Volatility Spillovers Across Petroleum Markets

Jozef Baruník[b,a]*, *Evžen Kočenda*[b,a], *and Lukáš Vácha*[a,b]

ABSTRACT

By using our newly defined measure, we detect and quantify asymmetries in the volatility spillovers of petroleum commodities: crude oil, gasoline, and heating oil. The increase in volatility spillovers after 2001 correlates with the progressive financialization of the commodities. Further, increasing spillovers from volatility among petroleum commodities substantially change their pattern after 2008 (the financial crisis and advent of tight oil production). After 2008, asymmetries in spillovers markedly declined in terms of total as well as directional spillovers. In terms of asymmetries we also show that overall volatility spillovers due to negative (price) returns materialize to a greater degree than volatility spillovers due to positive returns. An analysis of directional spillovers reveals that no petroleum commodity dominates other commodities in terms of general spillover transmission.

Keywords: Volatility spillovers, Asymmetry, Petroleum markets

http://dx.doi.org/10.5547/01956574.37.1.jbar

1. INTRODUCTION, MOTIVATION, AND RELEVANT LITERATURE

Research on the interdependencies observed on financial and commodities markets has led to analyzing not only returns and volatility, but also their spillovers (Dimpfl and Jung, 2012). The global financial and economic crisis, sharp fluctuations in commodity prices, the rapid financialization of petroleum commodities[1] and tight oil production from shale formations prompted a fresh surge of interest in how the dynamic links among commodities work (the relevant literature is shown presently). In this paper, we focus on petroleum commodities and analyze volatility spillovers across petroleum markets. In doing so we differentiate between spillovers due to negative and positive returns (negative and positive spillovers) as the asymmetry has been proven to play an important role in many economic and financial issues related to our analysis (Ramos and Veiga, 2013; Du et al., 2011; Nazlioglu et al., 2013; Bermingham and O'Brien, 2011).

Why do we care about volatility spillovers, and what are the implications for investors, regulators, and facility operators? Since volatility serves as a proxy measure of risk, substantial changes in volatility and its spillovers across markets are able to negatively impact risk-averse investors. Hence, knowledge of volatility spillover dynamics has important implications for investors and financial institutions in terms of portfolio construction and risk management as these spillovers and their direction may greatly affect portfolio diversification and insurance against risk

1. The term "financialization" relates to investments in commodities made by investors to diversify their portfolios.

a Institute of Information Theory and Automation, Academy of Sciences of the Czech Republic, Pod Vodarenskou Vezi 4, 182 00, Prague, Czech Republic

b Institute of Economic Studies, Charles University, Opletalova 21, 110 00, Prague, Czech Republic

* Corresponding author. E-mail addresses: barunik@utia.cas.cz; kocenda@fsv.cuni.cz; vachal@utia.cas.cz.

(Gorton and Rouwenhorst, 2005). Analyzing volatility spillovers also has important implications for the development of accurate asset pricing models, hedging strategies, and the forecasting of future equity and the volatility of oil price returns (Malik and Hammoudeh, 2007). Besides being used in risk management for a long time, volatility has recently become even more important as it is now directly tradable using swaps and futures (Patton and Sheppard, 2014). Further, volatility spillovers are closely associated with market co-movements and this phenomenon becomes quite pronounced during crisis events when, usually, financial market volatility sharply increases and spills across markets (Reinhart and Rogoff, 2008). Analyzing and measuring volatility spillovers enables providing "early warning systems" for dormant crises and to map the development of existing crises (Diebold and Yilmaz, 2012). Knowledge of volatility spillovers then becomes a segment of information useful for regulators, operators, and policy makers that may lead to the introduction of regulatory and institutional rules to reduce the cross-market impact of excessive price movements.

Petroleum-based commodities form an asset class where spillovers historically play a prominent role (Haigh and Holt, 2002), given the importance of these commodities for the economy and economic development (Hamilton, 1983) and the fact that shocks' transmission into oil prices significantly affects the U.S. and the global economy (Kilian, 2008; Hamilton, 1996; Gronwald, 2012). However, the research on volatility spillovers among petroleum commodities is rather limited and the asymmetric aspect of spillovers is not adequately explored yet. In our paper we make two key contributions. First, we use high-frequency data to extend the literature on volatility spillovers among key petroleum commodities: crude oil, heating oil, and gasoline. Second, by augmenting the current methodology of Diebold and Yilmaz (2009, 2012), we are able to quantify negative and positive asymmetries in spillovers, including the directions and magnitudes over time. Among other results, we rigorously show that negative volatility spillovers are larger than positive spillovers across petroleum-based commodities. Such negative asymmetry is most visible before 2008 while later asymmetries in spillovers considerably decline.

Petroleum-based commodities are essential to our economies primarily from an industrial perspective.[2] Accordingly, crude oil prices are driven by distinct demand and supply shocks (Kilian, 2008; Hamilton, 2009; Lombardi and Van Robays, 2011). Further, Kilian (2009) shows that shifts in the price of oil are driven to different extents by aggregate or precautionary demand related to market anxieties about the availability of future oil supplies. Kilian and Vega (2011) support this finding by showing that energy prices do not respond instantaneously to macroeconomic news but Mason and Charles (2013) argue that the spot price of crude oil and its futures prices do contain jumps. Finally, Sari et al. (2011) argue that global risk perceptions have a significantly suppressing effect on oil prices in the long run.

Besides the above forces, oil prices might also be linked to large speculative trades (Hamilton, 2009; Caballero et al., 2008) and short run destabilization in oil prices may be caused by financial investors (Lombardi and Van Robays, 2011). These findings are in line with petroleum's increasing financialization after 2001 as shown in Fratzscher et al. (2013) and the expanding financialization of commodities in general (Mensi et al., 2013; Creti et al., 2013; Dwyer et al., 2011; Vivian and Wohar, 2012).

2. The importance of crude oil can be documented by the 89.4 million barrels of global daily consumption in 2012 as reported by the U.S. Energy Information Administration. The corresponding figures for the largest consumption regions in millions of barrels daily are 29 for Asia, 18.5 for the US, and 14.4 for Europe; U.S. Energy Information Administration, accessed on April 24, 2014 (http://www.eia.gov/cfapps/ipdbproject/IEDIndex3.cfm?tid = 5&pid = 5&aid = 2).

Due to their real economic importance and their ongoing financialization, petroleum-based commodities are naturally sensitive to economic development as well as market volatility. The evidence in Vácha and Baruník (2012) indicates that during periods of recession there exists a much higher downside risk to a portfolio formed from oil-based energy commodities. The asymmetric risk and accompanying volatility spillovers are thus a feature one would like to measure and monitor effectively. The research related to volatility spillovers among energy commodities is surprisingly limited, though. On weekly data, Haigh and Holt (2002) analyze the effectiveness of crude oil, heating oil, and unleaded gasoline futures in reducing price volatility for an energy trader: uncertainty is reduced significantly when volatility spillovers are considered in the hedging strategy. Using daily data for the period 1986–2001, Hammoudeh et al. (2003) analyzed the volatility spillovers of three major oil commodities (West Texas Intermediate, heating oil, and gasoline) along with the impact of different trading centers. Spillovers among various trading centers were also analyzed by Awartani and Maghyereh (2012), who investigated the dynamics of the return and volatility spillovers between oil and equities in the Gulf region. The spillover effect between the two major markets for crude oil (NYMEX and London's International Petroleum Exchange) has been studied by Lin and Tamvakis (2001), who found substantial spillover effects when both markets are trading simultaneously. More recently, Chang et al. (2010) have found volatility spillovers and asymmetric effects across four major oil markets: West Texas Intermediate (USA), Brent (North Sea), Dubai/Oman (Middle East), and Tapis (Asia-Pacific).

It is not surprising that different classes of petroleum commodities are affected by similar shocks given their potential substitution effect (Chevallier and Ielpo, 2013) or economic linkages (Casassus et al., 2013). However, the spillovers might evolve differently depending on the qualitative nature of the shocks. In terms of volatility spillovers, it is of key importance to identify how negative or positive shocks transmit to other assets. Changes in the volatility of one commodity are likely to trigger reactions in other commodities. We hypothesize that such volatility spillovers might exhibit substantial asymmetries and we aim to quantify them precisely.

Much of the research studying volatility spillovers among markets have employed multivariate GARCH family models, VEC models, etc. However, these methods have interpretative limitations as, most importantly, they are not able to quantify spillovers in sufficient detail. In our analysis we utilize more efficient techniques. Recently, Diebold and Yilmaz (2009) introduced a methodology for the computation of a spillover index (the DY index) based on forecast error variance decomposition from vector autoregresssions (VARs).[3] The methodology was further improved in Diebold and Yilmaz (2012) who introduced spillover direction and variable ordering in VARs. Another improvement of the original DY index has been introduced by Klößner and Wagner (2014), who developed a new algorithm for the fast calculation of the index along with the computation of the minimum and maximum values of the index. Finally, based on the idea of realized semivariance due to Barndorff-Nielsen et al. (2010), Baruník et al. (2013) extended the information content of the DY index with the ability to capture asymmetries in spillovers that materialize due

3. While the DY index has been widely adopted to analyze spillovers on financial markets, to the best of our knowledge, only one study applies the methodology to measuring volatility spillovers on commodity markets, albeit without assessing asymmetries in spillovers. Using daily data, Chevallier and Ielpo (2013) find that volatility spillovers among commodities have been increasing in the period 1995–2012. They even show that the inclusion of commodities in a broad portfolio of assets increases total spillovers. Among the commodities, the biggest net contributors to spillovers are precious metals and energy commodities. Hence, exploring asymmetry in spillovers among key energy commodities represents an important area that has not been explored yet.

to negative and positive returns/shocks—negative and positive spillovers. We employ this methodology for our analysis.

Our contribution is centered on finding substantial asymmetries in volatility spillovers across petroleum commodities, but our results are much richer. During the 1987–2014 period we document considerable volatility spillovers among petroleum commodities that substantially change their character after 2008: an increase in the magnitude of spillovers but a decline in their asymmetries. The increase in volatility spillovers seems to correlate with two important factors. First, the progressive financialization of the commodities has occurred since the beginning of the 21st century and the 2008 financial crisis deeply affected financial markets; the observed correlation resonates well with the findings of Tang and Xiong (2012), Creti et al. (2013), or Mensi et al. (2013). Second, the year 2008 is fundamentally important because it brought about much more activity in tight oil exploration and an increase in U.S. oil production that later resulted in a supply shock in global markets as documented by the International Energy Agency (IEA) Medium Term Oil Market Report-2013 (IEA, 2013).[4] In terms of asymmetries in spillovers we show that overall volatility spillovers due to negative returns occur across petroleum commodities to a much larger extent than positive volatility spillovers. Further, after 2008 the asymmetries in spillovers markedly declined for both total spillovers as well as directional spillovers. Analysis of directional spillovers also reveals that no commodity dominates other commodities in terms of spillover transmission.

The paper is organized as follows. In Section 2 we introduce the methodology to quantify asymmetries in volatility spillovers, namely the spillover index with realized variance and semivariance, and an intuitively appealing spillover asymmetry measure. Data of the used energy commodities are described in Section 3. We display our results and inferences in Section 4. Finally, we briefly conclude.

2. MEASURING ASYMMETRIES IN VOLATILITY SPILLOVERS

To define a measure of asymmetries in volatility spillovers, we begin with a description of the two methodological frameworks that we finally combine into a new spillover asymmetry measure.

2.1 Realized Variance and Semivariance

Consider a continuous-time stochastic process for log-prices p_t evolving over a time horizon $[0 \le t \le T]$, which consists of a continuous component and a pure jump component, $p_t = \int_0^t \mu_s ds + \int_0^t \sigma_s dW_s + J_t$, where μ is a locally bounded predictable drift process and σ is a strictly positive volatility process, and all is adapted to a common filtration $\mathcal{F}$. The quadratic variation of the log-prices p_t is

$$[p_t, p_t] = \int_0^t \sigma_s^2 ds + \sum_{0 < s \le t} (\Delta p_s)^2, \tag{1}$$

4. Tight oil is an industry convention that generally refers to oil produced from very low permeability shale, sandstone, and carbonate formations. The prospects of the tight oil impact on petroleum production are analyzed and documented in Maugeri (2013) and EIA (2014).

where Δp_s denotes the size of the jump, if present. A natural measure for quadratic variation has been formalized by Andersen et al. (2001) and Barndorff-Nielsen (2002), who propose to estimate it as the sum of squared returns and coined the term "realized variance" (RV). Formally, let us suppose that the natural log prices $p_0,\ldots,p_n$ are equally spaced on the interval $[0,t]$. Then,

$$RV = \sum_{i=1}^{n} (p_i - p_{i-1})^2 \tag{2}$$

converges in probability to $[p_t,p_t]$ with $n \to \infty$. More recently, Barndorff-Nielsen et al. (2010) introduced estimators that capture the variation only due to negative or positive returns $(p_i - p_{i-1})$ using an estimator of realized semivariance:

$$RS^- = \sum_{i=1}^{n} (p_i - p_{i-1})^2 I_{(p_i - p_{i-1} < 0)} \tag{3}$$

$$RS^+ = \sum_{i=1}^{n} (p_i - p_{i-1})^2 I_{(p_i - p_{i-1} > 0)}. \tag{4}$$

The realized semivariances provide a complete decomposition of the realized variance, as $RV = RS^- + RS^+$, and can serve as measures of downside and upside risk. The decomposition holds exactly for any n. Barndorff-Nielsen et al. (2010) show the limiting behavior of the realized semivariance, which converges to $1/2\int_0^t \sigma_s^2 ds$ and the sum of the jumps due to negative and positive returns.

2.2 Measuring Volatility Spillovers

Diebold and Yilmaz (2009) introduce a volatility spillover measure based on forecast error variance decompositions from vector auto regressions (VARs). Variance decompositions record how much of the H-step-ahead forecast error variance of some variable i is due to innovations in another variable j, hence the measure provides a simple intuitive way of measuring volatility spillovers. The methodology, however, has its limitations. First, it relies on the Cholesky-factor identification of VARs, and thus the resulting variance decompositions can be dependent on variable ordering. Second, a more crucial shortcoming of this methodology is that it allows measuring total spillovers only. Both limitations were successfully eliminated in their subsequent work, Diebold and Yilmaz (2012), which uses a generalized vector autoregressive framework in which forecast error variance decompositions are invariant to variable ordering, and explicitly includes the possibility to measure directional volatility spillovers.

Third, and most important to us, Diebold and Yilmaz (2009, 2012) use the daily or weekly range-based volatility of Garman and Klass (1980) to compute spillovers. While range-based estimators provide an efficient way of estimating volatility, it is appealing to take advantage of the availability of high-frequency data to improve the understanding of the transmission mechanism. While it is extremely easy to analyze volatility due to negative and positive returns using high frequency data (as described in our paper), daily data does not fully allow this decomposition. While we know from the literature that variance can be computed efficiently from the data using range-based estimators, to the best of our knowledge, feasible semivariance estimation based on high frequency data has not been established in the literature yet. Hence, following Barndorff-Nielsen et al. (2010), we can conveniently decompose daily volatility into negative and positive semivariance providing a proxy of downside (upside) risk. Replacing the total volatility that enters the computation by the measure of downside or upside risk will allow us to measure the spillovers due to negative and positive returns and test if they are transmitted in the same magnitude. Thus, we consider $\mathbf{RV_t} = (RV_{1t}, \ldots, RV_{nt})'$ to measure total volatility spillovers, and $\mathbf{RS_t^-} = (RS_{1t}^-, \ldots, RS_{nt}^-)'$ and $\mathbf{RS_t^+} = (RS_{1t}^+, \ldots, RS_{nt}^+)'$ to measure volatility spillovers due to negative and positive returns, respectively. For ease of exposition we label them as negative and positive (volatility) spillovers.

To measure negative and positive spillovers, we use the Diebold and Yilmaz (2012) directional spillover measure, which follows directly from the variance decomposition associated with an N-variable vector autoregression fitted to volatility (in our case semivariances). To set the stage, consider an N-dimensional vector $\mathbf{RV_t} = (RV_{1t}, \ldots, RV_{nt})'$ holding the realized variance of N assets, which is modeled by a covariance stationary vector autoregression VAR(p) as

$$\mathbf{RV_t} = \sum_{i=1}^{p} \mathbf{\Phi}_i \mathbf{RV}_{t-i} + \epsilon_t, \tag{5}$$

with $\epsilon_t \sim N(0, \mathbf{\Sigma}_\epsilon)$ being a vector of independently and identically distributed disturbances and $\mathbf{\Phi}_i$ for $i = 1, \ldots, p$ coefficient matrices. Provided that the VAR process is invertible, it has the moving average representation $\mathbf{RV}_t = \sum_{i=0}^{\infty} \mathbf{\Psi}_i \epsilon_{t-i}$, where the $N \times N$ matrices holding coefficients $\mathbf{\Psi}_i$ can be obtained from the recursion $\mathbf{\Psi}_i = \sum_{j=1}^{p} \mathbf{\Phi}_j \mathbf{\Psi}_{i-j}$ with $\mathbf{\Psi}_0$ being the identity matrix; $\mathbf{\Psi}_0 = \mathbf{I}_N$ and $\mathbf{\Psi}_i = 0$ for $i < 0$. The moving average representation is key to understanding the dynamics of the system as they allow the computation of variance decompositions. These in turn allow decomposition of the forecast error variances of each variable in the system into parts, which are attributable to various system shocks. Diebold and Yilmaz (2012) build the spillover index on the idea of assessing the fraction of the H-step-ahead error variance in forecasting the i th variable that is due to shocks to the j th variable for $j \neq i$, for each i. In order to obtain variance decompositions, which are invariant to variable ordering in the VAR system, Diebold and Yilmaz (2012) use the framework of the generalized VAR of Koop et al. (1996) and Pesaran and Shin (1998). The framework allows for correlated shocks but accounts for them by using the observed distribution of the errors, under a normality assumption. In this way, the shocks to each variable are not orthogonalized. Hence the resulting sum of the contributions to the variance of the forecast error may not necessarily equal one.

2.2.1 Total spillovers

To define the spillover index, Diebold and Yilmaz (2012) consider a H-step-ahead generalized forecast error variance decomposition matrix Ω, which has following elements ω_{ij}^H for $H = 1, 2, \ldots$

$$\omega_{ij}^H = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (\mathbf{e}_i' \mathbf{\Psi}_h \mathbf{\Sigma}_\epsilon \mathbf{e}_j)^2}{\sum_{h=0}^{H-1} (\mathbf{e}_i' \mathbf{\Psi}_h \mathbf{\Sigma}_\epsilon \mathbf{\Psi}_h' \mathbf{e}_i)}, \tag{6}$$

where $\mathbf{\Sigma}_\epsilon$ is the variance matrix for the error vector ϵ_t, σ_{jj} is the standard deviation of the error term for the j th equation, $\mathbf{e}_i$ is selection vector, with one as the i th element and zero otherwise, and $\mathbf{\Psi}_h$ moving average coefficients from the forecast at time t. The sum of the elements in each row of the variance decomposition table is not equal to one, $\sum_{j=1}^{N} \omega_{ij}^H \neq 1$, as the shocks are not necessarily orthogonal in this framework. Hence we need to normalize each element by the row sum as $\tilde{\omega}_{ij}^H = \frac{\omega_{ij}^H}{\sum_{j=1}^{N} \omega_{ij}^H}$. Using the contributions from the variance decomposition, Diebold and Yilmaz (2012) then define the total spillover index, which measures the contribution of spillovers from volatility shocks across variables in the system to the total forecast error variance as

$$\mathcal{S}^H = 100 \times \frac{1}{N} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\omega}_{ij}^H. \tag{7}$$

Note that by construction, $\sum_{j=1}^{N} \tilde{\omega}_{ij}^H = 1$ and $\sum_{i,j=1}^{N} \tilde{\omega}_{ij}^H = N$, thus the contributions of spillovers from volatility shocks are normalized by the total forecast error variance.

2.2.2 Directional spillovers

The spillover index as defined by Eq. (7) helps us understand how much the shocks to the volatility spill over across the studied assets. The main advantage of the generalized VAR framework is, however, the possibility to identify directional spillovers using the normalized elements of the generalized variance decomposition matrix. Directional spillovers allow us to further uncover the transmission mechanism, as we can decompose the total spillovers to those coming from, or to, a particular asset in the system.

Diebold and Yilmaz (2012) propose to measure the directional spillovers received by asset i from all other assets j as:

$$\mathcal{S}_{i\leftarrow\bullet}^H = 100 \times \frac{1}{N} \sum_{\substack{j=1 \\ i \neq j}}^{N} \tilde{\omega}_{ij}^H. \tag{8}$$

In a similar fashion, the directional spillovers transmitted by asset i to all other assets j can be measured as:

$$\mathcal{S}_{i\rightarrow\bullet}^H = 100 \times \frac{1}{N} \sum_{\substack{j=1 \\ i \neq j}}^{N} \tilde{\omega}_{ji}^H. \tag{9}$$

2.2.3 Net spillovers and net pairwise spillovers

Directional spillovers can also be used to obtain the net volatility spillover from asset i to all other assets j as a simple difference between gross volatility shocks transmitted to and received from all other assets:

$$\mathcal{S}_i^H = \mathcal{S}_{i\rightarrow\bullet}^H - \mathcal{S}_{i\leftarrow\bullet}^H. \tag{10}$$

The net volatility spillover tells us how much each asset contributes to the volatility in other assets, in net terms.

Finally, it is also interesting to define the pairwise volatility spillover between asset i and j as the difference between the gross shocks transmitted from asset i to asset j and those transmitted from j to i:

$$\mathcal{S}_{ij}^{H} = 100 \times \frac{1}{N}(\tilde{\omega}_{ji}^{H} - \tilde{\omega}_{ij}^{H}). \tag{11}$$

2.3 Measuring asymmetric spillovers

Finally, we describe how to capture and measure asymmetric volatility spillovers. Specifically, we are able to account for spillovers from volatility due to negative returns $\mathcal{S}^-$ and positive returns $\mathcal{S}^+$, as well as directional spillovers from volatility due to negative returns $\mathcal{S}_{i\leftarrow\bullet}^-$, $\mathcal{S}_{i\rightarrow\bullet}^-$, and positive returns $\mathcal{S}_{i\leftarrow\bullet}^+$, $\mathcal{S}_{i\rightarrow\bullet}^+$. Based on the previous exposition, to isolate asymmetric volatility spillovers, we need to replace the vector of volatilities $\mathbf{RV_t} = (RV_{1t},\ldots,RV_{nt})'$ with the vector of negative semivariances $\mathbf{RS_t^-} = (RS_{1t}^-,\ldots,RS_{nt}^-)'$ or the vector of positive semivariances $\mathbf{RS_t^+} = (RS_{1t}^+,\ldots,RS_{nt}^+)'$. Please note that we drop the H index to ease the notational burden from here on, but it remains a parameter for the estimation of spillover indices. If the contributions of RS^- and RS^+ are equal, the spillovers are symmetric, while the differences in realized semivariance result in asymmetric spillovers. Moreover, we assume that the values of the volatility spillover indices differ over time. To capture the time-varying nature, we compute indices using a 200-day moving window that runs from point $t-199$ to point t; more details are provided in Section 4.1.

2.3.1 Spillover Asymmetry Measure

In order to better quantify the extent of volatility spillovers we introduce a spillover asymmetry measure ($\mathcal{SAM}$) that is formally defined as

$$\mathcal{SAM} = 100 \times \frac{\mathcal{S}^+ - \mathcal{S}^-}{1/2(\mathcal{S}^+ + \mathcal{S}^-)}, \tag{12}$$

where $\mathcal{S}^-$ and $\mathcal{S}^+$ are volatility spillover indices due to negative and positive semivariances, RS^- and RS^+, respectively, with a H-step-ahead forecast at time t. $\mathcal{SAM}$ defines and illustrates the extent of asymmetry in spillovers due to RS^- and RS^+. When $\mathcal{SAM}$ takes a value of zero, spillovers coming from RS^- and RS^+ are equal. When $\mathcal{SAM}$ is positive, spillovers coming from RS^+ are larger than those from RS^- and the opposite is true when $\mathcal{SAM}$ is negative.

2.3.2 Directional Spillover Asymmetry Measure

While the spillover asymmetry measure ($\mathcal{SAM}$) defined by Eq. (12) measures to what extent the spillovers from volatility are asymmetric, we can decompose this measure and study the source of asymmetry among the studied assets. We define the asymmetry measure for directional spillovers received by asset i from all other assets j as

$$\mathcal{SAM}_{i\leftarrow\bullet} = 100 \times \frac{\mathcal{S}_{i\leftarrow\bullet}^+ - \mathcal{S}_{i\leftarrow\bullet}^-}{1/2(\mathcal{S}_{i\leftarrow\bullet}^+ + \mathcal{S}_{i\leftarrow\bullet}^-)}. \tag{13}$$

Table 1: Descriptive Statistics for Realized Volatility of Crude Oil, Heating Oil, and Gasoline over the Sample Period from September 1, 1987 through February 12, 2014

	Mean	St.dev.	Skewness	Kurtosis	Minimum	Maximum
Crude oil	0.3199	0.3465	4.5004	35.3530	0.1778	0.0056
Heating oil	0.3042	0.2857	5.7352	88.6317	0.1780	0.0074
Gasoline	0.3543	0.3519	4.7872	42.1653	0.1960	0.0060
	$\times 10^{-3}$	$\times 10^{-3}$			$\times 10^{-4}$	

In a similar fashion, we can measure the degree of asymmetry in directional spillovers transmitted by asset i to all other assets j:

$$\mathcal{SAM}_{i\to\bullet} = 100 \times \frac{\mathcal{S}^{+}_{i\to\bullet} - \mathcal{S}^{-}_{i\to\bullet}}{1/2(\mathcal{S}^{+}_{i\to\bullet} + \mathcal{S}^{-}_{i\to\bullet})}. \tag{14}$$

$\mathcal{SAM}_{i\leftarrow\bullet}$ and $\mathcal{SAM}_{i\to\bullet}$ allow us to identify the extent to which volatility from (or to) the i th asset spills over to (or from) other assets symmetrically. For example, if a negative spillover from one asset in the system is larger than a positive spillover, $\mathcal{SAM}_{i\to\bullet}$ will be different from zero, and we expect it to be negative. This information would stay hidden in the original Diebold and Yilmaz (2012) framework.

3. DATA

The data set consists of transaction prices for crude oil, heating oil, and gasoline traded on the New York Mercantile Exchange (NYMEX); the data were obtained from Tick Data, Inc. We use the data from Globex during the main trading hours of 9:00–14:30 EST. From the raw irregularly spaced prices we extract 5-minute logarithmic returns using the last-tick method for the RV, RS^{-}, and RS^{+} estimators. The 5-minute choice is guided by the volatility signature plot and previous literature employing the same data. The sample period goes from September 1, 1987 through February 12, 2014; the time span is based on (high-frequency) data availability and not on the end of OPEC's administrative pricing. In 2006, NYMEX changed the grade of gasoline, and instead of unleaded gasoline (HU) contracts, started to trade reformulated gasoline blendstock for oxygen blending (RBOB) futures. For the gasoline data, we use unleaded gasoline until late 2006, and RBOB gasoline from 2006. We eliminate transactions executed on Saturdays and Sundays, U.S. federal holidays, December 24 to 26, and December 31 to January 2, due to the low activity on these days, which could lead to estimation bias.

Table 1 reports the summary statistics for the estimated realized measures. The daily prices are plotted in Figure 1.

4. RESULTS

This section summarizes the results of the volatility spillover analysis of petroleum commodities. For easier orientation we divide our results into three parts. The first part shows the dynamics of spillovers and uncovers important patterns in the volatility transmission mechanism. The second part introduces asymmetries and shows the importance of understanding the differences

Figure 1: Normalized Prices of Crude Oil, Heating Oil, and Gasoline over the Sample Period Extending from September 1, 1987 through February 12, 2014.

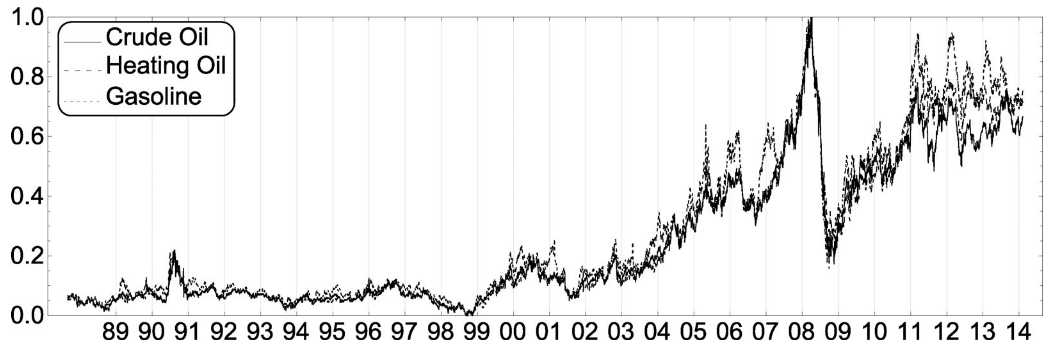


Table 2: Volatility Spillover Table: Rows (To), Columns (From). Panel (a) Shows Results Using RV, Panel (b) Shows Results Using Range-based Volatility

Panel (a)	Crude	Heating Oil	Gasoline	**FROM**
Crude	49.9025	21.9881	28.1094	50.0975
Heating Oil	25.3731	44.7523	29.8746	55.2477
Gasoline	25.1333	21.3211	53.5456	46.4544
TO	50.5064	43.3092	57.9839	**TOTAL**
				50.5998
Panel (b)	Crude	Heating Oil	Gasoline	**FROM**
Crude	48.8572	22.9206	28.2223	51.1428
Heating Oil	29.9725	41.8485	28.1790	58.1515
Gasoline	28.6242	21.5623	49.8135	50.1865
TO	58.5967	44.4829	56.4012	**TOTAL**
				53.1603

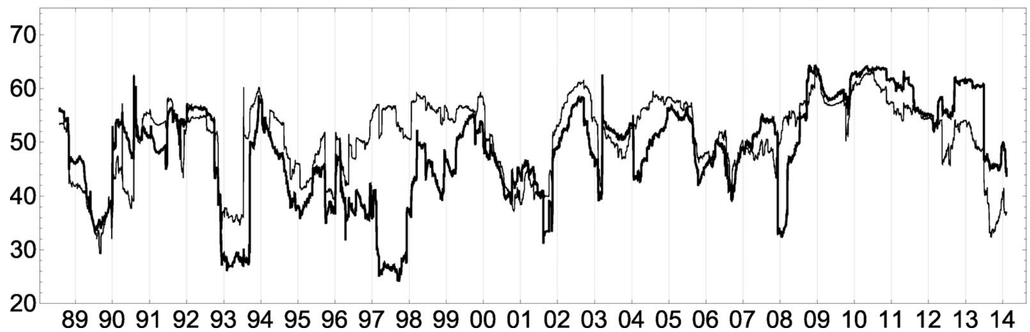
in information transmission from volatility spillovers due to negative and positive shocks. The last part examines directional spillovers along with asymmetries.

4.1 Extent to Which Uncertainty Spills Over Petroleum Markets

As an initial observation, average spillovers are reported in Table 2: total volatility spillovers exhibit values of 50% for the high-frequency-based volatility measure (panel a) and 53% for the daily range-based volatility measure (panel b). By reporting both measures we are able to compare our results using high frequency data to the original approach of Diebold and Yilmaz (2009, 2012), who utilize daily range-based data; see our earlier discussion in Section. Both measures deliver quantitatively similar results but this outcome is because the reported values are average spillovers.

More refined observations can be gauged from the total volatility spillover plot in Figure 2 that captures the dynamics of the volatility spillovers among the three commodities over the examined time period. The plot is constructed as a series of volatility spillover estimates employing

Figure 2: Total Spillover Plot: Spillovers from RV-based (bold) and Range-based (thin) Volatility. Crude Oil, Heating Oil, and Gasoline over the Sample Period Extending from September 1, 1987 through February 12, 2014.



200-day rolling windows, horizon $h = 10$, and VAR lag length of 2.[5] As the time span is 26 years, rich dynamics and important patterns emerge.

In Figure 2 we present the total volatility spillovers based on high frequency data (bold line) as well as spillovers from range-based volatility (thin line). Despite the fact that often both measures evolve similarly, some marked differences are visible. First, when both measures follow the same direction, spillovers based on high frequency data are of larger magnitude. Second, often both measures follow opposite directions; in this case spillovers based on high frequency data are mostly of a larger magnitude than those from range-based volatility. Hence, spillovers estimated with daily data are less pronounced than spillovers estimated from high frequency data. In our further account we report results based solely on high frequency data.

The first intriguing observation is the strong dynamics of the spillovers between the volatility of the commodities under study. As heating oil and gasoline are products of crude oil, we would expect that any information from one of the commodities will transmit quickly to the other one.[6] Interestingly, Figure 2 shows a different pattern. In total, spillovers from volatility are not so large. Moreover, the time-varying spillover index exhibits a great degree of fluctuation, ranging from about 25% to 65% (Figure 2). This means that the volatility of one commodity does not necessarily excessively impact the volatility of other commodities all the time, although the petroleum commodities are fundamentally tied through the production process.[7] An implication emerges:

5. The rolling window runs from point $t-199$ to point t. In addition to a 200-day window, we constructed the spillover index with rolling windows of 150 and 100 days to check the robustness of our results. We have also experimented with different h values, and we find that the results do not materially change and are robust with respect to the window and horizon selection. The VAR lag length was chosen based on AIC to produce the most parsimonious model; in addition, Diebold and Yilmaz (2012) provide a sensitivity analysis of the of the Diebold-Yilmaz index to the VAR lag structure and show that results do not materially change for lags of 2 to 6. We obtained similar results (for lags of 2 to 4) that are available upon request. In addition, we run the usual residual diagnostics to check for possible departures from assumptions on VAR. There is no dependence left in the residuals and our estimates are consistent.

6. In effect, all three petroleum commodities are tightly connected. Casassus et al. (2013) explicitly define the production relationship between crude oil (input) and heating oil (output), and the complementary relationship (in production) between gasoline and heating oil. Further, heating oil is produced as a by-product when crude oil is cracked to produce gasoline. This implies another production relationship between crude oil (input) and gasoline (output). About 40 and 20 percent of crude oil is refined into gasoline and heating oil, respectively.

7. This result is not totally surprising when paired with the pattern of the daily price returns of the three contracts (crude oil, heating oil, and gasoline), which show marked differences: heating oil and gasoline exhibit jumps, but they more spaced

when trading petroleum futures, the above evidence may be used to increase the benefits from portfolio diversification during periods of low spillovers. We will study this interesting observation later by looking at directional spillovers, which could potentially uncover the source of the uncertainty in petroleum markets.

Second, we are able to identify two distinct periods during which spillovers behave differently. During the first period, before 2008, the average value of spillovers is 45.4% and fluctuates within a 7% standard deviation, while after 2008, it is 58.3% with a considerably lower fluctuation of a 5% standard deviation. Hence 2008 is a dividing point: we can observe a structural break that is behind a change in the volatility transmission mechanism.[8] The differences between pre-2008 and post-2008 periods are even more striking when we consider some details. The lowest levels of spillovers in 1989, 1993, 1997, and 2001 are in sharp contrast to the rest of the plotted spillovers, but at the same time the highest peaks of the spillovers before 2008 reach only the average level of the post-2008 period.

There are two fundamental issues related to the year 2008. One is the financial crisis and its effect on financial markets and the economy. This issue has already received much attention in the literature and, without a doubt, plays an important role in our results. However, there is a second issue that profoundly impacts petroleum commodity markets in a direct manner. Exploration and production of crude oil from shale formations with very low permeability—tight oil—began to emerge in 2008 at a quantitatively new level in the U.S. The dramatic increase in tight oil production and its proportion in overall U.S. production is well documented by the U.S. Energy Information Administration (2014). It is well documented that the "growth in crude oil production from tight oil and shale formations supported by identification of resources and technology advances have supported a nearly fourfold increase in tight oil production from 2008, when it accounted for 12% of total U.S. crude oil production, to 2012, when it accounted for 35% of total U.S. production." (EIA, 2014; ES-2).[9] In his comprehensive analysis Maugeri (2013; p.1) also documents a rising trend in U.S. tight oil production and specifically emphasizes that "the correlation between drilling intensity and shale oil production will shape the evolution of U.S. oil production more than any

out than crude oil. Each of the three commodities has a rather distinct short-term behavior, although ultimately prices do realign after big price jumps. Further, rather than interpreting the results presented in Table 2 and Figure 2 we present them as useful observations. The reason is that the NYMEX crude oil contract is for light sweet crude (West Texas Intermediate crude (WTI) or other deliverable light sweet crudes). This is the U.S. benchmark, but not necessarily what has been mostly refined in the U.S. The majority of crude oils refined in the U.S. are heavy sour ones (especially in Texas which has the majority of complex refining capacity). Hence the correlation between crude oil, heating oil, and gasoline may not necessarily reflect what happens in the physical market. In addition, WTI has had its own issues of suppressed prices due to excess domestic supply and the inability to export any of it. Refined products do not have the same restrictions (they can be exported freely) and may take longer to adjust to WTI prices as their pricing should be closely correlated to heavier crudes from Venezuela, Saudi Arabia, Canada, etc. We are thankful to an anonymous referee for the above valuable insights.

8. As in Zeileis et al. (2003), we employ the supF testing methodology to formally identify an endogenous break in the spillover index on September 14, 2008; the date precedes the official collapse of Lehman Brothers by one day. The structural break in the volatility transmission mechanism may be due to the advent of tight oil production rather than the financial crisis, though.

9. The great potential of tight oil is boldly documented also in Miller et al. (2008), who argue that "In recent years, the formation known as the Bakken Shale in eastern Montana and western North Dakota has seen enormous growth in oil and gas production. Scientists from the United States Geological Survey have commented that the area has the potential to become "the next Saudi Arabia". The above statement might sound like a gross exaggeration but according to the data from the North Dakota Industrial Commission (Department of Mineral Resources, Oil and Gas Division) Inglesby et al.(2012; p.33) note that the growth of oil production in the Bakken formation "rose from less than 30,000 barrels per day (bbl/d) in 2008 to 469,000 bbl/d by the end of 2011."

other factor". Since the drilling intensity to a large extent depends on the oil price, significant changes and volatility in oil prices may substantially impact tight oil exploration and production. This is yet another reason why an understanding of volatility spillovers on petroleum markets is worthwhile.

Similar to the evidence on the post-2008 tight oil production we also offer quantitative support in terms of petroleum commodities financialization. The increase in volatility spillovers in 2002 and mainly 2008 has a parallel in rising energy commodity prices after 2002 (Figure 1). These patterns are deeply related to the financialization of the commodities during the previous years. Increased demand for commodities as portfolio investments resulted in a dramatic surge of their portfolio weights and energy commodities became important parts of index portfolios (Tang and Xiong, 2012). According to Cheng and Xiong (2013), investment inflows to various commodity futures indices totaled $200 billion between 2000 and mid-2008. Henderson et al. (2013) document that between 2003 and 2011, financial commodity investments increased from $15 to 400 billion. Increased demand for financial commodity investments, as a key source behind increases in energy commodity prices, have also been advocated by Singleton (2013); Tang and Xiong (2012); Henderson et al. (2013), and Hamilton and Wu (2014), among others.

We pair the above evidence with the presented development of spillovers and claim that the process of the advancing financialization of energy commodities highly correlates with the increase of spillovers from the early 2000s on, and this pattern is especially strong after 2008. The increased correlation of energy and non-energy commodities through the increasing presence of index investors (Tang and Xiong, 2012) further enlarges the grounds for volatility to spill over among other classes of commodities.

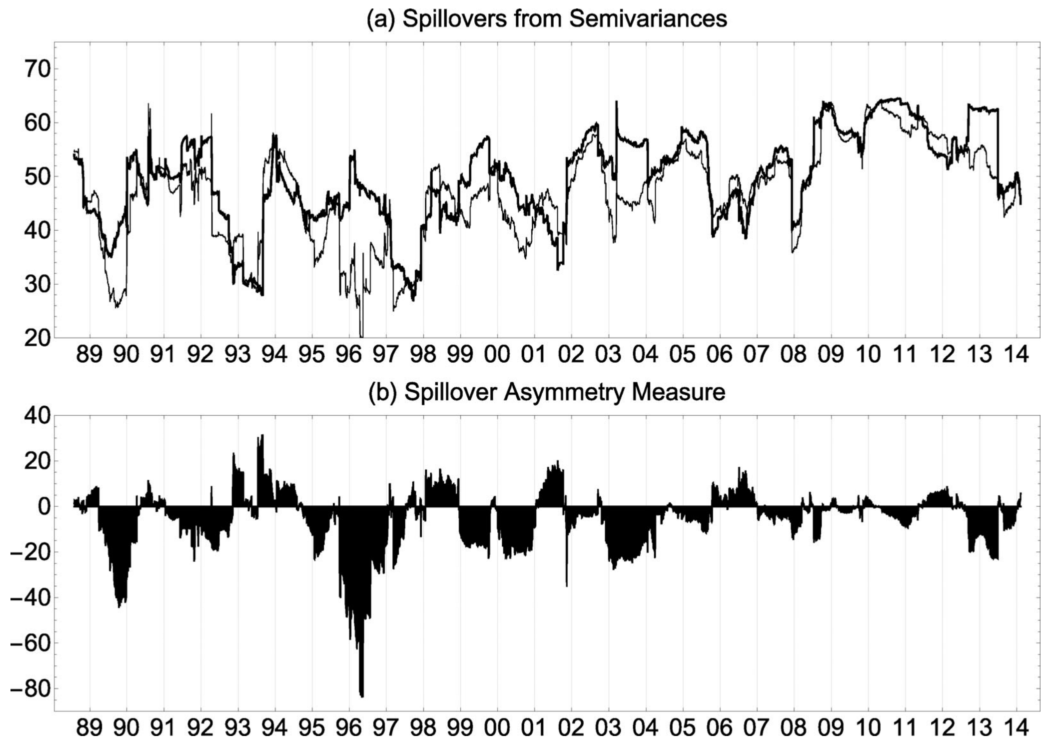
4.2 Asymmetric Transmission of Information in Petroleum Markets

Having a full picture of how uncertainty spills over the petroleum markets, we proceed to study possible asymmetries in the transmission mechanism. Earlier we argued that volatility spillovers might differ in their magnitude based on whether the shock originates from negative or positive returns. Based on the methodology proposed in earlier sections, we aim to compute negative and positive volatility spillovers, and quantify to what extent petroleum markets process information asymmetrically.

In panel (a) of Figure 3 we present two total spillover plots that are based on negative and positive semivariances. Hence, the plot captures patterns of total volatility spillovers that materialize due to negative and positive returns. Closer inspection of the plot reveals that both negative and positive spillovers share a common path but their developments are not identical. We can identify several periods during which spillovers due to negative and positive volatility diverge to various extents. The differences are better visible using the Spillover Asymmetry Measure ($\mathcal{SAM}$) in panel (b) of Figure 3.

$\mathcal{SAM}$ quantifies the differences in total volatility spillovers due to negative and positive returns and allows portraying the extent of asymmetry that is independent of the spillover levels. Positive values of $\mathcal{SAM}$ indicate that volatility spillovers due to positive returns are larger than spillovers due to negative returns. Negative values of $\mathcal{SAM}$ indicate that volatility spillovers due to negative returns are larger than spillovers due to positive returns. A zero $\mathcal{SAM}$ means that the impact of both negative and positive spillovers is equal and their effects cancel each other out. A direct observation is that this neutral position of markets is very rare. The principal evidence is that asymmetry in total spillovers is overwhelmingly driven by negative returns (shocks) and the extent of asymmetricity is not only in magnitude but also in duration.

Figure 3: Total Spillover Plot using (a) RS^+ (thin) and RS^- (bold) Semivariance for Crude Oil, Heating Oil, and Gasoline over the Sample Period Extending from September 1, 1987 through February 12, 2014. (b) Spillover Asymmetry Measure ($\mathcal{SAM}$)



The first period of negative returns driving volatility spillovers in petroleum markets (1989–1990) is associated with a decrease in total spillovers. Then, in 1991, a large supply shock due to the first Gulf War doubled crude oil prices in a few months; total volatility spillovers doubled as well. The most notable asymmetric effect is visible during the end of 1995 and 1996. The year 1995 was for many years the last year when the U.S. produced more oil than it imported.[10] Economically this is an important issue that had to be absorbed by markets and that is also in line with one of the oil-specific demand shocks peaking in 1995 and evidenced in Kilian (2009). The even larger extent of negative spillovers in 1996 should be paired with the Energy Information Administration (EIA) data showing that in "March 1996 primary inventories of crude oil were the lowest recorded in almost 20 years"[11] and the trend continued for some time. Low inventories of crude oil force refineries to buy extra crude oil and may also lead to supply problems of gasoline and other petroleum products. Low inventories of crude oil then likely cause price volatility and spillovers in petroleum commodities markets. The issue of the volatility in petroleum markets in connection

10. U.S. Energy Information Administration (EIA) (http://www.eia.gov/countries/country-data.cfm?fips = US#pet). Accessed on September 23, 2014.

11. U.S. Energy Information Administration (EIA) (http://www.eia.gov/petroleum/archive/abohn1.pdf). Accessed on September 23, 2014.

with the low inventories of crude oil was specifically addressed by the EIA in its 1997 Report on Petroleum, chapter 5 (EIA, 1997).

The following years are marked by resumed growth after the short-lived Asian Crisis. Crude oil prices rose quickly during 1999–2000 due to a large increase in consumption, and peaked before the beginning of the U.S. recession in 2001. Interestingly, the periods 1993–1994 and 2001–2002, time-wise related to these large increases in prices, were themselves marked by large decreases in prices. Positive values of $\mathcal{SAM}$ during both periods point at positive spillovers being transmitted to a larger extent than negative ones. Still, the extent of positive asymmetries is much lower when compared to negative asymmetries.

Finally, we emphasize the negative $\mathcal{SAM}$ during 2003–2004 that is associated with the second Gulf War and unrest in Venezuela. These two exogenous geopolitical events contributed to the last period during which bad news had a substantially larger influence on petroleum markets compared to good news. After 2004, oil prices increased due to increasing demand and the markets were still influenced by negative returns-based volatility spillovers more than by positive ones. However, after 2004 the magnitude of the asymmetries decisively declined. After the 2007–2008 financial crisis the absence of excessive fluctuations of volatility spillovers is even more pronounced. The low fluctuations in the $\mathcal{SAM}$ measure can be partly caused by increasing financialization. As commodities become significant parts of diversified portfolios (for example via index commodity vehicles), risk-sharing increases and the room for risk premia shrinks (Tang and Xiong, 2012). Further, an impressive increase in the financialization of the petroleum commodities does not mean a proportional increase in the number of stocks or related assets futures. Rather, financialization propagates via increases in portfolio sizes and the number of transactions. Increases in trading activities in particular might well induce a decline in spillover asymmetries via the price-setting mechanism on the market. As a consequence, higher total volatility spillovers occur simultaneously with lower asymmetries between volatility spillovers induced by positive or negative shocks.

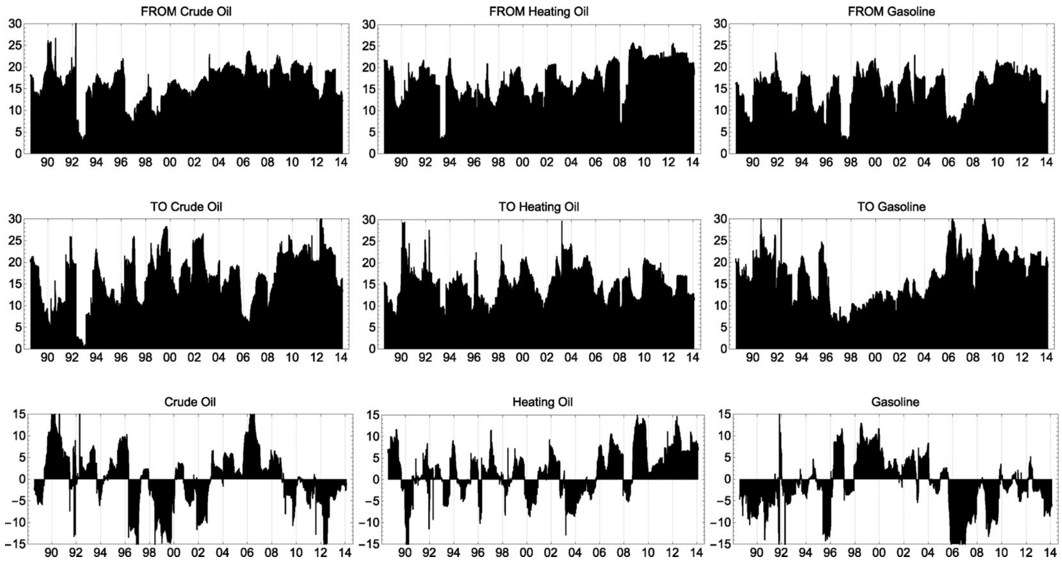
Another reason for the post-2008 symmetrical transmission of information may be that oil markets are currently in a very long period of calm volatility. After 2008, the volatility of petroleum markets decreased steadily, and currently it is at the lowest levels since the crude futures markets were established in the early 1980s. Oil prices have rarely been so stable for such a long period since the 1970s. An important factor is also the fact that OPEC suppliers' ability to exert market power was reduced in the 2008 turmoil and its aftermath as argued by Huppmann and Holz (2012) and the availability of crude oil has been increasing with tight oil production.

Overall we may conclude that the asymmetric effects in spillovers are substantial and volatility due to negative shocks drives the total spillovers.

4.3 Directional Asymmetric Spillovers

Earlier, we established that asymmetry in volatility spillovers among petroleum commodities is a phenomenon that does matter. We now proceed with results on asymmetries in directional spillovers; e.g. spillovers going FROM one commodity TO other commodities. The basis for the importance of directional spillovers lies in production and complementary links among petroleum commodities. Casassus et al. (2013) show that economic linkages among commodities create a source of long-term correlation between futures returns. Cross-commodity relationships and feedback-based co-movements among them form a ground for why changes in the volatility of one commodity are likely to trigger strong reactions in other commodities, and even more so in commodities of the same class.

Figure 4: Directional Spillover Plots: Directional Spillovers FROM (first row), TO (second row), and Net Spillovers (third row) on *RV*.



In Figure 4, we present directional spillovers FROM and TO a specific commodity. In the first row of the figure, we show the dynamic patterns of how a specific commodity transmits volatility to other commodities. In the second row, we demonstrate the extent of spillovers that commodities receive. In the third row we provide the net effect of the directional spillovers: a difference between “contribution from” and “contribution to” plotted in the first two rows. The net spillovers in the positive domain represent the position when a commodity is a “spillover giver”: it transmits net volatility spillovers to other commodities. The negative domain contains net spillovers that a specific commodity receives from other ones: in this case the commodity is said to be a “spillover receiver”. Some patterns emerge. Until 1995 crude oil was predominantly a spillover giver, then chiefly a net receiver until 2003, and again a net giver until 2008. The post-crisis period is characterized by crude oil being a spillover receiver virtually until the present. Gasoline behaves differently: it is a spillover receiver until the mid-1990s and then from 2004 on, including the 2007–2008 financial crisis period. Heating oil seems to be quite moderate in terms of transmitting and receiving net spillovers from other commodities. The net effects alternate very often and during most of the period under research net spillover values do not exceed the 5% mark. Only after 2005 heating oil becomes a net giver and the extent of net spillovers significantly increases when compared to the previous period.

In Figure 5, we present net pairwise spillovers that show the dynamics of the net spillovers between specific pairs of commodities. The transmission of pairwise net spillovers is quite balanced in all three pairs. The key information in Figure 5 is that no commodity dominates other commodities in terms of spillover transmission in general. The patterns of net pairwise spillovers reflect production and complementary relationships between commodities as well.

Finally, the directional spillovers described above can be further decomposed to the effects that the negative and positive returns exert on volatility spillovers. In panels (a) and (b) of Figure 6, we present the asymmetric directional spillovers in the form of plots of the directional spillover asymmetry measures ($\mathcal{SAM}_{i\leftarrow\bullet}$; panel (a) and $\mathcal{SAM}_{i\rightarrow\bullet}$; panel (b)).

Figure 5: Net Pairwise Spillover Plots

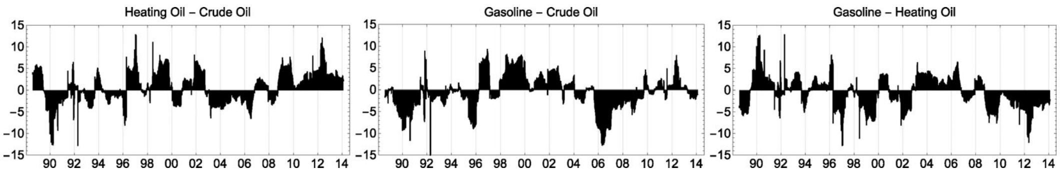
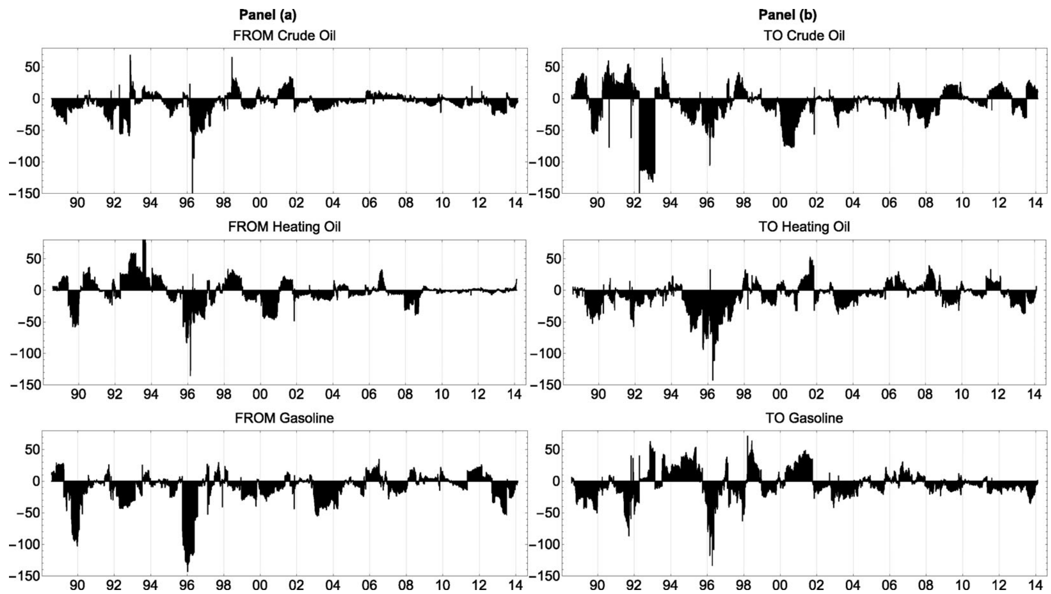


Figure 6: Asymmetric Directional Spillover Plots. Panel (a): Direction FROM ($\mathcal{SAM}_{i\to\bullet}$). Panel (b): Direction TO ($\mathcal{SAM}_{i\leftarrow\bullet}$).



The plots in Figure 6, panel (a), portray the dynamics of the asymmetry in spillovers FROM specific commodities outwards. There is a clear pattern of negative asymmetry that is most pronounced for the direction from crude oil and from gasoline: the positive values of $\mathcal{SAM}_{i\leftarrow\bullet}$ and $\mathcal{SAM}_{i\to\bullet}$ are small and infrequent and negative values, in the case of the direction from gasoline, on several occasions reach impressive values. The dominant negative spillovers in 1992–1993 are likely associated with the steps mandated by the Clean Air Act (CAA) Amendments adopted in 1990 by the U.S. government. The specific provisions led to increases in the production of oxygenated gasoline and a number of costly adjustments were forced on refineries and fuel distribution systems while industry profitability declined sharply and continued at low levels.[12] Guo and Kliesen (2005; p.628) claim that "crude oil price volatility is mainly driven by exogenous (random) events

12. The production of oxygenated gasoline rose chiefly in the U.S., but increases in oxygenate production capacities occurred in 1992 also in Canada, Europe, South America, and the Far East. About 31% of total gasoline sales were affected during the 1992–1993 winter oxygenated gasoline season. U.S. Energy Information Administration (US EIA), 2002. Petroleum Chronology of Events 1970–2000. http://www.eia.gov/pub/oil_gas/petroleum/analysis_publications/chronology/petroleumchronology2000.htm. Accessed on November 1, 2013.

such as significant terrorist attacks and military conflicts in the Middle East". In this spirit, it would be tempting to attribute large negative spillovers from crude oil and gasoline in 1996 to the disaster of the supertanker Sea Empress that caused enormous environmental damage off the coast near Wales by spilling 70,000 tons of crude oil on February 15, 1996. This event, however, is only spuriously related to crude oil and product markets. The negative effect was for shipping's image, rather than the returns on either shipping (freight) or oil. Large negative spillovers in 1996 should be rather attributed to factors impacting the U.S. crude oil inventories, of which "the net result was new record lows for stocks of crude oil, distillate, and gasoline, which, in turn, contributed to higher price volatility" (EIA, 1997; p. 99).

For the rest of the period under research the spillovers are chiefly governed by negative semivariances but their asymmetries decline after 2008. This pattern is in line with our findings presented earlier.

In Figure 6, panel (b), we present asymmetries in spillovers TO commodities: they provide clear evidence that the directional spillovers were induced mainly by negative returns (shocks). Lengthy and often profound periods when negative returns play a key role are most visible for the direction to crude oil. Further, spillovers to heating oil exhibit a massive asymmetric effect of prolonged and deep duration for about four years (1993–1997) that can be associated with the succession of events culminating in the Asian financial crisis coupled with a decline in oil prices. Spillovers to gasoline show a relatively balanced distribution of sources divided between negative and positive returns until 2006. Afterwards, spillovers due to negative returns dominate in a mild but persistent fashion until the end of our data span.

For all three commodities a common pattern of large spillovers in the negative domain is visible for example in 1996, 2003, and 2013. As discussed earlier, the historically low level of U.S. crude oil inventories in 1996 correlates with the pressure and volatility spillovers on petroleum commodities markets (EIA, 1997). A less dramatic decline in U.S. crude oil inventories occurred in mid-2013 due to an increase in U.S. refinery runs, a decrease in crude oil imports, and other reasons.[13] Because of the production relationship discussed in Casassus et al. (2013), both events are attested to by asymmetric directional spillovers from and to all three petroleum commodities. Finally, the invasion of Iraq in 2003 prompted the interest of investors in crude oil futures markets and the ensuing extent of speculation activity heightened volatility on various markets. Hence, the Iraq War in 2003 might be a reasonable cause behind the increased volatility on markets with crude oil (Zhang et al., 2009) and is also visible for other oil-based commodities. As before, asymmetries in directional spillovers decline after the financial crisis.

5. CONCLUSION

In this paper we study asymmetries in volatility spillovers due to negative and positive returns across petroleum commodities. To capture the asymmetric transmission mechanism, we combine two existing methodological approaches: the volatility spillover index of Diebold and Yilmaz (2009, 2012) together with realized semivariances due to Barndorff-Nielsen et al. (2010). As a result we are able to detect and quantify asymmetries in volatility spillovers in high frequency data within a specific class of assets: the major petroleum commodities crude oil, gasoline, and heating oil. Our data sample covers the 1987–2014 period.

13. U.S. Energy Information Administration (US EIA), 2013. http://www.eia.gov/oog/info/twip/twiparch/2013/130725/twipprint.html. Accessed on September 23, 2014.

We show that volatility spillovers began to rise from the early 2000s and substantially increased after 2008. At the same time, volatility spillovers became more stable. The increase in volatility spillovers correlates with the progressive financialization of petroleum commodities after 2002. After 2008 the degree of (negative and positive) asymmetries markedly declines and negative and positive shocks exhibit quantitatively similar effects on volatility spillovers. Finally, an analysis of directional spillovers reveals that no commodity dominates other commodities in terms of spillover transmission in general, and asymmetries in directional spillovers decline after the financial crisis. Thus, the results of directional spillovers are in line with those of total spillovers and resonate with economic relationships among petroleum commodities.

Our results also form grounds for some less-than-orthodox implications. Our findings defy a common belief that the financial crisis should prompt spillovers to be more volatile. We provide evidence of just the opposite: spillovers from price developments in 2008 and later are less volatile than before the 2007–2008 financial crisis. Further, we show that the occurrence of negative volatility spillovers correlates with low levels of crude oil inventories in the U.S. and often with world events that hamper crude oil supply. Negative spillovers frequently indicate the extent of real or potential crude oil unavailability.

Finally, the decline in asymmetries in volatility spillovers after 2008 correlates with the ongoing financialization of commodities and the advent of tight oil exploration and production in the U.S. The extent of financialization reached impressive levels in 2008 and the financial crisis had a substantial immediate impact on financial and commodities markets. In this respect, the increase in the crude oil supply due to the U.S. tight oil production since 2008 might be a factor that was beneficial in lowering asymmetry. The key reason is that the advent of the U.S. tight oil decreased oil market vulnerability to supply shocks as compared to the past.

ACKNOWLEDGMENTS

We benefited from valuable comments we received from Joe Brada, Ionut Florescu, Geoff Pearce (Associate Editor), two anonymous referees, and participants at several presentations. The support of GACR grant no. 14-24129S is gratefully acknowledged. The usual disclaimer applies.

REFERENCES

Andersen, T., T. Bollerslev, F. Diebold, and P. Labys (2001). The distribution of realized exchange rate volatility. *Journal of the American Statistical Association* 96(453): 42–55. http://dx.doi.org/10.1198/016214501750332965.

Awartani, B. and A. I. Maghyereh (2012). Dynamic spillovers between oil and stock markets in the gulf cooperation council countries. *Energy Economics* 36, 28–42. http://dx.doi.org/10.1016/j.eneco.2012.11.024.

Barndorff-Nielsen, O., S. Kinnebrock, and N. Shephard (2010). *Volatility and Time Series Econometrics: Essays in Honor of Robert F. Engle*, Chapter Measuring Downside Risk-Realised Semivariance. Oxford University Press.

Barndorff-Nielsen, O. E. (2002). Econometric analysis of realized volatility and its use in estimating stochastic volatility models. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 64(2): 253–280. http://dx.doi.org/10.1111/1467-9868.00336.

Baruník, J., E. Kočenda, and L. Vácha (2013). Asymmetric volatility spillovers: Revisiting the Diebold-Yilmaz (2009) spillover index with realized semivariance. *arXiv.org Papers No. 1308.1221*. Available at: http://ideas.repec.org/p/arx/papers/1308.1221.html.

Bermingham, C. and D. O'Brien (2011). Testing for asymmetric pricing behaviour in Irish and UK petrol and diesel markets. *The Energy Journal* 32(3). http://dx.doi.org/10.5547/ISSN0195-6574-EJ-Vol32-No3-1.

Caballero, R. J., E. Farhi, and P.-O. Gourinchas (2008). Financial crash, commodity prices and global imbalances. Technical report, National Bureau of Economic Research. http://dx.doi.org/10.3386/w14521.

Casassus, J., P. Liu, and K. Tang (2013). Economic linkages, relative scarcity, and commodity futures returns. *Review of Financial Studies* 26(5): 1324–1362. http://dx.doi.org/10.1093/rfs/hhs127.

Chang, C.-L., M. McAleer, and R. Tansuchat (2010). Analyzing and forecasting volatility spillovers, asymmetries and hedging in major oil markets. *Energy Economics* 32(6): 1445–1455. http://dx.doi.org/10.1016/j.eneco.2010.04.014.

Cheng, I.-H. and W. Xiong (2013). The financialization of commodity markets. Technical report, National Bureau of Economic Research. http://dx.doi.org/10.3386/w19642.

Chevallier, J. and F. Ielpo (2013). Volatility spillovers in commodity markets. *Applied Economics letters* 20(13): 1211–1227. http://dx.doi.org/10.1002/9781118710098.

Creti, A., M. Joëts, and V. Mignon (2013). On the links between stock and commodity markets volatility. *Energy Economics* 37, 16–28. http://dx.doi.org/10.1016/j.eneco.2013.01.005.

Diebold, F. X. and K. Yilmaz (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal* 119(534): 158–171. http://dx.doi.org/10.1111/j.1468-0297.2008.02208.x.

Diebold, F. X. and K. Yilmaz (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting* 28(1): 57–66. http://dx.doi.org/10.1016/j.ijforecast.2011.02.006.

Dimpfl, T. and R. C. Jung (2012). Financial market spillovers around the globe. *Applied Financial Economics* 22(1): 45–57. http://dx.doi.org/10.1080/09603107.2011.597721.

Du, X., C. L. Yu, and D. J. Hayes (2011). Speculation and volatility spillover in the crude oil and agricultural commodity markets: A bayesian analysis. *Energy Economics* 33(3): 497–503. http://dx.doi.org/10.1016/j.eneco.2010.12.015.

Dwyer, A., G. Gardner, and T. Williams (2011). Global commodity markets-price volatility and financialisation. *RBA Bulletin*, June, 49–57.

(EIA) Energy Information Administration (1997). Petroleum 1996: issues and trends. DOE/EIA-0615. ftp://ftp.eia.doe.gov/pub/oil_gas/petroleum/analysis_publications/petroleum_issues_trends_1996.

(EIA) Energy Information Administration (2014). Annual Energy Outlook 2014. U.S. Energy Information Administration, U.S. Department of Energy, Washington DC. http://www.eia.gov/forecasts/aeo/.

Fratzscher, M., D. Schneider, and I. Van Robays (2013). Oil prices, exchange rates and asset prices. (no. 1302). Technical report, Discussion Papers, DIW Berlin.

Garman, M. B. and M. J. Klass (1980). On the estimation of security price volatilities from historical data. *Journal of business* 53(1): 67–78. http://dx.doi.org/10.1086/296072.

Gorton, G. B. and K. G. Rouwenhorst (2005). Facts and fantasies about commodity futures. *Financial Analysts Journal* 62(2): 47–68. http://dx.doi.org/10.2469/faj.v62.n2.4083.

Gronwald, M. (2012). Oil and the US macroeconomy: A reinvestigation using rolling impulse response. *The Energy Journal* 33(4): 143–159. http://dx.doi.org/10.5547/01956574.33.4.7.

Guo, H. and K. L. Kliesen (2005). Oil price volatility and US macroeconomic activity. *Federal Reserve Bank of St. Louis Review* 87(November/December 2005).

Haigh, M. S. and M. T. Holt (2002). Crack spread hedging: accounting for time-varying volatility spillovers in the energy futures markets. *Journal of Applied Econometrics* 17(3): 269–289. http://dx.doi.org/10.1002/jae.628.

Hamilton, J. D. (1983). Oil and the macroeconomy since World War II. *Journal of Political Economy* 91(2): 228–248. http://dx.doi.org/10.1086/261140.

Hamilton, J. D. (1996). This is what happened to the oil price-macroeconomy relationship. *Journal of Monetary Economics* 38(2): 215–220. http://dx.doi.org/10.1016/S0304-3932(96)01282-2.

Hamilton, J. D. (2009). Understanding crude oil prices. The *The Energy Journal* 30(2): 179–206. http://dx.doi.org/10.5547/ISSN0195-6574-EJ-Vol30-No2-9.

Hamilton, J. D. and J. C. Wu (2014). Risk premia in crude oil futures prices. *Journal of International Money and Finance* 42, 9–37. http://dx.doi.org/10.1016/j.jimonfin.2013.08.003.

Hammoudeh, S., H. Li, and B. Jeon (2003). Causality and volatility spillovers among petroleum prices of WTI, gasoline and heating oil in different locations. *The North American Journal of Economics and Finance* 14(1): 89–114. http://dx.doi.org/10.1016/S1062-9408(02)00112-2.

Henderson, B., N. Pearson, and L. Wang (2013). New evidence on the financialization of commodity markets. *SSRN eLibrary*.

Huppmann, D. and F. Holz (2012). Crude oil market power a shift in recent years? The *The Energy Journal* 33(4): 1–22. http://dx.doi.org/10.5547/01956574.33.4.1.

(IEA) International Energy Agency (2013). Medium Term Oil Market Report-2013, London, May 14, 2013. http://www.iea.org/newsroomandevents/pressreleases/2013/may/name, 8080, en.html.

Inglesby, T., R. Jenks, S. Nyquist, and D. Pinner (2012). *Shale gas and tight oil: Framing the opportunities and risks*. McKinsey, New York City.

Kilian, L. (2008). Exogenous oil supply shocks: How big are they and how much do they matter for the U.S. economy? *The Review of Economics and Statistics* 90(2): 216–240. http://dx.doi.org/10.1162/rest.90.2.216.

Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *The American Economic Review* 99(3): 1053–1069. http://dx.doi.org/10.1257/aer.99.3.1053.

Kilian, L. and C. Vega (2011). Do energy prices respond to US macroeconomic news? A test of the hypothesis of predetermined energy prices. *Review of Economics and Statistics* 93(2): 660–671. http://dx.doi.org/10.1162/REST_a_00086.

Klößner, S. and S. Wagner (2014). Exploring all VAR orderings for calculating spillovers? Yes, we can! A note on Diebold and Yilmaz (2009). *Journal of Applied Econometrics* 29(1): 172–179. http://dx.doi.org/10.1002/jae.2366.

Koop, G., M. H. Pesaran, and S. M. Potter (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics* 74(1): 119–147. http://dx.doi.org/10.1016/0304-4076(95)01753-4.

Lin, S. X. and M. N. Tamvakis (2001). Spillover effects in energy futures markets. *Energy Economics* 23(1): 43–56. http://dx.doi.org/10.1016/S0140-9883(00)00051-7.

Lombardi, M. J. and I. Van Robays (2011). Do financial investors destabilize the oil price? European Central Bank, Working Paper No.1346.

Malik, F. and S. Hammoudeh (2007). Shock and volatility transmission in the oil, us and gulf equity markets. *International Review of Economics & Finance* 16(3): 357–368. http://dx.doi.org/10.1016/j.iref.2005.05.005.

Mason, N. A. W. and F. Charles (2013). Jump processes in the market for crude oil. The *The Energy Journal* 34(1): 33–48.

Maugeri, L. (2013). *The shale oil boom: a U.S. phenomenon*. Harvard Kennedy School.

Mensi, W., M. Beljid, A. Boubaker, and S. Managi (2013). Correlations and volatility spillovers across commodity and stock markets: Linking energies, food, and gold. *Economic Modelling* 32, 15–22. http://dx.doi.org/10.1016/j.econmod.2013.01.023.

Miller, B. A., J. M. Paneitz, S. Yakeley, K. A. Evans, et al. (2008). Unlocking tight oil: Selective multistage fracturing in the bakken shale. In *SPE Annual Technical Conference and Exhibition*. Society of Petroleum Engineers. http://dx.doi.org/10.2118/116105-MS

Nazlioglu, S., C. Erdem, and U. Soytas (2013). Volatility spillover between oil and agricultural commodity markets. *Energy Economics* 36, 658–665. http://dx.doi.org/10.1016/j.eneco.2012.11.009.

Patton, A. J. and K. Sheppard (2014). Good volatility, bad volatility: Signed jumps and the persistence of volatility. *Review of Economics and Statistics* (forthcoming).

Pesaran, H. H. and Y. Shin (1998). Generalized impulse response analysis in linear multivariate models. *Economics letters* 58(1): 17–29. http://dx.doi.org/10.1016/S0165-1765(97)00214-0.

Ramos, S. B. and H. Veiga (2013). Oil price asymmetric effects: Answering the puzzle in international stock markets. *Energy Economics* 38, 136–145. http://dx.doi.org/10.1016/j.eneco.2013.03.011.

Reinhart, C. M. and K. S. Rogoff (2008). Is the 2007 US sub-prime financial crisis so different? An international historical comparison. *American Economic Review* 98(2): 339–344. http://dx.doi.org/10.3386/w13761.

Sari, R., U. Soytas, and E. Hacihasanoglu (2011). Do global risk perceptions influence world oil prices? *Energy Economics* 33(3): 515–524. http://dx.doi.org/10.1016/j.eneco.2010.12.006.

Singleton, K. J. (2013). Investor flows and the 2008 boom/bust in oil prices. *Management Science* 60(2): 300–318. http://dx.doi.org/10.1287/mnsc.2013.1756.

Tang, K. and W. Xiong (2012). Index investment and financialization of commodities. *Financial Analysts Journal* 68(5): 54–74. http://dx.doi.org/10.2469/faj.v68.n6.5.

Vácha, L. and J. Baruník (2012). Co-movement of energy commodities revisited: Evidence from wavelet coherence analysis. *Energy Economics* 34(1): 241–247. http://dx.doi.org/10.1016/j.eneco.2011.10.007.

Vivian, A. and M. E. Wohar (2012). Commodity volatility breaks. *Journal of International Financial Markets, Institutions and Money* 22(2): 395–422. http://dx.doi.org/10.1016/j.intfin.2011.12.003.

Zeileis, A., C. Kleiber, W. Kramer, and K. Hornik (2003). Testing and dating of structural changes in practice. *Computational Statistics & Data Analysis* 44(1): 109–123. http://dx.doi.org/10.1016/S0167-9473(03)00030-6.

Zhang, X., L. Yu, S. Wang, and K. K. Lai (2009). Estimating the impact of extreme events on crude oil price: An emd-based event analysis method. *Energy Economics* 31(5): 768–778. http://dx.doi.org/10.1016/j.eneco.2009.04.003.