The effects of oil price shocks on stock market volatility: Evidence from European data

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Abstract

The paper investigates the effects of oil price shocks on stock market volatility in Europe by focusing on three measures of volatility, i.e. the conditional, the realised and the implied volatility. The findings suggest that supply-side shocks and oil specific demand shocks do not affect volatility, whereas, oil price changes due to aggregate demand shocks lead to a reduction in stock market volatility. More specifically, the aggregate demand oil price shocks have a significant explanatory power on both current- and forward-looking volatilities. The results are qualitatively similar for the aggregate stock market volatility and the industrial sectors' volatilities. Finally, a robustness exercise using short- and long-run volatility models supports the findings.

JEL: C13, C32, G10, G15, Q40

Keywords: Conditional Volatility, Realised Volatility, Implied Volatility, Oil Price Shocks, SVAR

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1. Introduction and brief review of the literature

There is a consensus among academics and practitioners that oil and stock markets are often intertwined with the global economic activity. Ascertaining exact nature and sources of the linkage between oil and stock markets and the global economic activity has proved to be a promising area for researchers over the last few decades. The research interest mainly concentrates either on the impact of oil prices on stock market developments or the effects of oil prices on the economy. Adding to this literature, the main objective of the paper is to research into the effects of three oil price shocks (namely, supply side shocks, aggregate demand shocks and oil specific demand shocks) on stock market volatility, with particular reference in the European stock market.

The seminal paper by Jones and Kaul (1996) was among the first to reveal a negative relationship between the oil prices and stock market returns. In addition, Sadorsky (1999) concludes that oil price changes are important determinants of stock market returns. In particular, he shows that stock markets respond negatively to a positive oil price change. Filis (2010), Chen (2009), Miller and Ratti (2009), Park and Ratti (2008), Driesprong *et al.* (2008) and Gjerde and Sættem (1999) second these findings by Sadorsky (1999) and Jones and Kaul (1996).

The aforementioned negative relationship does not hold for stock markets operating in oil-exporting countries. Arouri and Rault (2011) show that for the oil-exporting countries there is a positive relationship between oil price shocks and stock market returns. Other authors, though, do not find any relationship between oil price shocks and stock market returns (Jammazi and Aloui, 2010; Cong *et al.*, 2008; Haung *et al.*, 1996). Filis *et al.* (2011) provide an extensive review of the literature in the particular area.

Studies particularly focused on the European stock markets reveal that positive oil price changes tend to negatively affect stock returns; nevertheless, the exact relationship depends on the sector. In particular, oil-related stock market sectors tend to appreciate in the event of a positive oil price change, whereas the reverse holds for oil-intensive sectors (see, for example, Scholtens and Yurtsever, 2012; Arouri, 2011; Arouri and Nguyen, 2010).

Furthermore, a strand of the literature distinguishes the effects of oil price shocks on stock market activity according to their origin. Hamilton (2009a,b) and Kilian (2007a,b), in particular, suggest that different shocks in the oil market have different effects on stock markets. Kilian (2009) provide evidence that the response of aggregate stock returns differs depending on the cause of the oil price shock. Hamilton (2009a,b) disaggregates oil price shocks into two components, namely, the demand-side oil price shocks (which are caused by increased aggregate demand, e.g. due to the industrialisation of China) and supply-side oil prices shocks (which are caused by alteration in the world oil production). In addition, Kilian (2009) identifies a third origin, the precautionary demand shocks or oil specific demand shocks. These are oil price shocks that are related with the uncertainty of the future availability of oil.

Baumeister and Peersman (2012), Basher *et al.* (2012), Kilian and Lewis (2011), Filis *et al.* (2011), Lippi and Nobili (2009), Kilian and Park (2009), Apergis and Miller (2009), Lescaroux and Mignon (2008), Kilian (2008) and Barsky and Kilian (2004) also illustrate the importance of taking into consideration the origins of the oil price shock in this area of interest. For example, Hamilton (2009a,b) maintain that oil price shocks are mainly demand driven in the last decades and thus supply-side events do not exercise significant effects in oil prices. A similar picture is painted by Baumeister and Peersman (2009). Lippi and Nobili (2009) proponent that supply-side oil price shocks have a negative effect in the economy, whereas the opposite is observed for the demand-side oil price shocks. In addition, Kilian and Park (2009) demonstrate that the supply-side oil price shocks do not have any effects on stock market returns, whereas stock markets tend to react negatively to oil specific demand shocks. On the other hand, they find that aggregate demand oil price shocks trigger a positive response from the stock markets. In the same line of reasoning, Filis et al. (2011) find evidence that the supply-side shocks do not seem to impact stock market returns, whereas the reverse holds for the demand-side shocks. Similarly, Basher *et al.* (2012) show that supply-side oil price shocks do not exercise an impact on the emerging stock market returns, whereas the aggregate demand oil price shocks seem to have a positive effect. Finally, they find evidence that the oil specific demand shocks put downward pressure on stock returns.

Despite the fact that evidence proposes that the origin of the oil price shock triggers different responses from the stock markets, the majority of the literature does not consider them when examines its effects (see, *inter alia*, Arouri and Rault, 2011; Arouri and Khuong, 2010; Bjornland, 2009; Chen, 2009; Park and Ratti, 2008).

As aforementioned, the aim of this paper is to direct the attention of the research on the effects of the oil price shocks on stock market volatility. Studies in the early 80s and 90s (see, for example, Pindyck, 1991 and Bernanke, 1983, among others) reveal that increased energy prices generate uncertainty to firms, resulting in the delay of investment decisions. Furthermore, some authors opine that oil price innovations exercise an impact on aggregate uncertainty and they have significant negative effects on investments (see, *inter alia*, Ratti et al., 2011; Rahman and Serletis, 2011; Elder and Serletis, 2010). In addition, Bloom (2009) documents that stock market uncertainty increases after major shocks, such as the 2001 terrorist attack in US, OPEC oil supply disruptions, etc. Nevertheless, these studies have not considered the origins of the oil price shocks. We argue, though, that Bloom's choice of major shocks coincides with events that trigger certain oil price shocks, as these have been identified by Hamilton (2009a,b) and Kilian (2009, 2007a,b). For example, the 2001 terrorist attack in US triggered an oil specific demand shock, whereas OPEC oil supply disruptions cause supply-side oil price shocks. Thus, disentangling oil price shocks is of importance in understanding better stock market uncertainty.

In addition, the literature has well established that the aforementioned firm's uncertainty and aggregate uncertainty can be represented by individual stock price volatility and stock market volatility, respectively (see, for example, Baum *et al.*, 2010 and Bloom, 2009).

Even though the characteristics of stock market volatility have been studied extensively in the past[1] , the literature remains silent on the effects of the different oil price shocks on stock market volatility. Rather, a plethora of research output centres its attention solely on spillover effects between the oil price volatility and stock market returns and volatility or the relationship between oil price volatility and firm investments[2]. This paper comes to fill this void.

More specifically, the contribution of the paper is threefold. First, it contributes to the literature that studies the effects of three different oil price shocks – oil supply shock, aggregate demand shock and oil specific demand shock[3] – on the stock market. Unlike previous studies that examine the response of stock returns on oil price shocks, we investigate the response of stock market volatility, as a measure of uncertainty of stock market investments, using a Structural VAR model. Second, we provide evidence from both aggregate stock market indices and industrial sector indices, as according to Arouri *et al.* (2012, p.2) "*the use of equity sector indices is, in our opinions, advantageous because market aggregation may ask the characteristics of various sectors*". Third, in contrast to studies that mainly focus on the responses of stock market returns in individual countries in Europe or in the US (Arouri 2011, Arouri and Nguyen 2010, and Scholtens and Yurtsever 2012 are notable exceptions), emphasis of this research is placed on the pan-European stock market.

[1] See, among others, Xekalaki and Degiannakis (2010), Becker *et al.* (2007), Andersen *et al.* (2005), Andersen *et al*. (2001) and Bollerslev *et al*. (1992).
[2] See, *inter alia*, Arouri *et al.* (2012), Henriques and Sadorsky (2011), Sadorsky (2011), Arouri *et al.* (2011), Vo (2011), Malik and Ewing (2009), Chiou and Lee (2009).
[3] Definitions of these shocks can be found in Kilian and Park (2009).

In light of empirical evidence that underlines the relative importance of the demand-driven oil price shocks, we expect stock market volatility in Europe to be more sensitive to the aggregate demand shock and the oil specific demand shock than to the supply-side shock.

Three volatility measures are utilised; conditional volatility, realised volatility and implied volatility. The use of three different volatility estimates is motivated by the fact that part of the literature illustrates that implied volatility (a forward-looking measure) is more informational efficient compared to other volatility estimates, which represent the current-looking measures of volatility[4]. Thus, it is important to identify any differences in their responses to oil price shocks. Koopman *et al.* (2005) propose that both implied volatility and realised volatility are informationally accurate. Conversely, authors such as Becker *et al.* (2007) and Corrado and Truong (2007) suggest that implied volatility indices do not provide any incremental information compared to other volatility indices. Engle (2002), though, argues that there is not a simple answer as to which volatility measure is the most accurate, as it depends upon the statistical approach adopted for the evaluation of forecasts.

We provide evidence that supply-side shocks and oil specific demand shocks do not affect stock market volatility, whereas, oil price changes due to aggregate demand shocks lead to a reduction in stock market volatility. The results hold for the industrial sectors' volatilities, as well. Prominent among our results is the finding that oil price shocks have a qualitatively similar impact for both the current-looking volatility measures and the implied volatility, which is a forward-looking measure.

The rest of the paper is organised as follows: Section 2 presents the volatility measures and the model used, Section 3 describes the dataset, Section 4 presents the empirical findings of the research and Section 5 concludes the study.

2. Methodology

In the next section three measures of volatility are defined, i.e. conditional volatility, realised volatility and implied volatility, whereas in section 2.2 the Structural VAR model is presented.

2.1. Volatility estimates

According to the literature there are three main frameworks for measuring volatility. The first two correspond to the current market volatility measures, whereas the third is a

[4] See for example Blair et al. (2001), Christensen and Prabhala (1998), Fleming (1998) and Day and Lewis (1992).

forward-looking measure of volatility. In this paper we examine all these three volatility estimates.

The *conditional volatility* is the conditional standard deviation of the asset returns given the most recently available information. The conditional variance process of y_t can be defined as $V(y_t \mid I_{t-1}) \equiv V_{t-1}(y_t) \equiv \sigma_t^2$, for I_{t-1} denoting the information set investors know when they make their investment decisions at time $t-1$.

The *realised volatility* is based on the idea of using high frequency data to compute measures of volatility at a lower frequency, i.e. using hourly log-returns to generate a measure of daily volatility. By the term monthly realized volatility we denote the daily estimate of monthly variance.

Implied volatility is the instantaneous standard deviation of the return on the underlying asset, which would have to be input into a theoretical pricing model in order to yield a theoretical value identical to the price of the option in the marketplace, assuming all other inputs are known.

2.1.1. Conditional Volatility

The conditional variance of the daily log-returns process, y_t, is estimated with Ding's *et al*. (1993) APARCH model. The APARCH model has an appealing feature that it allows nesting tests of different types of asymmetry and functional forms (Hentschel, 1995). For instance, Laurent (2004) argues that the APARCH model nests at least seven GARCH specifications. The asymmetric power ARCH, or APARCH model is estimated assuming that the demeaned daily log-returns are conditionally Student-t distributed[5]:

$$
\begin{gathered}
y_t = c_0 + \varepsilon_t \\
\varepsilon_t = \sigma_t z_t \\
\sigma_t^{\delta} = a_0 + a_1\left(\left|\varepsilon_{t-1}\right| - \gamma_1 \varepsilon_{t-1}\right)^{\delta} + b_1 \sigma_{t-1}^{\delta} \\
z_t \overset{i.i.d.}{\sim} T(0,1;\nu) \\
f_{(t)}(z_t;\nu) = \frac{\Gamma((\nu+1)/2)}{\Gamma(\nu/2)\sqrt{\pi(\nu-2)}}\left(1+\frac{z_t^2}{\nu-2}\right)^{-\frac{\nu+1}{2}},
\end{gathered}
\tag{1}
$$

where $a_0 > 0$, $\delta > 0$, $b_1 \geq 0$, $a_1 \geq 0$ and $-1 < \gamma_1 < 1$, $\nu > 2$.

[5] The incorporation of a first-order autoregressive term, AR(1), in the conditional mean, provides qualitative similar results.

The APARCH model with Student-t distributed standardized innovations accounts for i) volatility clustering, ii) power transformation of the conditional variance, iii) asymmetric and leptokurtic unconditional distribution of log-returns, and iv) asymmetric conditional distribution of log-returns. Therefore, it is considered as of the most successfully applied model in estimating conditional volatility. For technical details, the reader is referred to Xekalaki and Degiannakis (2010).

The monthly conditional volatility is computed by summing the τ daily conditional variance. Therefore, the annualized conditional volatility of month t, or $CV_t^{(m)}$, is computed as the square root of the sum of the conditional variances from the 16th of the previous month up to and including the 15th of the current month[6]:

$$CV_t^{(m)} = 100\sqrt{12\sum_{j=1}^{\tau}\sigma_{t_j}^2}\,, \tag{2}$$

where $\sigma_{t_j}^2$ denotes the daily conditional variance for the $j = 1,...,\tau$ trading days of month t.

2.1.2. Realised Volatility

Merton (1980) was the first who noted the idea of using high frequency data to compute measures of volatility at a lower frequency. The concept of the realised volatility is based on the integrated volatility, $\sigma_{[a,b]}^{2(IV)} = \int_a^b \sigma^2(t)dt$. Financial literature assumes that the instantaneous logarithmic price, $\log p(t)$, of a financial asset follows a diffusion process, $d\log p(t) = \sigma(t)dW(t)$, where $\sigma(t)$ is the volatility of the instantaneous log-returns process and $W(t)$ is the standard Wiener process. Theory of quadratic variation of semi-martingales provides consistent estimate of integrated volatility by the realised variance, $RV_{[a,b]} = \sum_{j=1}^{\tau}\left(\log P_{t_j} - \log P_{t_{j-1}}\right)^2$, assuming that the time interval $[a,b]$ is partitioned in τ equidistance points in time; see Andersen *et al*. (2003) and Barndorff-Nielsen and Shephard (2002).

For present study's purposes we measure the monthly realised volatility, partitioning the monthly time interval in daily equidistance points in time, for τ denoting the number of trading days. Therefore, the annualized realised volatility of month t, or $RV_t^{(m)}$, is computed

[6] The use of the daily observations from the 16th of the previous month up to the 15th of the current month is justified by the availability of the monthly data on the 15th of each month.

as the square root of the sum of the squared daily log-returns from the 16th of the previous month up to the 15th of the current month:

$$RV_t^{(m)} = 100\sqrt{12\sum_{j=1}^{\tau}\left(\log P_{t_j} - \log P_{t_{j-1}}\right)^2} \; . \qquad (3)$$

We estimate monthly volatility by summing up daily volatility. However, this measure would be biased by the number of trading days in the month. That is, volatility in the month with more trading days would be greater than volatility in any other month, even the volatility does not change. In order to check the robustness of the results, we also estimate $RV_t^{(m)}$ by scaling each month's volatility with $\sqrt{22/\tau}$, assuming equal number of trading days for each month. The results remain qualitatively similar.

2.1.3. Implied volatility index - VSTOXX

Studies, see i.e. Blair *et al*. (2001), characterize implied volatility measures are less informative than volatility estimated from asset returns, because they induce biases and contain mis-specification problems. In 1993, the Chicago Board of Options Exchange published the first implied volatility index. The computation of implied volatility indices takes into account the latest advances in financial theory, eliminating measurement errors that had characterized the implied volatility measures.

Market participants consider the implied volatility index as an important tool for measuring investors' sentiment. Investors and risk managers refer to volatility indices as *fear index* or *investor fear gauge*. The VSTOXX Volatility Index (which is the volatility index for the Eurostoxx 50 Index, also named as EURO STOXX 50 Volatility Index) measures the implied variance across all options of a given time to expiry. The main index is designed as a rolling index at a fixed 30 days to expiry. This is achieved using linear interpolation of the two nearest of the eight available sub-indices. The index is calculated based on eight expiry months with a maximum time to expiry of two years.

The annualized implied volatility of month t, or $VSTOXX_t^{(m)}$, is computed as the average of the daily $VSTOXX_{t_j}$ from the 16th of the previous month up to the 15th of the current month:

$$VSTOXX_t^{(m)} = \sqrt{\tau}^{\,-1}\sqrt{\sum_{j=1}^{\tau} VSTOXX_{t_j}^2} \; , \qquad (4)$$

where $VSTOXX_{t_j}$ denotes the daily implied volatility for the $j=1,...,\tau$ trading days of month t. VSTOXX index is based on option prices and it is constructed by STOXX limited[7].

2.2. Structural VAR model

Using a Structural VAR framework, we examine the effects of three oil prices shocks on stock market volatility (VOL). Namely, the oil price shocks are the supply-side shocks, aggregate demand shocks and oil specific demand shocks, as these are identified from changes in world oil production (PROD), global economic activity (GEA) and changes in oil prices (OP), respectively. VOL is the generic name of the volatility series. For each SVAR model the volatility variable will be named after the method of estimation (i.e. conditional, realised or implied volatility) and the name of the index (either aggregate or industrial)[8].

The structural representation of the VAR model of order *p* takes the following general form:

$$\mathbf{A}_0\mathbf{y}_t = \mathbf{c}_0 + \sum_{i=1}^{p}\mathbf{A}_i\mathbf{y}_{t-i} + \boldsymbol{\varepsilon}_t \tag{5}$$

where, $\mathbf{y}_t$ is a [4×1] vector of endogenous variables, i.e. $\mathbf{y}_t = [PROD_t, GEA_t, OP_t, VOL_t]$, $\mathbf{A}_0$ represents the [4x4] contemporaneous matrix, $\mathbf{A}_i$ are [4x4] autoregressive coefficient matrices, $\boldsymbol{\varepsilon}_t$ is a [4×1] vector of structural disturbances, assumed to have zero covariance and be serially uncorrelated. The covariance matrix of the structural disturbances takes the following form $E[\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t'] = \mathbf{D} = [\sigma_1^2\ \sigma_2^2\ \sigma_3^2\ \sigma_4^2] \times \mathbf{I}$. In order to get the reduce form of our structural model (1) we multiply both sides with $\mathbf{A}_0^{-1}$, such as that:

$$\mathbf{y}_t = \mathbf{a}_0 + \sum_{i=1}^{p}\mathbf{B}_i\mathbf{y}_{t-i} + \mathbf{e}_t \tag{6}$$

where, $\mathbf{a}_0 = \mathbf{A}_0^{-1}\mathbf{c}_0$, $\mathbf{B}_i = \mathbf{A}_0^{-1}\mathbf{A}_i$, and $\mathbf{e}_t = \mathbf{A}_0^{-1}\boldsymbol{\varepsilon}_t$, i.e. $\boldsymbol{\varepsilon}_t = \mathbf{A}_0\mathbf{e}_t$. The reduced form errors $\mathbf{e}_t$ are linear combinations of the structural errors $\boldsymbol{\varepsilon}_t$, with a covariance matrix of the form $E[\mathbf{e}_t\mathbf{e}_t'] = \mathbf{A}_0^{-1}\mathbf{D}\mathbf{A}_0^{-1'}$.

The structural disturbances can be derived by imposing suitable restrictions on $\mathbf{A}_0$. The following short-run restrictions are imposed in the model:

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[7] The interested reader can find all the necessary information about volatility index in the following link: http://www.stoxx.com/indices/index_information.html?symbol=V2TX.

[8] For example the realised volatility of the industrial sector will be named RV_INDUSTRIAL.

$$\begin{bmatrix} \varepsilon_{1,t}^{SS} \\ \varepsilon_{2,t}^{ADS} \\ \varepsilon_{3,t}^{OSS} \\ \varepsilon_{4,t}^{VS} \end{bmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \times \begin{bmatrix} e_{1,t}^{PROD} \\ e_{2,t}^{GEA} \\ e_{3,t}^{OP} \\ e_{4,t}^{VOL} \end{bmatrix}$$

where, SS=supply-side shocks, ADS=aggregate demand shock, OSS=oil specific demand shock and VS=volatility shock.

The restrictions in the model are explained as follows. The oil production is not responding contemporaneously to an increase/decrease of oil demand, caused by higher/lower economic activity, due to the adjustment costs of oil production. However, oil supply disruption (supply-side shock) can influence the global economic activity, the price of oil and the stock market volatility, within the same month. The global economic activity is not contemporaneously influenced by oil prices due to the time that is required for the world economy to react. On the contrary, an aggregate demand shock will have an immediate impact on oil prices and stock market volatility, considering the reaction time of the commodities and financial markets. Turning to the oil price innovation, any increase in the price can be driven by supply-side event, aggregate demand-side events, as well as, oil specific demand events. Thus, oil production shocks, as well as, aggregate demand shocks can contemporaneously trigger responses from the oil prices. In highly liquid markets as the European market, the stock market volatility reacts contemporaneously to all aforementioned oil price shocks.

To proceed to the estimation of the reduced form of model (1), it is first necessary to establish the stationarity of the variables. The ADF and PP unit root tests suggest that all variables are I(0). The lag length of the VAR model was identified using the Akaike Information Criterion (AIC). The AIC selects a VAR model with four lags[9].

3. Data description

In order to estimate the volatility figures we use daily data from January 1999 to December 2010 on aggregate European stock market indices. In particular, the stock market index used is Eurostoxx 50, which is Europe's leading blue chips stock market index and the data have been extracted from *Datastream*®. In addition, we consider the following industrial sectors indices, which have been constructed by *Dow Jones*: *Financials, Oil&Gas, Retail,*

[9] Results are available upon request. The SVAR models do not suffer from autocorrelation and no inverse roots of the characteristic polynomial lie outside the unit circle. Thus, we conclude that the SVAR models satisfy the stability condition.

Consumption Goods, Health, Industrial, Basic Materials, Technology, Telecommunications and *Utilities*. The industrial sector indices data have been extracted from *Datastream*®. For consistency purposes we have also considered the pan-European stock market index constructed by *Dow Jones*. As mentioned in section 2.1 once the daily volatility figures have been estimated, we then convert them into monthly figures.

Furthermore, we use monthly data for the same time period for oil production, oil prices and global economic activity. Brent crude oil is chosen, as a proxy of world oil price, due to the fact that this type of oil represents the 60% of the world oil daily consumption (Maghyereh, 2004). We use oil production data, as a proxy for oil supply. Both Brent crude oil price and oil production data have been extracted from the Energy Information Administration. Finally, we adopt Kilian's (2009) measurement of the global economic activity based on dry cargo freight rates[10]. Prices are expressed in dollar terms and are transformed in log-returns.

Figure 1 presents the volatility measures for the Eurostoxx50 index (realised volatility-RV_STOXX50, conditional volatility-CV_STOXX50 and implied volatility-VSTOXX), the growth rate of the world oil production, the global economic activity and the oil price returns[11].

[FIGURE 1 HERE]

It is immediately apparent that volatility (in all three expressions) reaches a peak near the end of 2008 and again in May 2010. These periods coincide with the world financial crisis and the Greek debt crisis, respectively. Similar patterns are observed in the volatility measures of the pan-European stock market index by Dow Jones and of all industrial sectors' indices (not presented visually here, though). During 2008, we also observe a trough in the global economic activity and extreme negative returns for the oil prices. This period has been also characterised by demand driven oil price shocks. These preliminary findings may suggest that stock market volatility responds heavily to demand driven oil price shocks. Nevertheless, the impulse responses from the SVAR model will provide us with a clearer picture.

Furthermore, Table 1 presents some descriptive statistics for the volatility measures of the Eurostoxx 50 index and the three oil variables. The mean values of the realised volatility and conditional volatility are very close, whereas the VSTOXX mean value is higher. In

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[10] The data can be found in Lutz Kilian personal website (http://www-personal.umich.edu/~lkilian/)

[11] The volatility graphs for the pan-European stock market index and the industrial sectors indices are available upon request.

addition, all volatility measures exhibit a significant variation over time which is evident by the minimum, maximum and standard deviation statistics. Naturally, the volatility measures are positively skewed and leptokurtic.

[TABLE 1 HERE]

As far as the oil variables are concerned, the global economic activity is the most volatile one, followed by the oil price returns. Both variables are positively skewed, whereas the oil production growth rates are negatively skewed. The skewness measures suggest that there are more negative oil log-returns and changes in the global economic activity, whereas the oil production exhibits more positive returns.

4. Estimation results

The purpose of the SVAR model is to examine the dynamic adjustments of each of the variables to exogenous stochastic structural shocks (see, *inter alia*, Bjornland and Leitemo, 2009; Kilian and Park, 2009). Thus, next we present the SVAR model findings for the volatility indices of the Eurostoxx50 and the industrial sectors in terms of the impulse response functions (IRF) and the variance decomposition[12].

Section 4.1 describes the estimation results based on current-looking measures of stock market volatility (conditional and realised volatilities). The results on the aggregate stock market and industrial sector indices are summarised in Sections 4.1.1 and 4.1.2, respectively. Section 4.2 describes the estimation results based on the forward-looking measure of stock market volatility (implied volatility).

4.1. Current-looking volatility measures

4.1.1. Aggregate European stock market indices

The impulse responses (Figure 2) depict that the reaction of the volatility measures of the Eurostoxx50 index on the three oil shocks differ quite substantially.

[FIGURE 2 HERE]

Changes in world oil production do not exercise any significant impact on stock market volatility. The argument that the OPEC's decisions on oil production levels do not impact stock markets nowadays, finds support here. Thus, this finding does not come with a surprise. Furthermore, the fact that stock market volatility is not reacting to supply-side oil prices shocks complements the evidence provided by Basher *et al.* (2012), Filis *et al.* (2011)

[12] The SVAR results for the pan-European stock market index constructed by *Dow Jones*® are qualitatively similar and thus they are not presented here. They are available upon request.

and Kilian and Park (2009), who argue that changes in oil production do not affect stock price returns. Similar observation can be made for the oil specific demand shock, as its effect is not significant on any volatility measure. A plausible explanation of this result lies in the nature of firms' responses to oil price changes. We argue that firms, nowadays, engage in effective hedging strategies which reduce the effects of adverse oil price movements (Arouri, 2011), mainly caused by idiosyncratic oil price shocks (or oil specific demand shocks). On the contrary, increases in world's aggregate demand, which implies increased economic activity, tend to reduce stock market volatility, as expected. A positive aggregate demand shock can be regarded as good news to the stock market. In the event of a positive aggregate demand shock, uncertainty about future cash flows decreases, driving down stock market volatility. One can also argue positive news about global economic activity is associated with a more stable business environment, which, in turn, reduces the uncertainty in the market. From an opposite angle, Bloom (2009) has shown that negative news about the global economic activity, such as those during the Asian crisis in 1997 and the credit crunch in 2008, tend to increase stock market volatility. In general, stock markets tend to respond favourably when the world economic developments are positive. The preliminary findings had already provided with an initial idea about the inverse link between aggregate demand oil price shocks and stock market volatility. Overall, the response is significant for about 6 months and dynamic convergence is achieved after 12 months after the shock, for both volatility measures.

In regard with the variance decomposition (Table 2), we observe that the effects of the supply-side and oil specific demand shocks are very small and it further suggests that these shocks do not exercise an impact on stock market volatility. Furthermore, the effects of the aggregate demand shocks are small in the short-run; however their explanatory power exhibits an increasing pattern as the forecasting window increases. This is suggestive of the fact that the aggregate demand shocks have a very important role in the European stock market volatility.

[TABLE 2 HERE]

In more detail, about 9%-18% (depending on the volatility measure) of the variation in the volatility of the Eurostoxx50 index is associated with the oil price shocks, during the first few months. In a period of 24 months a total of 24%-38% of the variability of the volatility is explained by the oil price shocks. The main contributor to this variability is the aggregate demand oil price shock in both volatility measures. Linking these findings with the evidence on stock market returns (see, for example, Kilian and Park, 2009; Hamilton, 2009a,b) it is suggested that supply-side shocks do not seem to influence any of the stock markets characteristics (i.e. returns and volatilities), whereas demand-side shocks – and in particular the aggregate demand oil price shocks – do.

Overall, the results suggest that increases in oil prices due to increased global economic activity (aggregate demand shock) reduce stock market volatility, as positive development is the global economic activity is regarded as positive information by the stock markets.

4.1.2. European industrial sectors

Having analysed the effects of the three oil shocks on the aggregate stock market volatility, we proceed to the analysis of these effects on the industrial sectors[13].

The impulse responses (Figure 3 and 4) suggest that the reaction of the volatility measures of the industrial sectors on the three oil shocks is similar to these of the Eurostoxx50 volatility measures. More specifically, the aggregate demand shock is exercising a significant negative effect on industrial sectors' volatility (the same result holds for both the realised volatility and the conditional volatility). The supply-side oil price shocks and the oil specific demand shocks do not seem to influence any of the sectors' realised or conditional volatilities.

[FIGURE 3 HERE]

[FIGURE 4 HERE]

The only exemption is the *Oil&Gas* sector. Both the realised and conditional volatility of the *Oil&Gas* sector respond negatively to the two demand-side shocks (i.e. aggregate demand shock and oil specific demand shock). This finding is expected since any increase in oil price is received as positive news for the companies listed in the *Oil&Gas* sector. The effects remain significant for about 3-4 months and they are fully absorbed after 8 to10 months. It could be argued that supply-side shocks should also benefit the *Oil&Gas* sector; nevertheless, we cannot find such evidence in this study.

Overall, the findings suggest that disruptions or increases in world oil production do not provide any information for the volatility of any sector, even the *Oil&Gas* one. The opposite holds for the aggregate demand oil price shocks.

The variance decomposition analysis (Table 3 and 4) illustrates that the three oil price shocks exercise the highest influence on the RV_OIL&GAS and CV_OIL&GAS (about

[13] The descriptive statistics and figures of the industrial sectors' volatility measures are available upon request.

53%), as expected, and it is followed by the RV_CONSUMPTION and CV_CONSUMPTION (about 40%). The latter is expected to be influenced heavily from the oil price shocks considering that Europe is mainly an oil importing region. Regarding the remaining industrial indices, the three oil price shocks explain about 10%-20% of the variability of their volatility. The lowest influenced is observed in the realised and conditional volatility of the *Financials* sector (about 10%), suggesting that the *Financials* sector's volatility is mainly influenced by other variables, rather than the oil price shocks. The main contributor of this influence, in all cases, is the aggregate demand shock, a similar finding with the aggregate European stock market volatility.

[TABLE 3 HERE]

[TABLE 4 HERE]

4.2. Forward-looking volatility measure

The impulse responses (Figure 5) of the Eurostoxx50 implied volatility (VSTOXX) measure is essential the same with those produced by the conditional and realised volatilities.

[FIGURE 5 HERE]

Again, both supply-side oil price shocks and oil specific demand shocks do not exercise any significant impact on implied volatility, whereas positive aggregate demand oil price shocks trigger a negative response.

In terms of the variance decomposition (Table 5), we observe that the explanatory power of the three oil price shocks on implied volatility exhibits a peak in the medium-term and starts to decline thereafter until it reaches a stable level after 24 months.

[TABLE 5 HERE]

More specifically, in the first month about 9% of the variation in the implied volatility is associated with the oil price shocks, whereas in a period of 6-12 months this figure increases to an average of 22%. The main contributor to this variability is the aggregate demand oil price shock, as also suggested by the conditional and realised volatilities.

Comparing the results among the three volatility measures, we observe that these measures provide qualitatively and quantitatively similar information. Hence, the implied volatility index (a forward-looking volatility measure) does not provide additional information compared to the conditional and realised volatility measures, which estimate the market volatility at the current time. This is a very interesting finding considering that several aforementioned studies have concluded that implied volatility indices provide superior information (see Xekalaki and Degiannakis, 2010; Becker *et al.*, 2007; Andersen *et al.*, 2005; Andersen *et al*., 2001 and Bollerslev *et al*., 1992). Despite the fact that this result may come as a surprise, it does not remain without a possible explanation. It is worth noting that this result does not contradict the forward-looking feature of the implied volatility measure. The impulse responses of the current-looking volatility measures depict that the effects of the aggregate demand oil price shocks do not fade out immediately, but rather they require about 12 months to be fully absorbed. This means that the impact remains for the future months and this is what it is captured by the implied volatility response to the aggregate demand oil price shocks. The uncharacteristically prolonged response of the implied volatility is also artifact of its long memory, stemming from the estimate of (Equations 7 and 8 in Section 5).

5. Robustness checks

In order to test for the robustness of our results a battery of alternative approaches has been employed. More specifically, we estimate two volatility models (one with short memory and one with long memory) and we examine whether the aggregate demand oil price shock series has explanatory power on stock market volatility. The choice of the aggregate demand oil price shock series is justified by the fact that it was the only oil price shock that showed to have a significant effect on stock market volatility, based on the impulse response functions. Because stock market volatility is found invariant to the supply-side shock and the oil specific demand shock, we deliberately discard these two shocks from our robustness exercise.

First, we construct the aggregate demand oil price shock series (*ADS*). In order to achieve that we proceed to a historical decomposition of the effects of all three oil price shocks on the oil price returns.

The historical decomposition procedure can be summarised in three steps. In the first step, we estimate a structural VAR on changes in oil production, global economic activity and oil price returns, identifying the supply-side shock, the aggregate demand shock and the oil specific demand shock, respectively. In a second step, based on information up to and including the period t, we use the estimated VAR model to forecast the endogenous variables for periods $t+1$, $t+2$,..., $t+s$. In a third step, using the structural decomposition we decompose the forecast errors into the cumulative contributions of the structural shocks. For example, a $t+1$ vector of forecast errors, $\mathbf{e}_{t+1}$, can be decomposed as $\mathbf{e}_{t+1} = \sum_{i=1}^{3} \mathbf{e}_{t+1}^{(i)}$, where i

denotes the contribution of the *ith* structural shock to each element in the vector of forecast errors[14].

Thus, having decomposed the oil price returns series into the three components (i.e. the three oil price shocks), the *ADS* series will represent the cumulative effect of the aggregate demand shocks on oil price log-returns. The historical decomposition of the oil-price returns is depicted in Figure 6. The upper, middle and lower panel depicts the cumulative effect of the supply-side shock, aggregate demand shock and oil-specific demand shock on the oil price returns, respectively.

[FIGURE 6 HERE]

Next, we estimate a short-memory volatility model, which incorporates the ADS series as an explanatory variable. The model is as follows:

$$\sigma_t = \beta_0 + \beta_1 \sigma_{t-1} + \beta_2 ADS_t + u_t, \tag{7}$$

where, σ_t denotes the monthly volatility estimate (realised, conditional and implied), ADS_t is the monthly cumulative effect of the aggregate demand shock on oil price returns and $u_t \sim N\left(0, \sigma_u^2\right)$, is the error term.

The statistical significance of coefficient β_2 denotes that the ADS_t provides additional explanatory power than the lagged monthly volatility estimate. Naturally, the β_1 is expected to be statistically significant due to the high autocorrelation of volatility.

Furthermore, a fractionally integrated model that has also been considered in order to capture the long memory property of volatility. This is estimated as follows:

$$(1-L)^{\beta_1}\left(\sigma_t - \beta_0 - \beta_2 ADS_t\right) = u_t, \tag{8}$$

where the error term $u_t \sim N\left(0, \sigma_u^2\right)$, the fractional differencing operator $(1-L)^{\beta_1}$ is defined as $(1-L)^{\beta_1} = \sum_{j=0}^{\infty} \frac{\Gamma(j-\beta_1)}{\Gamma(j+1)\Gamma(-\beta_1)} L^j$, for $0 < \beta_1 < 1$, and $\Gamma(.)$ is the Gamma function. The statistical significance of coefficient β_2 suggests that ADS_t provides additional explanatory power compared to the long memory property of volatility (as expressed by the β_1 estimate).

[TABLE 6 HERE]

[TABLE 7 HERE]

The estimation results, summarised in Tables 6 and 7, indicate that the ADS exercises a negative and significant effect on stock market volatility. The results are qualitatively

[14] See Burbidge and Harrison (1985) for additional information on historical decomposition.

similar for the three volatility measures and for both the aggregate stock market and industrial sector indices. In particular, a positive aggregate demand shock causes a reduction in the stock market volatility, which confirms the findings of the SVAR model. The results are, thus, of particular importance as they could facilitate traders, investors, researchers or policy makers, should they need to forecast stock market volatility, price derivatives, manage risk and formulate regulation.

6. Concluding remarks

The study examines the effects of three oil prices shocks (i.e., supply-side shock, aggregate demand shock and oil specific demand shock) on stock market volatility using a Structural VAR framework. We consider two volatility measures, namely the conditional volatility and the realised volatility, which measure the current stock market volatility. We also examine the effects of oil price shocks on implied volatility, as well, which is a forward-looking volatility measure.

We conclude that supply-side and oil specific demand shocks do not affect volatility, whereas, aggregate demand shocks influence volatility at a significant level. This finding holds for both the current-looking volatility and the implied volatility measures of aggregate stock market and industrial sector indices. Furthermore, the two volatility models (short- and long-memory models) verify the SVAR results, suggesting that the effect of the aggregate demand oil price shocks on volatility is negative and significant for all indices and all measures. The findings of the study are essential in pricing financial derivatives, selecting portfolios, measuring and managing investment risk. Investors, risk managers, even policy makers of Central Banks and Capital Market Commissions will find the outcomes of the study useful in handling market's uncertainty in relation with the state of the oil price shocks. For example, supervisors of financial institutions must hold capital based on its internal model's estimates of Value-at-Risk. The Value-at-Risk internal model can take into consideration the interrelation between oil price shocks and stock market volatility. Basel Committee, in order to strengthen bank capital requirements and introduce enhanced regulatory requirements on bank liquidity, may take advantage of the ability to model the relationship between aggregate demand oil price shocks and volatility of European stock markets.

It is essential that further studies will distinguish such effects for oil-importing and oil-exporting countries and conditional correlation models can be used to identify the aforementioned relationships in a time-varying environment. Finally, following Andersen *et* *al.* (2005), an interesting question underpinning this research is whether and, if so, how the betas of European stock market sectors respond to different oil price shocks.

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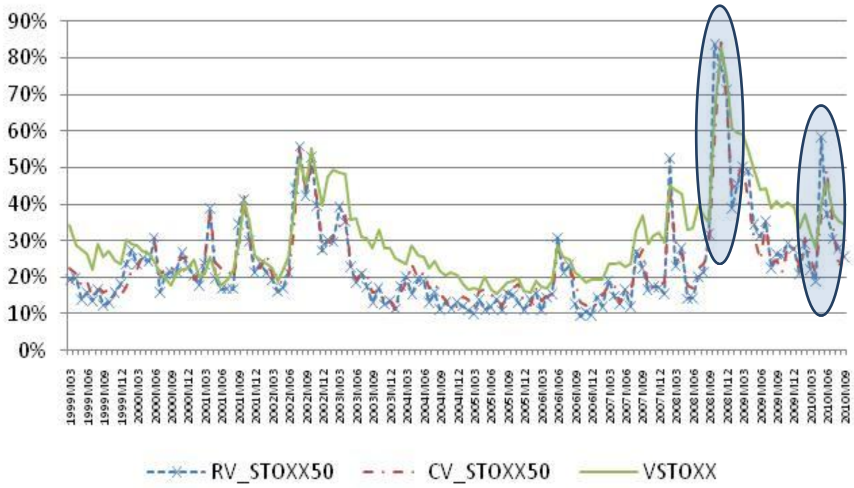
Figures

Figure 1: Volatility measures of the Eurostoxx 50 index, oil production growth rate, global economic activity and oil price returns.

Volatility Measures of the Eurostoxx 50



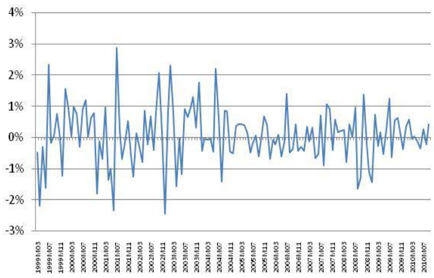
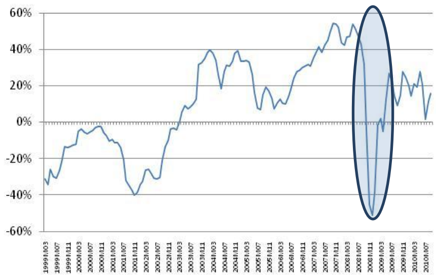
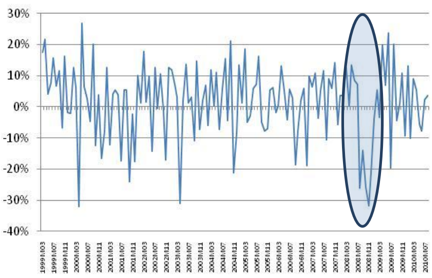
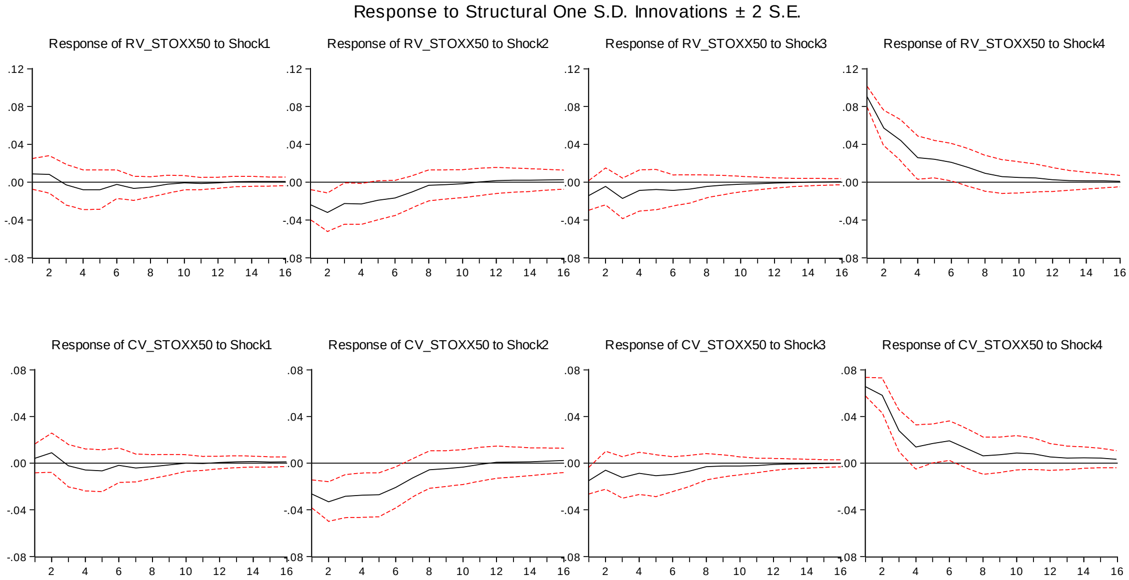
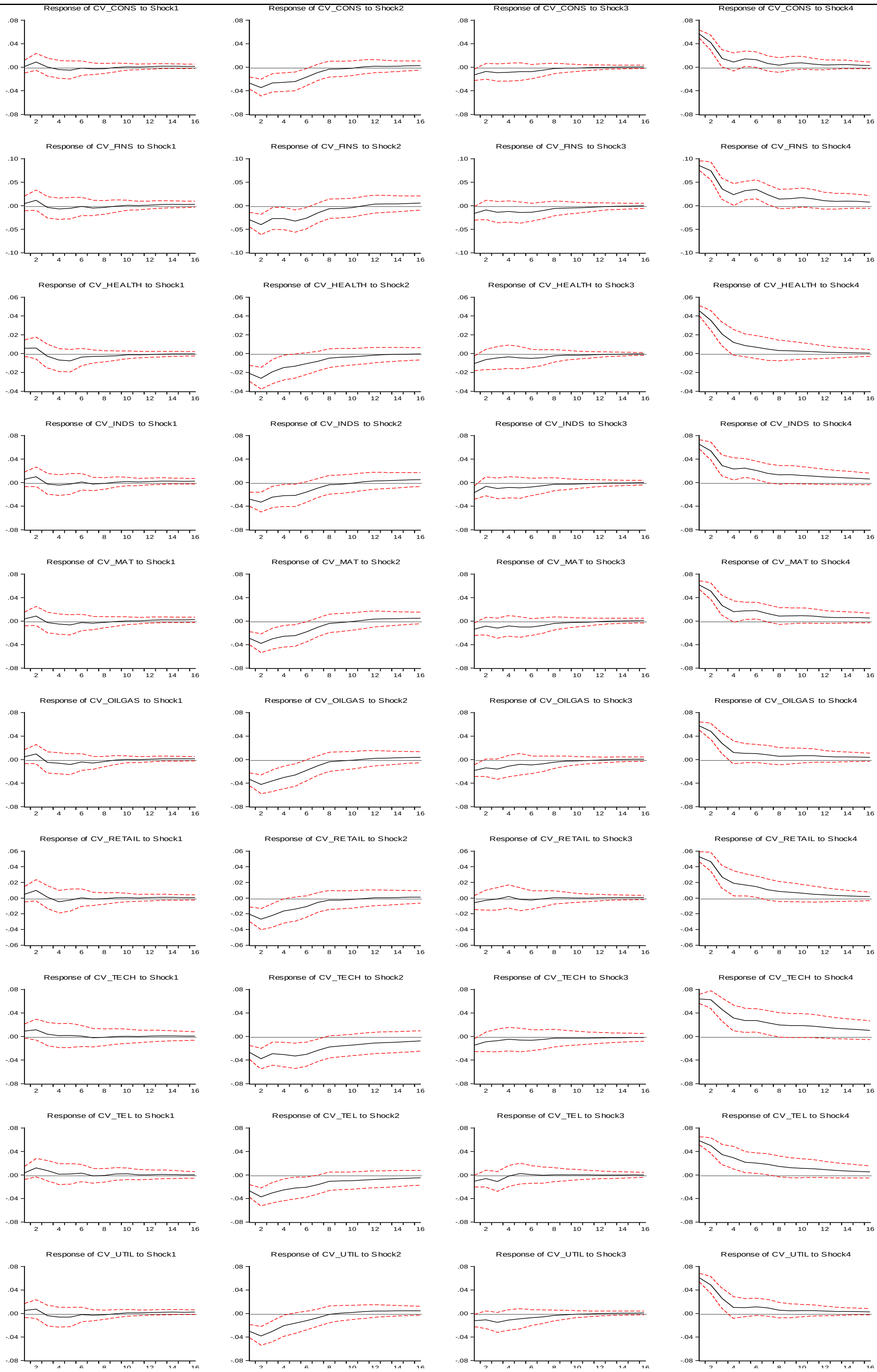
Oil Production Growth Rate (PROD)	Global Economic Activity (GEA)	Oil Price Returns (OP)
		

Figure 2: Impulse Responses of RV_STOXX50 and CV_STOXX50.



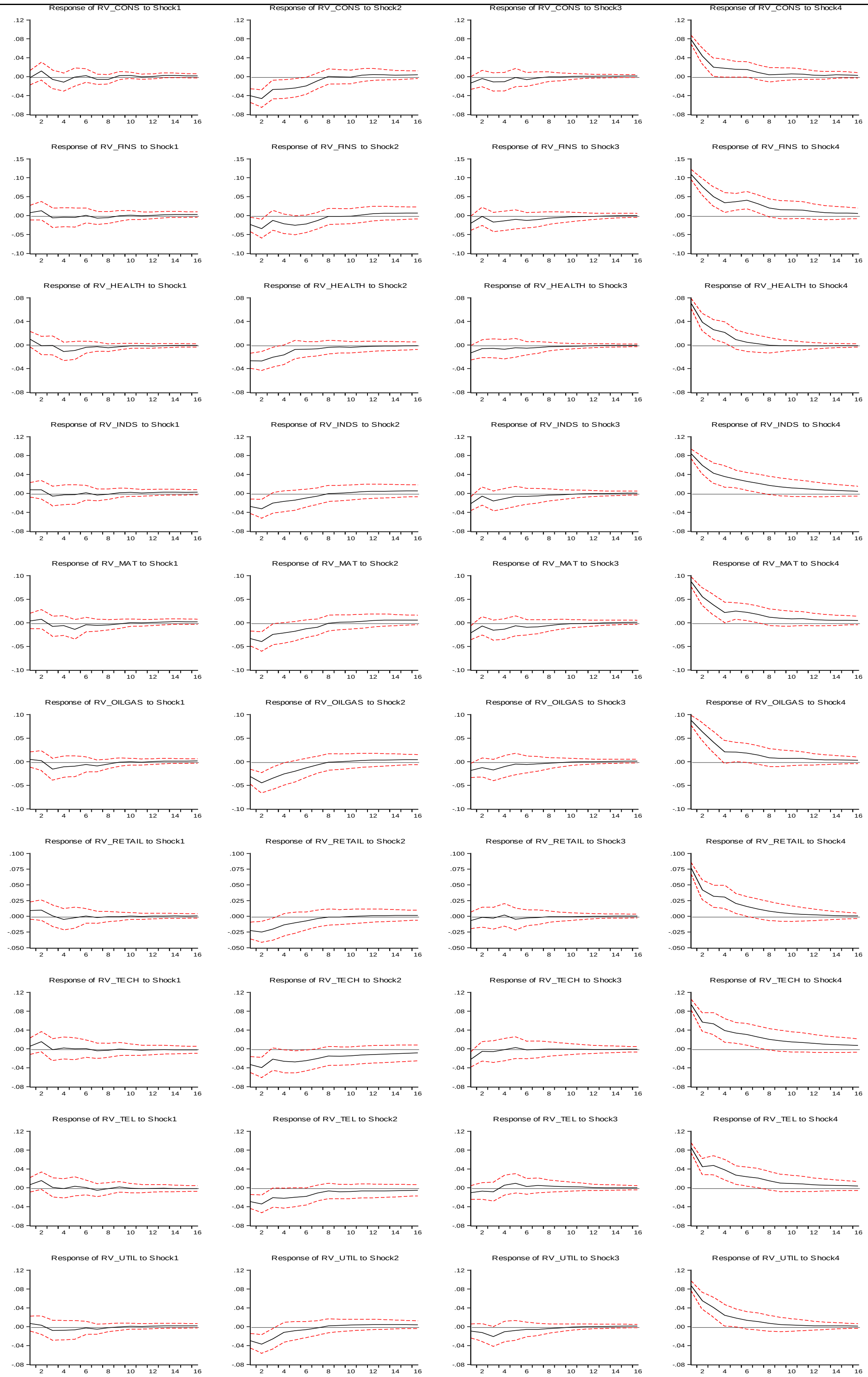
Note: Shock 1 refers to the supply-side shock (PROD), Shock 2 refers to the aggregate demand shock (GEA), Shock 3 refers to the oil specific demand shock (OP) and Shock 4 refers to the volatility shock (VOL).

Figure 3: Impulse Responses of the industrial sectors' conditional volatilities.



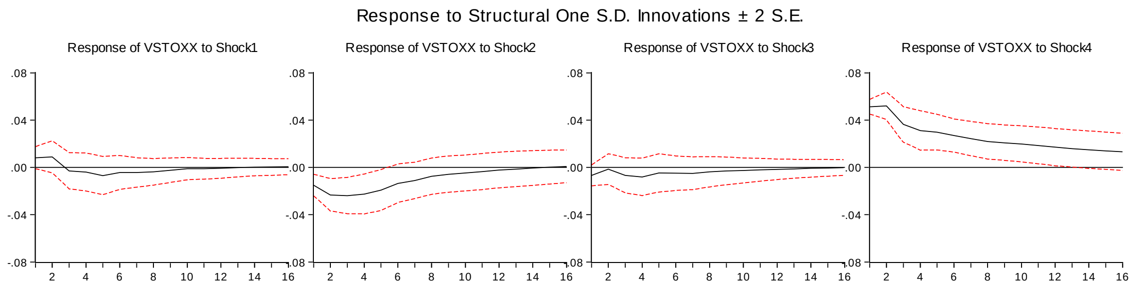
Note: Shock 1 refers to the supply-side shock (PROD), Shock 2 refers to the aggregate demand shock (GEA), Shock 3 refers to the oil specific demand shock (OP) and Shock 4 refers to the volatility shock (VOL).
The order of the industrial indices are as follows: *Consumer Goods*, *Financials*, *Health*, *Industrials*, *Basic Material*, *Oil&Gas*, *Retail*, *Technology*, *Telecommunications*, *Utilities*.

Figure 4: Impulse Responses of the industrial sectors' realised volatilities.



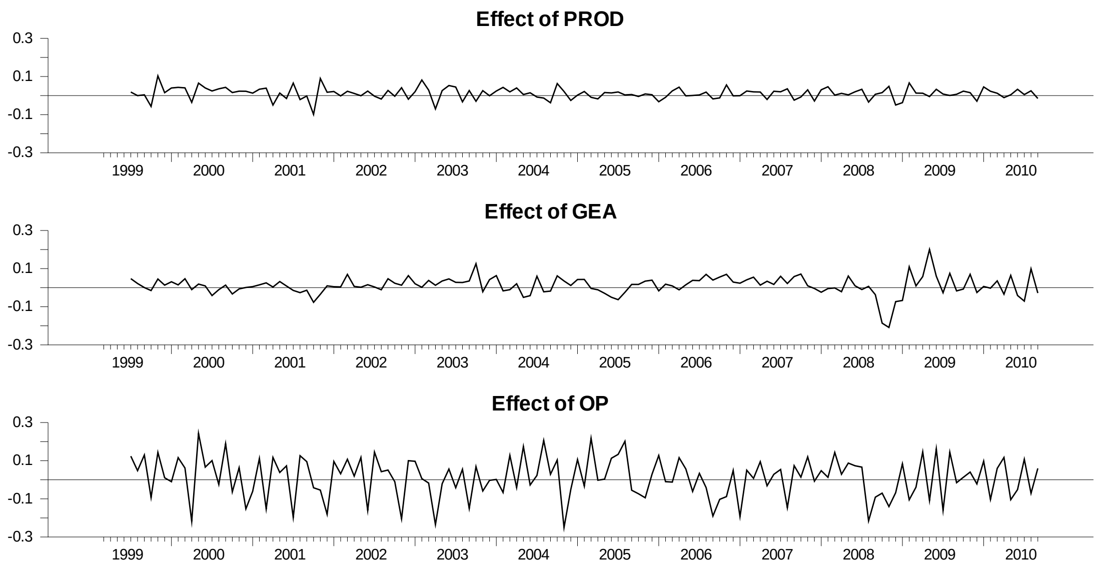
Note: Shock 1 refers to the supply-side shock (PROD), Shock 2 refers to the aggregate demand shock (GEA), Shock 3 refers to the oil specific demand shock (OP) and Shock 4 refers to the volatility shock (VOL).
The order of the industrial indices are as follows: *Consumer Goods*, *Financials*, *Health*, *Industrials*, *Basic Material*, *Oil&Gas*, *Retail*, *Technology*, *Telecommunications*, *Utilities.*

Figure 5: Impulse Responses of VSTOXX.



Note: Shock 1 refers to the supply-side shock (PROD), Shock 2 refers to the aggregate demand shock (GEA), Shock 3 refers to the oil specific demand shock (OP) and Shock 4 refers to the volatility shock (VOL).

Figure 6: Historical Decomposition of Oil Price Returns.



Note: This figure depicts historical decomposition of the oil price returns. The upper (middle, lower) panel depicts the cumulative effect of the supply-side shock (PROD), the aggregate demand shock (GEA) and the oil-specific demand shock (OP).

Tables

Table 1: Descriptive statistics of RV_STOXX50, CV_STOXX50, VSTOXX, PROD, GEA and OP.

	RV_STOXX50	CV_STOXX50	VSTOXX	PROD	GEA	OP
Mean	23.41%	23.94%	30.48%	0.06%	8.89%	1.49%
Maximum	83.55%	85.70%	82.72%	2.89%	54.30%	26.75%
Minimum	9.38%	10.61%	15.45%	-2.44%	-51.30%	-32.11%
Std. Dev.	13.20%	11.57%	12.38%	0.91%	26.19%	11.98%
Skewness	2.038	2.170	1.448	0.045	-0.259	-0.643
Kurtosis	8.013	9.510	5.466	3.813	2.099	3.248

Table 2: Variance Decomposition – Current-looking volatility measures.

Volatility Measure	Time Period	PROD	GEA	OP	VOL
CV_STOXX50	1	0.318	13.389	4.334	81.959
	3	0.873	22.524	3.613	72.990
	6	1.238	30.827	4.793	63.141
	12	1.370	30.799	5.035	62.796
	18	1.417	30.720	5.004	62.859
	24	1.469	30.872	4.988	62.671
RV_STOXX50	1	0.835	6.425	2.197	90.542
	3	0.924	13.082	3.188	82.806
	6	1.459	16.996	3.773	77.771
	12	1.801	17.057	4.092	77.050
	18	1.816	17.175	4.087	76.921
	24	1.837	17.257	4.088	76.818

Table 3: Variance Decomposition – Industrial sectors – Conditional Volatility.					
Industrial sector	Time Period	PROD	GEA	OP	VOL
CV_CONSUMER	1	0.04105	18.0963	3.97052	77.8922
	3	1.03125	32.4045	3.61692	62.9473
	6	1.20629	40.2086	4.61741	53.9677
	12	1.31018	39.8584	4.77912	54.0524
	18	1.45074	39.705	4.73764	54.1066
	24	1.56107	39.8382	4.73764	53.8631
CV_FINANCIALS	1	0.27831	10.7337	3.15151	85.8365
	3	0.95159	18.1702	3.0277	77.8506
	6	1.04201	24.2855	4.62298	70.0495
	12	1.12005	23.5867	5.06639	70.2269
	18	1.28088	23.6219	4.96934	70.1279
	24	1.45144	24.0705	4.90703	69.571
CV_HEALTH	1	1.22322	16.777	4.07704	77.9228
	3	1.37515	27.3975	3.09657	68.1308
	6	3.04791	31.2977	3.5477	62.1067
	12	3.36313	32.0552	3.93312	60.6485
	18	3.37275	32.0556	3.94709	60.6246
	24	3.3727	32.0558	3.94708	60.6244
CV_INDUSTRIAL	1	0.62348	15.027	5.3342	79.0153
	3	1.23732	22.6861	3.8773	72.1993
	6	1.157	26.4947	4.46518	67.8831
	12	1.1737	25.263	4.48806	69.0753
	18	1.36132	25.3829	4.3681	68.8877
	24	1.51265	26.0653	4.3078	68.1142
CV_MATERIALS	1	0.28495	17.943	3.92154	77.8505
	3	0.86182	30.029	3.80046	65.3087
	6	1.25674	35.6899	5.0614	57.992
	12	1.33202	34.8198	5.46355	58.3846
	18	1.49483	34.9077	5.36156	58.2359
	24	1.65423	35.1899	5.32808	57.8278
CV_OIL&GAS	1	0.52025	23.7492	7.23176	68.4988
	3	1.18125	36.7335	7.06484	55.0204
	6	1.8483	43.4956	7.65192	47.0042
	12	2.09462	42.8753	8.00695	47.0232
	18	2.15193	42.8498	7.92557	47.0727
	24	2.22034	43.0125	7.89596	46.8712

CV_RETAIL	1	0.75457	13.1533	1.05536	85.0368
	3	1.64064	22.1003	0.57449	75.6846
	6	1.69859	25.0061	0.63189	72.6634
	12	1.66014	24.5233	0.62673	73.1899
	18	1.69588	24.4783	0.64802	73.1778
	24	1.71982	24.5356	0.66437	73.0802
CV_TECHNOLOGY	1	1.68888	14.4082	4.21653	79.6864
	3	1.71655	22.0778	2.5365	73.6691
	6	1.24896	31.1126	2.33212	65.3063
	12	1.07055	32.9725	2.21435	63.7426
	18	1.03425	33.0633	2.18002	63.7225
	24	1.02698	33.0428	2.16952	63.7607
CV_TELECOMMUNICATIONS	1	0.3086	17.7102	2.64539	79.3358
	3	1.97908	29.0347	2.64088	66.3454
	6	1.60388	33.5286	2.07586	62.7917
	12	1.48391	34.4417	1.84691	62.2275
	18	1.45568	34.7526	1.803	61.9887
	24	1.44764	34.844	1.79333	61.915
CV_UTILITIES	1	0.54323	19.335	3.12126	77.0005
	3	0.89482	31.272	4.73463	63.0986
	6	1.46511	34.4648	6.29527	57.7748
	12	1.58069	34.1397	6.5359	57.7437
	18	1.76665	34.5144	6.45937	57.2596
	24	1.90042	34.7715	6.43394	56.8942

Table 4: Variance Decomposition – Industrial sectors – Realised Volatility.

Industrial sector	Time Period	PROD	GEA	OP	VOL
RV_CONSUMER	1	0.04565	20.672	2.29441	76.9879
	3	1.33782	33.8628	2.41952	62.3798
	6	1.97986	38.3806	2.9936	56.646
	12	2.40929	38.1632	2.98492	56.4426
	18	2.54313	38.2369	3.0039	56.2161
	24	2.60908	38.301	3.02181	56.0681
RV_FINANCIALS	1	0.49498	4.42609	3.16536	91.9136
	3	1.13097	8.41176	3.09396	87.3633
	6	1.05986	12.1545	4.0093	82.7764
	12	1.21465	11.8632	4.33898	82.5832
	18	1.34222	12.4592	4.27659	81.922
	24	1.476	12.9796	4.2451	81.2993
RV_HEALTH	1	1.58446	12.0845	2.86428	83.4668
	3	1.02134	20.188	2.58358	76.2071
	6	2.97149	21.4084	3.26278	72.3573
	12	3.35235	21.8914	3.58715	71.1692
	18	3.37727	21.9606	3.59941	71.0627
	24	3.38228	21.9842	3.60085	71.0327
RV_INDUSTRIAL	1	0.68778	9.15656	5.62758	84.5281
	3	0.94328	14.5157	4.89125	79.6498
	6	0.85716	14.8578	5.05265	79.2324
	12	0.91703	14.2116	4.97917	79.8922
	18	1.06814	14.7076	4.89914	79.3251
	24	1.18099	15.1543	4.86943	78.7953
RV_MATERIALS	1	0.15249	12.3487	4.84597	82.6528
	3	0.82122	20.5373	4.55745	74.0841
	6	2.01679	22.2354	5.48122	70.2666
	12	2.2017	21.6978	5.83422	70.2663
	18	2.30592	22.2116	5.75469	69.7278
	24	2.41735	22.5427	5.72654	69.3134
RV_OIL&GAS	1	0.231	11.3947	3.78719	84.5871
	3	1.50748	22.8078	4.32821	71.3565
	6	2.45933	25.7115	4.54275	67.2864
	12	2.8764	25.2687	4.58549	67.2694
	18	2.90528	25.5085	4.57743	67.0088
	24	2.94477	25.7099	4.5898	66.7555

RV_RETAIL	1	1.26258	7.93259	0.64978	90.1551
	3	1.69779	14.9768	0.51573	82.8097
	6	1.6629	15.3522	0.69026	82.2946
	12	1.65921	15.1493	0.71461	82.4769
	18	1.67259	15.2114	0.72079	82.3952
	24	1.68415	15.2531	0.72898	82.3338
RV_TECHNOLOGY	1	0.32981	10.6097	4.61063	84.4499
	3	1.43372	16.6987	2.86743	79.0001
	6	1.11957	21.2468	2.26143	75.3722
	12	1.13673	23.7168	2.00492	73.1416
	18	1.17524	24.7174	1.96134	72.146
	24	1.20144	25.0432	1.95172	71.8036
RV_TELECOMMUNICATIONS	1	0.53754	10.4097	1.20533	87.8475
	3	1.90242	17.0721	1.5078	79.5176
	6	1.54601	19.8576	1.88056	76.7159
	12	1.63096	20.404	2.02587	75.9391
	18	1.66546	21.0169	1.99595	75.3217
	24	1.70046	21.238	1.98843	75.0731
RV_UTILITIES	1	0.52452	10.4482	0.97392	88.0534
	3	0.72767	18.247	4.24764	76.7777
	6	1.25227	17.9609	4.997	75.7898
	12	1.4318	17.9779	5.20114	75.3892
	18	1.55453	18.4291	5.20351	74.8129
	24	1.63201	18.6198	5.21536	74.5328

Table 5: Variance Decomposition – Forward-looking volatility.

Volatility Measure	Time Period	PROD	GEA	OP	VOL
VSTOXX	1	2.269	7.611	1.542	88.578
	3	1.864	16.264	1.147	80.725
	6	1.970	19.856	1.714	76.460
	12	1.881	17.707	1.800	78.612
	18	1.760	16.495	1.688	80.057
	24	1.758	16.100	1.639	80.503

Table 6: Short memory model. Estimated values and the relative significance level of β_1, β_2 coefficients.

Volatility measure	β_1	p-value	β_2	p-value
CV_STOXX50	0.733	0.00**	-0.625	0.00**
CV_CONSUMER	0.706	0.00**	-0.591	0.00**
CV_FINANCIALS	0.766	0.00**	-0.668	0.00**
CV_HEALTH	0.710	0.00**	-0.432	0.00**
CV_INDUSTRIAL	0.745	0.00**	-0.594	0.00**
CV_MATERIALS	0.766	0.00**	-0.630	0.00**
CV_OIL&GAS	0.752	0.00**	-0.737	0.00**
CV_RETAIL	0.735	0.00**	-0.436	0.00**
CV_TECHNOLOGY	0.846	0.00**	-0.561	0.00**
CV_TELECOMMUNICATIONS	0.786	0.00**	-0.512	0.00**
CV_UTILITIES	0.703	0.00**	-0.663	0.00**
RV_STOXX50	0.612	0.00**	-0.520	0.00**
RV_CONSUMER	0.611	0.00**	-0.721	0.00**
RV_FINANCIALS	0.720	0.00**	-0.504	0.015*
RV_HEALTH	0.579	0.00**	-0.532	0.00**
RV_INDUSTRIAL	0.709	0.00**	-0.554	0.00**
RV_MATERIALS	0.678	0.00**	-0.657	0.00**
RV_OIL&GAS	0.679	0.00**	-0.705	0.00**
RV_RETAIL	0.624	0.00**	-0.446	0.00**
RV_TECHNOLOGY	0.734	0.00**	-0.543	0.00**
RV_TELECOMMUNICATIONS	0.674	0.00**	-0.548	0.00**
RV_UTILITIES	0.641	0.00**	-0.589	0.00**
VSTOXX	0.889	0.00**	-0.371	0.00**

*denotes significance at 5%, ** denotes significance at 1%

Table 7: Long memory model. Estimated values and the relative significance level of β_1, β_2 coefficients.

Volatility measure	β_1	p-value	β_2	p-value
CV_VSTOXX50	0.485	0.00**	-0.602	0.00**
CV_CONSUMER	0.479	0.00**	-0.527	0.00**
CV_FINANCIALS	0.486	0.00**	-0.652	0.00**
CV_HEALTH	0.482	0.00**	-0.407	0.00**
CV_INDUSTRIAL	0.484	0.00**	-0.574	0.00**
CV_MATERIALS	0.487	0.00**	-0.583	0.00**
CV_OIL&GAS	0.487	0.00**	-0.649	0.00**
CV_RETAIL	0.485	0.00**	-0.417	0.00**
CV_TECHNOLOGY	0.493	0.00**	-0.447	0.00**
CV_TELECOMMUNICATIONS	0.488	0.00**	-0.447	0.00**
CV_UTILITIES	0.482	0.00**	-0.651	0.00**
RV_STOXX50	0.468	0.00**	-0.531	0.00**
RV_CONSUMER	0.437	0.00**	-0.691	0.00**
RV_FINANCIALS	0.475	0.00**	-0.505	0.019*
RV_HEALTH	0.436	0.00**	-0.568	0.00**
RV_INDUSTRIAL	0.475	0.00**	-0.578	0.00**
RV_MATERIALS	0.467	0.00**	-0.690	0.00**
RV_OIL&GAS	0.474	0.00**	-0.716	0.00**
RV_RETAIL	0.453	0.00**	-0.457	0.00**
RV_TECHNOLOGY	0.478	0.00**	-0.476	0.012*
RV_TELECOMMUNICATIONS	0.462	0.00**	-0.503	0.00**
RV_UTILITIES	0.461	0.00**	-0.660	0.00**
VSTOXX	0.494	0.00**	-0.338	0.00**

*denotes significance at 5%, ** denotes significance at 1%