can be also spotted in Panels A and C. The increased linkages in the system around July in Fig. 3 can be attributed to the increased transmissions from the oil market into the markets of equities, foreign exchange and commodities markets.

Fig. 5 plots the net pairwise directional dynamic connectedness of oil volatility with the volatility of each of the markets over the sample period. The net pairwise connectedness with equities indicate that the oil market is consistently a net giver to US equities. A similar pattern can be seen with gold, silver and other commodities. However, the net pairwise spillover with the Euro/Dollar rate is always alternating, with the oil market being a net receiver at some periods.

Finally in Fig. 4, we see an increase in transmissions from the oil market to US equities, gold, silver, wheat and corn that are parallel to the pattern of transmissions observed in the previous figures. Similar increased transmissions are noted in the Euro/Dollar and soybeans markets. Overall, the dynamic analysis results are consistent with the static connectedness matrix presented in Table 3.

## 6. Alternative volatility measures

This section checks whether results in the previous section are robust to the choice of the volatility measure. To that end we use two alternative volatility measures that are widely used in the literature, namely squared returns and conditional-volatility from a GARCH model.

First we use daily squared returns to proxy the latent volatility.<sup>24</sup> For each of the underlying assets we compute the continuously compounded returns by taking the logarithmic first differences of the price series. The squared returns of the markets are computed across the same sample length which covers the period from 27th of July 2012 to the 3rd of June 2015. The price data on all series are from DataStream.

Table 5, Panel A reports the matrix of market spillovers. The panel shows similar transmission patterns to those reported in Table 4. The oil market is a net transmitter of volatility to all markets in the system. The pairwise connectedness of the oil market is highest with equities and lowest with agricultural commodities. There is some transmissions to precious metals and foreign exchange. The oil market spills 17.3% on equities and receives no transmissions in the opposite direction. The same net pairwise pattern is observed with every other market in the system. The total directional connectedness from oil to the whole system is 137% while it is as little as 3% in the opposite direction. The total transmission in the whole system is around 27%. These results are in line with the results obtained from implied volatility measure.

It is well known that squared returns are noisy measure of volatility. Therefore, we use another measure of volatility by taking the fitted values of a GARCH model as a measure of the latent volatility. Specifically, we estimate an AR(1)-GARCH(1,1) model for each of the return series.

Panel B of Table 5 reports the results based on GARCH volatilities. As is clear from the table, there is little discernible change in

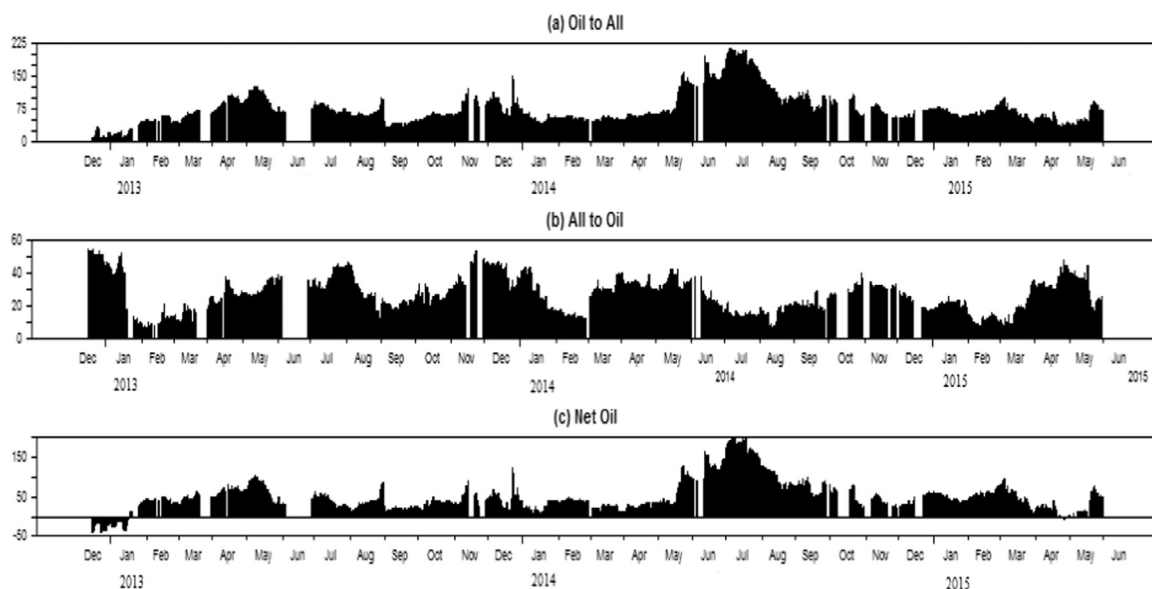
<sup>22</sup> The sharp drop in oil prices in 2014–2015 has led to a severe slowdown of the biofuel industry.

<sup>23</sup> Note also that the connectedness is strong within commodity groups and weak across groups. For instance gold and silver are very well connected compared to each with other commodities.

<sup>24</sup> On using squared returns to measure volatility see Foster and Nelson (1996) and Triacca (2007).



**Fig. 3.** Dynamic total implied volatility spillover index. *Notes:* This figure shows the spillover index over the sample period 27th July 2012 to 3rd June 2015 estimated with a rolling window of 200 day and predictive horizon for the underlying variance decomposition is 10-step-ahead forecasts.



**Fig. 4.** Direction of implied volatility spillovers. *Notes:* This figure shows the directional spillovers from Oil to all markets' over the sample period 27th July 2012 to 3rd June 2015 estimated with a rolling window of 200 day and predictive horizon for the underlying variance decomposition is 10 day.

the results. The GARCH volatilities of oil remain central to transmissions within the system. Oil remains the net giver of shocks to all markets with high transmission to equities, moderate transmission to precious metals and exchange rates, and low transmission to agricultural products.

## 7. Conclusion

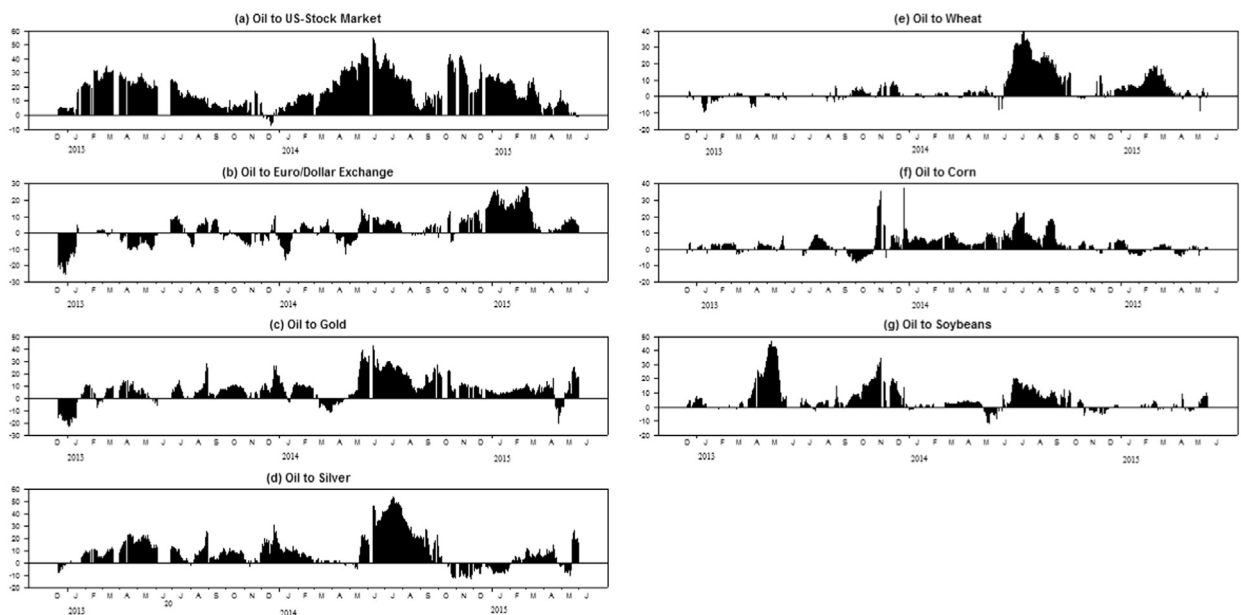
In this paper we contribute to the literature on the co-movement of oil and other markets by focusing on implied volatility linkages. We exploit the recently published implied volatility indexes by the CBOE to investigate risk transmissions between oil and US equities, the Euro/Dollar exchange rate, precious metals and agricultural commodities.

Our results indicate significant volatility transmission from the oil market to US equities, moderate transmission to the Euro/dollar exchange rate and precious metals, and low transmission to agricultural commodities. The information spillovers from all markets to the oil market are negligible. This leads us to conclude that in the risk association between oil and other markets, the oil market is dominant.

The total pairwise directional measures show that volatility transmission is highest with equities, followed by precious metals, then by the Euro/Dollar exchange rate. The lowest association was with agricultural products.

In comparison with the previous literature, we show that the strong integration between oil and food volatility which is observed with the big rise in energy prices and biofuel production after 2005 has disappeared. Moreover, our results indicate that transmissions between oil, precious metals and the Euro/Dollar exchange rate are dominated by shocks in the oil market.

These findings highlight the importance of oil in assessing the risk of other commodity investments. Similarly, they underline the importance of oil in formulating risk expectations regarding other markets. The risk transfer from oil to equities, precious metals and the Euro/Dollar exchange rates is significant, while the same risk transfer to agricultural commodities is negligible. This indicates



**Fig. 5.** Pairwise directional net volatility spillovers between the crude oil market and other markets. *Notes:* This figure shows the directional of net spillovers from oil to each market over the sample period 27th July 2012 to 3rd June 2015 estimated with a rolling window of 200- day and predictive horizon for the underlying variance decomposition is 10 day. Positive (negative) values indicate that oil is a net transmitter (receiver) of shocks to the respective market.

**Table 5**  
Direction of spillovers using alternative volatility measures.

To market <i>i</i>	From market <i>j</i>								
	Crude Oil	US-Stock	Euro/Dollar	Gold	Silver	Wheat	Corn	Soybeans	Contribution from others
<i>Panel A: Realized volatility</i>									
Crude Oil	97.3	0.0	0.2	0.0	2.2	0.1	0.1	0.1	3
US-Stock	17.2	79.8	0.1	0.4	0.1	1.7	0.3	0.4	20
Euro/Dollar	7.3	1.5	90.7	0.3	0.0	0.0	0.1	0.1	9
Gold	11.1	1.5	3.1	82.4	0.2	0.1	1.5	0.1	18
Silver	9.6	3.0	2.3	65.4	28.1	0.1	1.0	0.1	72
Wheat	1.5	1.7	0.5	0.1	0.2	92.3	1.0	2.7	8
Corn	1.0	1.2	0.2	2.0	0.3	31.6	60.9	2.7	39
Soybeans	1.3	0.1	1.2	1.2	2.3	9.2	13.5	71	29
Contribution to others	39	9	8	69	5	43	18	6	179
Contribution including own	137	89	98	152	33	135	78	77	Total spillover Index =22.4%
<i>Panel B: Conditional volatility</i>									
Crude Oil	98.5	0	0.3	0	1.1	0.1	0	0	2
US-Stock	16.1	80	0.1	0.2	0.4	2.6	0.5	0.1	20
Euro/Dollar	7.7	1.9	89.2	0.3	0.1	0.1	0.5	0.2	11
Gold	10.2	1.6	0.1	84	0.2	0.1	3.1	0.7	16
Silver	8.2	4.8	0.2	60.6	22.6	0.1	3.5	0	77
Wheat	1	0.2	0.2	0	2.4	91.5	1.6	3.1	9
Corn	1.4	1.3	1.1	0.2	1.4	34.5	58.6	1.5	41
Soybeans	1.4	0.9	1	1.2	1.6	8.3	11.3	74.3	26
Contribution to others	46	10.7	3	62.5	7.2	45.8	20.5	5.6	201
Contribution including own	145	91	92	147	30	137	79	80	Total spillover Index =25.1%

*Notes:* Realized volatility is measured as square returns. The conditional volatility is estimated by the AR(1)- GARCH (1,1) model. The underlying variance decomposition is based on a daily VAR system with two lags. The  $(i, j)$  value is the estimated contribution to the variance of the 10 step ahead implied volatility forecast error of market  $i$  coming from innovations to implied volatility of market  $j$ . The decomposition is generalized, and thus it is robust to the ordering shown in the column heading. The last column (labeled ‘Contribution from others’) is equal to the row sum excluding the diagonal elements, and gives the total directional spillovers from all others to markets. The row at the bottom is (labeled ‘Contributions to others’) equal to the column sum excluding the diagonal elements, and reports the total directional spillover from market  $j$  to others. Finally, The lower right corner is expressed in percentage points and reports the total volatility spillover index which equal to the grand off-diagonal column sum relative to the grand column sum including diagonals.

that forecasting the risk of equities, precious metals, and foreign exchange rates can be improved by accounting for oil volatility. In contrast, oil risk can be safely ignored in modelling and forecasting the expected volatility of agricultural commodities.

These results are also important for many groups of commodity investors who assume their exposures by forming derivatives

portfolios in the commodity paper markets. These investors include commodity index funds, managed futures funds, global macro funds and other hedge funds who assume non-linear exposures that are volatility sensitive and option like. For instance, the weak linkage between oil and food implies great diversification benefits of including oil and agricultural commodity options in a derivative portfolio.

Moreover, as the association between oil and precious metals is not very strong they are also useful to be included with oil and agricultural commodities. The risk transfer among commodities is not substantial and this indicates that including commodity options with equity options is double diversifying due to the weak volatility linkages among themselves and to the weak linkages with the volatility of equities.

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