Contemporaneous spillover effects between the US and the UK

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Abstract

This paper investigates both the dynamic and contemporaneous spillover effects between equity markets in the UK and the US. We use high frequency data and the "identification through heteroskedasticity" approach of Rigobon (2003) to capture the contemporaneous volatility spillover effects. Our results imply that during the time when trading hours overlap, higher stock market volatility in the US leads to higher volatility in the UK. We demonstrate the relevance of taking into account the information present during simultaneous trading by comparing the dynamics of the structural VAR with the dynamics of a traditional VAR. Our findings establish that the bi-directional dynamic linkages between the US and simultaneous trading periods are overestimated in the traditional VAR. These results have major implications for risk management and hedging strategies.

Keywords: Contemporaneous Spillovers; Identification through heteroskedasticity; Volatility Spillovers.

1 Introduction

Financial markets have become more and more connected in recent years, resulting in increasing levels of correlations between financial markets and assets (Bekaert et al., 2009). An example of the consequences of this increased interconnectedness is the recent outcome of the global financial crisis, which originated in the US and rapidly spread to other countries. This led to a period of high volatility and instability, and had a strong negative impact in terms of economic growth for both national and international economies. The recent crisis demonstrates that economic shocks originating in one market not only affect that particular market, but are also transmitted to other markets with serious global consequences. Understanding these "spillover effects" among markets and between financial assets is therefore of great importance.

The total volatility spillover between different markets and across different regions can be explained by dynamic and contemporaneous effects. The dynamic effects refer to the return/volatility spillovers that happen over time. This is the case when we have trading time differences, i.e., one market starts trading while the other is closed. As such, information from one market will have an impact on the other market in the next trading period. Contemporaneous spillover may be seen as the return/volatility spillover that takes place among a group of assets in different regions at the same time. This can be due to, for example, having overlapping trading hours. So, information from one asset could be transmitted to another asset on the same day. As such, it is important to investigate and distinguish between both effects, the contemporaneous and dynamic (lead-lag) spillover effects at the return/volatility level. Traditional studies measure spillover effects using methods based on univariate/ multivariate GARCH models (Kanas, 2000; Hakim and McAller, 2010; Fang et al., 2007; Capiello et al., 2006). These studies model spillover effects at return/volatility level through dynamic relations. However, these studies do not address the contemporaneous spillover.

The main contribution of this paper is analysing the contemporaneous spillover effects in volatility. Understanding these spillover effects is essential when the markets are trading simultaneously, i.e., what occurs in one market may spill-over to the other market the same day. We use the "identification through heteroskedasticity" approach of Rigobon (2003), to study this relationship between assets in different regions. We will examine not only the direct transmission channels between assets and markets, but also the indirect transmission channels as noted by Ehrmann et al. (2011).

An interesting case for capturing the contemporaneous effects is the relation between stocks in the US and the UK. The S&P 500 and FTSE 100 indices are common representatives of the stock market and economy in both countries. The issue we must face when we want to analyse the volatility transmission is the overlapping trading hours between the UK and the US. To analyse the contemporaneous effects we need to split the trading period of the UK and the US in two: the part *without* overlapping trading hours and the part *with* overlapping trading hours. We will be able to analyse the contemporaneous spillover effects by looking at the periods when the two stock exchanges are trading simultaneously.

Our results suggest that there is a high asymmetry in the contemporaneous effects, i.e., the opening of the US stock exchange has a stronger effect on the UK overlapping trading period. Hence, the spillover effects during overlapping trading hours either in the US or UK have an impact in the same day on the US non-overlapping trading hours. We find that an increase in the UK overlapping stock market leads to a higher increase in the US stock market, rather than the spillover from the non-overlapping trading period.

The dynamic linkages confirm once again the same day transmission of contemporaneous spillover effects and next day transmission of spillover effects due to non simultaneous trading. We highlight the implications of our model by comparing the dynamic linkages of our model with the dynamics generated by a traditional VAR. Our findings clearly reveal the importance of keeping in mind the information present during simultaneously trading, which is disregarded in traditional VAR. We show that the dynamic effects between the US and simultaneous trading periods, respectively vice versa are seriously overestimated in the traditional VAR.

These results are relevant firstly for risk management and international portfolio diversification. Investors and risk managers aim to have well-diversified portfolios and therefore need to know how correlations between assets change. We find the spillover effects are asymmetric with different sign and magnitude across assets as such an investor will need a portfolio adjustment. Secondly, they have implications for the efficient implementation of global hedging strategies, i.e., in reducing the risk of adverse price movements in assets. We prove that implementing hedging strategies based on reduced form results, without distinguishing between the contemporaneous/dynamic spillover effects, leads to an increase of our risk exposure instead of reducing it.

The rest of the paper is organized as follows. Section 2 briefly reviews the literature on spillover effects and its applications. Section 3 presents the model based on identification through heteroskedasticity. Section 4 discusses the data and Section 5 outlines the results. We conclude in Section 6.

2 Literature review

The literature on how different markets and assets interact over time is extensive, both at international and domestic level. In this paper, we classify the literature on spillover effects into three groups. The first group includes the papers relying on traditional methods, such as univariate/multivariate GARCH, VAR models to identify the lead-lag dynamics at return/volatility level. The second group focuses on sampling at higher frequencies when analysing volatility transmission between markets across regions in an attempt to estimate contemporaneous spillovers. The last group of studies use a different estimation technique that relies on heterogeneity in the data to solve the problem of simultaneity and identify the contemporaneous relationships.

2.1 *Traditional methods*

Among the first studies addressing the spillover effects in volatility is Engle et al. (1990) who introduce the concepts of "heat wave" and "meteor shower". A "heat wave" implies that financial asset volatility is influenced by internal factors such as past shocks (which may be regarded as a "volatility surprise"). From another perspective, volatility is closely related to information flow, meaning that news (defined by shocks, innovations) are transmitted across borders. Common changes in the financial assets from different states/regions correspond to the hypothesis of "meteor shower".

Engle et al. (1990) use a GARCH model to test whether news in the yen/dollar exchange rates in the New York market can predict volatility in Tokyo. The finding of a "meteor shower" effect contradicts the more natural expectation that volatility would instead continue in the same market the next day, the "heat wave" hypothesis. Later, Melvin and Melvin (2003) analyse the volatility transmission of exchange rates over different regions and find evidence of both effects, but the "heat wave" effects are larger in magnitude.

Hamao et al. (1990) propose one of the first methods to quantify the volatility spillover effects between different capital markets. In this sense they study the effects of volatility in three international markets[1]: Tokyo, London and New York using a GARCH-M model. To measure the volatility transmissions from one period to the next within markets ("heat waves") and across markets ("meteor showers") they divide the daily close-to-close returns into: close-to-open and open-to-close in order to analyse the spillover effects separately. They find that volatility in one market tends to continue after that market closes, producing volatility in markets opening several hours later even though these markets are geographically distant[2].

A similar approach belongs to Lin et al. (1994), who investigate how returns and volatility stock indices are correlated between Tokyo and New York[3]. They use daily data which is divided into daily and overnight returns, and estimate two models that were compared with the one of Hamao et al. (1990). The results show that daily returns of New York are correlated with those in Tokyo overnight.

Since then some studies have tried to measure the volatility transmission from one period to the next within ("heat waves") and across markets ("meteor showers") at both return and volatility level using different extensions of GARCH models.

[1]See also, Lee and Rui (2002) who examine the dynamic relationship between stocks and volume in same regions. They found a positive relationship between the volumes and return volatility, therefore the US trading volume has a predictive power for the other two stock markets.

[2]Koutmos and Booth (1995) use the same markets but estimate a multivariate E-GARCH model to test for spillover effects between the conditional first and second moments of returns. They find evidence of the "meteor shower" effect.

[3]See also Karolyi (1995) who investigates the return/ volatility spillovers in New York and Toronto stock exchanges.

Using an EGARCH model and assuming a constant conditional correlation over time, Kanas (2000) looks at the volatility spillover between stocks and exchange rates in the US, EU and Canada. He finds evidence of volatility spillover from stock returns to exchange rates in all countries but the reverse spillovers (exchange rates to stock returns) are insignificant. The return spillovers are symmetric, with the direction again from stocks to exchange rates in all countries with Germany as exception. The model is parsimonious, but assuming a constant correlation may be restrictive.[4]

Using a BEKK-GARCH, Fang et al. (2006) analyze the causal transmission between stocks and bonds. The results show that volatility of the stock market has a greater influence on bond volatility and there is a contemporaneous/dynamic spillover from the US to Japan. However, the model includes a large amount of parameters, which may rise exponentially.

RiskMetrics of J. P. Morgan (1996) is another technique similar to the BEKK model of Engle and Kroner (1995) that imposes the same dynamics on all elements of conditional variance but assumes the latest one is an integrated process. The model has been used by Martens and Poon (2001) to investigate the return and volatility spillover between Europe (France and UK) and US stock markets. Martens and Poon (2001) found no spillover at the return level but at the volatility level there exists a spillover from the US to Europe and vice versa. The disadvantage is that correlations may not be bounded between +/-1.

To overcome the problems of previous models, Engle (2002) introduced the DCC-GARCH[5] that allows for time-varying correlation and limits the number of unknown parameters. Conditional volatility may show asymmetric behaviour[6] which cannot be captured by the

[4]See, Hakim and McAller (2010) who study the interactions between different assets and regions assuming conditional correlations are constant. They find evidence of mean/volatility spillover from each market to all other markets, but the results shows also not constant correlations.

[5]Al-Zeaud ande ALshbiel (2012) evaluate the volatility spillover between US and EU using this model. They found evidence of a spillover from London to New York, Pairs and Frankfurt stock markets and within Europe a unidirectional spillover from Frankfurt to Paris and Paris to London.

[6]Volatility tends to increase more when negative shocks occur then when positive shocks occur.

Engle's (2002) model but the ADCC-GARCH model of Capiello et al. (2006) will capture the leverage effects to conditional volatilities and correlations. Savva et al. (2009) use this model to analyse the spillovers between the US and some major European (London, Frankfurt and Paris) stock markets using daily closing prices. The results show that domestic stock prices and their volatilities are influenced by the foreign market; there is more spillover from European markets to the US markets than reverse.

More recently, Diebold and Yilmaz (2009, 2012) use a different technique, the forecast error variance decomposition framework of a generalized VAR model for examining both return and volatility spillover effects among different markets in Euro area. This model can be used to examine the direction of spillover effects amongst the different asset markets and to extract periodizations of the spillover cycles (Louzis, 2012). Several other studies use the so called "spillover index" in their analysis (Summer et al., 2009; Wang et al., 2012; Suwanpong, 2010; Louzis, 2012).

A common problem of the above studies is that they model spillovers through dynamic relations and do not capture the contemporaneous spillover. For instance, when having overlapping trading hours the information from one asset could be transmitted to another asset on the same day. Another example is a more recent paper, Sakthivel et al. (2012) who analyse the volatility transmission of stock markets across different regions using weekly data. They focus on the long-run relation and miss the contemporaneous effects, the short-term dynamics when there are overlapping trading hours between regions.

2.2 *Sampling at higher frequencies*

As a solution to identify the contemporaneous spillover effects many papers sample at higher frequencies. Making the interval shorter by increasing the sampling frequency will allow for more information and could better capture the contemporaneous spillover effects. Practically, a sample with higher frequency will enable you to treat lagged effects as contemporaneous effects, i.e., daily returns are split into periods. These studies analyse the spillover effects between both, single and different markets over different regions.

Kim (2005) attempts to estimate the contemporaneous and dynamic spillover effects when having trading time differences by splitting each day returns into: daily, overnight and intraday periods. The investigation reveals that there is a significant contemporaneous spillover effect from intraday US returns to other country's overnight period. Intraday Japanese returns have a positive contemporaneous effect on all overnight returns that are examined, but the lagged effects are mixed.

Baur and Jung (2006) follow Kim's (2005) method of splitting daily returns to capture contemporaneous correlations and spillover effects between the US and German stock markets. They use high frequency data and the Aggregate-Shock (AS) model of Lin et al. (1994) for spillovers. Their main findings are that daytime returns significantly influence overnight returns in both markets and there is no spillover from the previous daytime returns of US to the morning German market.

The previous papers analyse the return/volatility transmission of spillover effects by looking at a single market/asset over different regions. With on-going globalization and the increased speed of spillover among markets/assets, it is important to analyse the contemporaneous/dynamic spillover effects between different markets/assets and regions.

Martinez and Tse (2007) analyse the volatility transmission using intraday data between bonds, foreign exchange and stock index futures markets in different regions. They find evidence in all markets of both interregional ("meteor shower") and intraregional ("heat wave") volatility effects but as Melvin and Melvin (2003) found, the latter one is more pronounced.

Clements et al. (2013) investigate the meteor shower and heat wave hypotheses at volatility level using high frequency data in the US, Japan and Europe foreign exchange, equity and bond future markets. The results show the presence of both effects, each market being influenced by the events that occur in other markets/zones.

Both papers use high frequency future dataset which will capture more information and help better estimate the spillover effects. But still they are not capable of estimating the contemporaneous spillover across different regions and assets; they are not paying attention to the overlapping periods.

Dimpfl and Jung (2012) apply a SVAR in estimating the volatility transmission in Japan, Europe, US equity future markets. To solve the problem with overlapping periods they apply the idea of Menkveld et al. (2007), Susmel and Engle (1994) who suggest that the observations should be restricted only to some relevant points in time. They found evidence of mean spillovers from US to Japan and Japan to Europe and for volatility spillovers all markets react more intensely to the previous market. Practically using this technique they are still avoiding analysing the contemporaneous effects and the linkages between the different assets.

2.3 *Different estimation technique*

Other studies are using a different estimation technique to estimate the contemporaneous spillover effects. This technique allows to properly identify the contemporaneous relationships by making use of the data's heteroskedasticity. If in a simultaneous equation model, we observe non-proportional changes in volatility over time, than we can use these changes to identify the contemporaneous spillover effects.

Rigobon (2003) introduces a new method to examine the contemporaneous relations among Argentina, Brazil and Mexico sovereign-bond yields and finds strong linkages across the emerging markets. The method allows solving the identification problem when having simultaneous equation models. Supposing structural shocks have known (zero) correlation the problem is solved by relying on heterogeneity in the data to identify the structural parameters that are consistent, regardless of how the heteroskedasticity is modelled.

Andersen et al. (2007) use a different approach based on heteroskedasticity to identify the reaction of US, German and British stock, bond and foreign exchange future markets to real-time U.S. macroeconomic news. The study is based on high frequency data, estimating first the contemporaneous relationship and then in a separate analysis the spillovers between bonds, stocks and exchange rates. The results show that there is a direct spillover among the equity markets and that bad news has negative/positive impact during contractions/expansion. However they do not focus so much on distinguishing between the contemporaneous and dynamic spillover effects by looking exactly at interactions across the overlapping periods.

Ehrmann et al. (2011) estimate the transmission between money, bond and equity markets within and between US and Europe. They use two daily returns avoiding contemporaneous effects, a multifactor model and the identification through heteroskedasticity to estimate the international spillovers. The results show a spillover within asset classes but also international cross-market spillover. For instance, there is a spillover from the US equity market to the European money and bond market but also an opposite spillover from the European money market to the US bond market. The US markets are explaining in proportion of 30% the European markets movements, whereas the last one only around 6%.

Spillovers between markets affect the stability of each country and therefore these relationships need to be understood. We study the contemporaneous and dynamic spillover effects having the stock markets across different regions at volatility level. To estimate the spillover effects properly we combine Rigobon's approach based on heteroskedasticity and the high frequency dataset with daily returns split in overlapping and non-overlapping periods. Badshah, Frijns, Tourani-Rad (2013) use a similar technique in analysing contemporaneous spillover among equity, gold and exchange rate implied volatility indices. However, this paper to our knowledge is the first to examine the contemporaneous and dynamic effects dealing with the overlapping trading period.

3 Model

In this study, we explore the stock markets (S) in the US and the UK. We follow the approach of Rigobon (2003) and implemented by Ehrmann et al. (2011) in assessing volatility spillover effects among our markets.

As Mykland and Sheppard (2010, 2012) after selecting the data, we can calculate the intraday returns for all assets based on the formula: $\Delta X_t = log(X_t) - log(X_{t-1})$, where the X_t is the intraday price. Once we have intraday returns, we construct realized variances[7] as $log(RV_t) = log(\sum_{t=1}^{N}(\Delta X_t)^2)$. We define the global trading day by splitting each calendar day in three periods: UK non-overlapping (UK) , UK overlapping (UK^0), US overlapping (US^0) and the US non-overlapping (US). All times are taken to be Greenwich Mean Time as follows:

$$\overbrace{8am \ldots 2:30pm}^{UK} \quad \overbrace{2:30pm \ldots 4:30pm}^{UK^0} \quad \overbrace{4:30pm \ldots 9pm}^{US}$$

$$\underbrace{2:30pm \ldots 4:30pm}_{US^0}$$

$$\underbrace{\hphantom{8am \ldots 2:30pm \quad 2:30pm \ldots 4:30pm \quad 4:30pm \ldots 9pm}}_{\text{Global Trading Day}}$$

When creating the global trading day, we account also for the Daylight Saving Time, i.e., the number of overlapping/non-overlapping trading hours is changing, e.g., from three hours overlapping trading to two hours overlapping trading.

We start by assuming that the realized variances are following a structural VAR (SVAR) process:

$$\mathbf{A}RV_t = c + \mathbf{\Phi}(\mathbf{L})RV_t + \varepsilon_t \tag{1}$$

[7]Andersen et al.(2003) demonstrate that by taking the logarithm of volatility the series will become close to the normal distribution allowing us to conduct the estimation in a straightforward manner.

where RV_t is a (4×1) vector representing the daily stock realized variance, respectively $RV_t^{UK^0}/RV_t^{US^0}$ are the overlapping periods, i.e.,

$$RV_t = \begin{pmatrix} RV_t^{UK,S} & RV_t^{UK^0,S} & RV_t^{US^0,S} & RV_t^{US,S} \end{pmatrix}' \tag{2}$$

c is a (4×1) vector of constants and $\mathbf{\Phi}(\mathbf{L})$ is a (4×4) matrix polynomial in the lag operator. The (4×4) matrix $\mathbf{A}$ represents the contemporaneous effects between the realized variances, i.e

$$\mathbf{A} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ \alpha_{21} & 1 & \alpha_{23} & 0 \\ \alpha_{31} & \alpha_{32} & 1 & 0 \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & 1 \end{pmatrix}, \tag{3}$$

where, e.g., α_{23} captures the contemporaneous spillover from $RV_t^{US^0}$ to $RV_t^{UK^0}$ and α_{32} captures the contemporaneous spillover from $RV_t^{UK^0}$ to $RV_t^{US^0}$. The other parameters are defined likewise. We set exclusion restrictions on matrix $\mathbf{A}$ according to our global trading day, allowing for spillovers in one direction, e.g., forward. The spillovers from both overlapping trading periods to UK as well as from the US to UK/US^0 and UK to UK^0 are set to zero, i.e

$$\alpha_{12} = \alpha_{13} = \alpha_{14} = \alpha_{24} = \alpha_{34} = 0$$

When analyzing the contemporaneous spillover effect between stocks in the US and UK markets we face a problem that is present also in simultaneous equations models, i.e. endogeneity. An initial point through the identification is to estimate the reduced-form VAR by premultiplying the Equation (1) by $\mathbf{A^{-1}}$:

$$RV_t = c^* + \mathbf{\Phi}(\mathbf{L})^* RV_t + u_t \tag{4}$$

The coefficients of Equation (4) can be estimated by OLS and are related to the structural coefficients by: $c^* = \mathbf{A^{-1}}c, \mathbf{\Phi}(\mathbf{L})^* = \mathbf{A^{-1}}\mathbf{\Phi}(\mathbf{L}), u_t = \mathbf{A^{-1}}\varepsilon_t$ and $u_t \sim N(0, \mathbf{\Omega_t})$ where

$$\mathbf{\Omega_t} = \mathbf{A^{-1}\Sigma_t\ A^{-1}}'.$$

However, because of simultaneity, matrix **A** cannot be identified from Equation (1) through OLS of the reduced-form VAR, i.e., Equation (4). Therefore, most of the studies that focus on long-term and lead-lag relations to identify the spillover effects between different markets/assets and regions, are not able to capture the contemporaneous spillover effect.

Some others, use Cholesky decompositions and sign restrictions for the identification of contemporaneous spillover effect. However, orthogonalization is an assumption on the direction of causality. In addition, imposing a large number of restrictions is not reasonable.

Rigobon (2003) proposes a way to solve the simultaneity issue, based on identification through heteroskedasticity, i.e., the regime-switching model. In this approach, the existence of heteroskedastic regimes can solve the identification problem when having a simultaneous equation model.

Practically, for the identification of the matrix **A**, containing the spillover effects, we have to impose three assumptions. First, we assume that the structural shocks, ε_t, from Equation (1) are uncorrelated. The variance of ε_t shows conditional heteroskedasticity. Namely, $\varepsilon_t \sim N(0, \mathbf{\Sigma_t})$, where $\mathbf{\Sigma_t} = \begin{pmatrix} \sigma^2_{1t} & 0 & 0 & 0 \\ 0 & \sigma^2_{2t} & 0 & 0 \\ 0 & 0 & \sigma^2_{3t} & 0 \\ 0 & 0 & 0 & \sigma^2_{4t} \end{pmatrix}$ is a diagonal matrix based on the first assumption. Second, the matrix **A** is stable across time/regimes. Third, there must exist at least two regimes of distinct variances $\mathbf{\Omega_t}$. If the first assumption holds, the system is identified by considering a change in the variance of shocks.

For example, if we observe a significant improvement in the variance of the equity shocks in the US that will affect the covariance between equities in the US and UK, i.e., we are able to better examine the responsiveness of the UK equity to the US equity shocks. If there is no significant change between variances or they shift proportionally the system is not identified. This is the case when equations are dependent, i.e., we don't know which shock is better over regimes, as such we cannot explore the relationships between variables.

Specifically, following Ehrmann et al. (2011) we start by computing rolling windows variances from the reduced form residuals, u_t, that contain only the contemporaneous effects. We define five heteroskedastic regimes based on when the fifty day rolling variances are higher than the residuals average standard deviation over the full sample times the threshold value of 0.8. The first regime consist of observations where all variables show lower than normal volatility. The other four regimes are defined likewise: a high UK^{S} volatility regime, a high $\mathrm{UK}_0^{\mathrm{S}}$ regime, a high $\mathrm{US}_0^{\mathrm{S}}$ regime and a high US^{S} regime. The basic idea is that in a regime where one variable has higher volatility while the others have low volatility, we achieve more information on the others variable responses to the variable with high volatility shocks since they are more likely to occur, and vice versa.

The covariance matrices of each regime are used then in the GMM estimation of the spillover effects coefficients.

$$min\ \mathbf{d}'\ \mathbf{d}\ with\ \mathbf{d} = \mathbf{A}'\boldsymbol{\Omega}_\mathbf{t}\mathbf{A} - \boldsymbol{\Sigma}_\mathbf{t} \tag{5}$$

$$s.t.\ \boldsymbol{\Sigma}_\mathbf{t}\ is\ diagonal, \mathbf{A}\ restrictions$$

where $\boldsymbol{\Sigma}_\mathbf{t}$ is the variance of the structural shocks assumed to be uncorrelated, which we are interested in, and $\boldsymbol{\Omega}_\mathbf{t}$ is the variance-covariance matrix that we estimate in each regime t.

We rely on 1000 bootstrap replications to obtain the significance of our parameters, $\boldsymbol{\Phi}_\mathbf{1}$ and the matrix $\mathbf{A}$. For each regime, we use Cholesky decomposition to create new data with the same covariance structure in each of the bootstrap replications. Since we excluded observations which were not sufficiently close to one of our regimes, we recursively simulate the dependent variables and estimate the VAR again. As such, the simulation and estimation procedure is able to account for the gaps and lags in the data. For each draw, using our regime-dependent VAR covariance matrices, we estimate the coefficients by GMM, which allows us to calculate the p-values and confidence intervals for the parameter estimates.

4 Data

We use high frequency data sampled at a 5-minute[8] frequency for the US and UK stock markets. The data are taken from Thomson Reuters Tick History and cover the period from 3 January 2007 to 31 December 2013. Days where one market is closed, as well as public holidays are eliminated from the sample. For our analysis we employ the S&P500/FTSE 100 indices for the US/UK stocks traded on New York Stock Exchange/London Stock Exchange.

In Figure 1, we provide a time series plot of the 5-minutes equity volatilities in each trading periods. We notice two sharp increases in the equity markets, the first one due to global financial crisis in October 2008 and the second one before and after October 2011, related to the European Debt Crisis.

INSERT FIGURE 1 HERE

In Table 1, we provide summary statistics for the realized variances on stocks over all regions. As can be seen, the highest level of volatility is in the US equity market, followed by the US and UK overlapping trading periods. The highest mean volatility and variability is in the US overlapping trading period, as we can notice from the maximum, minimum and mean. Equity markets have positive skewness in all trading periods. The positive skewness implies that positive changes in equity markets occur more often than negative changes. The kurtosis is close to normal in all four series implying that large changes occur not so often as in the case of normally distributed series. Running Augmented Dicky Fuller (ADF) tests, we can reject the null hypothesis of a unit root, confirming stationarity with the ADF test statistic, significant at 1% level in all trading zones.

INSERT TABLE 1 HERE

[8]See Liu et al. (2012) that consider almost 400 realized measures, across seven different classes of estimators, and compare them with the simple "realized variance" (RV) estimator. They found that it is difficult to significantly beat the 5-minute RV.

Our objective is to analyse the contemporaneous spillover effects in financial markets. Generally, we can measure this contemporaneous spillover by a correlation as can be seen from Table 2.

INSERT TABLE 2 HERE

We can notice from Table 2, the existence of a positive relationship between stocks in both UK/US trading periods. During the two overlapping trading periods, we can see the highest positive relationship between stocks markets. The correlation matrix tell us the relationship between stocks but does not give us the direction. Further, we are going to analyse the relationship between variables, using the identification through heteroskedasticity approach of Rigobon (2003).

5 Results

5.1 *The Reduced Form VAR*

We start our analysis with the estimation of the reduced form VAR using Equation (5). Relying on Akaike Information Criterion (AIC) to select the optimal lag length, we find a lag length of 5 days to be optimal. As such, we carry out all our analysis with a 5-day lag length.

Further, we look at the relationships between the realized variances performing Granger causality tests. Granger (1969) shows that if the past values of a variable/group of variables, i are found to be helpful for predicting another variable/group of variables, j, then i is said to Granger - cause j; otherwise it is said to fail to Granger - cause j.

The results of the Granger causality tests for realized variances of stocks markets are presented in Table 3 with corresponding values of F-tests. We observe a strong, significant bidirectional causality between stocks markets in all trading periods.

INSERT TABLE 3 HERE

Overall, these results imply that in all four trading periods stock market volatility significantly Granger causes the volatility in every trading period. Regarding the US/UK overlapping trading periods, we notice a lot of interactions between variables. However, the causality running from $\mathrm{UK}_0^{\mathrm{S}}$ to $\mathrm{US}_0^{\mathrm{S}}$ is stronger that vice versa. Another strong causality can be seen between $\mathrm{UK}_0^{\mathrm{S}}$ / $\mathrm{US}_0^{\mathrm{S}}$ and US^{S}. $\mathrm{UK}_0^{\mathrm{S}}$ Granger cause US^{S} stronger than $\mathrm{US}_0^{\mathrm{S}}$. The causality tests give us information only about which variable we can use in the future as explanatory variable, to clarify the behaviour of other variables in the VAR. As such, we still don't know if we have a positive or negative relationship, what is the speed, or persistence between our variables.

Table 4 reports the dynamic reduced form VAR effects, matrix $\mathbf{\Phi_1^*}$ as given in Equation (4). We notice a spillover effect of 0.07 from ${RV_{t-1}}^{UK^0,S}$ to the $RV_t^{US^0,S}$, while to the $RV_t^{US,S}$ is higher with the value around 0.099. A significant and strong spillover effect is found between the US and both overlapping periods. For instance, a 1% increase in ${RV_{t-1}}^{US,S}$ leads to an increase into the next day of 0.219% in the UK overlapping period, respectively, 0.316% in the US overlapping period. However, we cannot identify the share of spillover due to either contemporaneous or dynamic interactions between our variables.

INSERT TABLE 4 HERE

5.2 *Structural Form Results*

Having already the residuals from the reduced form VAR, the next step is to estimate matrix $\mathbf{A}$ containing the contemporaneous spillover effects between our variables. However, before being able to estimate Equation (7) we need to define the regimes in such way that at least two regimes have different variances, a necessary condition to achieve identification. We compute 50 day rolling windows, from which we define 5 regimes and calculate their covariance matrix that we use in the GMM estimation.

I. Contemporaneous Relationships

In Table 5, we present the contemporaneous relations, matrix $\mathbf{A}$ as given in Equation (7) together with the bootstrap results. The coefficients have negative signs as matrix $\mathbf{A}$ is on the left-hand side of Equation (1), as such when taken to the right-hand side the spillover effects become positive:

$$RV_t^{UK^0,S} = -0.13RV_t^{UK,S} + \mathbf{0.25}RV_t^{US^0,S} \tag{6}$$

$$RV_t^{US^0,S} = 0.11RV_t^{UK,S} + \mathbf{0.17}RV_t^{UK^0,S} \tag{7}$$

$$RV_t^{US,S} = \mathbf{0.22}RV_t^{UK,S} + \mathbf{0.29}RV_t^{UK^0,S} + \mathbf{0.36}RV_t^{US^0,S} \tag{8}$$

We notice a high and positive contemporaneous spillover of 0.25 from the US overlapping trading period to the UK overlapping trading period. The coefficient suggest that a 1% increase in $RV_t^{US^0,S}$ leads to a contemporaneous increase of 0.25% in the $RV_t^{UK^0,S}$. Vice versa, from the $RV_t^{UK^0,S}$ to the $RV_t^{US^0,S}$ the spillover is smaller, approximately 0.17 indicating that the opening of NYSE has a bigger impact on the LSE than the other way around. This is inconsistent with the Granger causality findings which just consider the lagged effects without attention paid to contemporaneous effects.

Equation (10) explains the spillover effect from $RV_t^{UK,S}$, $RV_t^{UK^0,S}$ and $RV_t^{US^0,S}$ to $RV_t^{US,S}$. We observe the highest and most significant spillover of 0.36 from the US overlapping trading period to the US non-overlapping trading period, which again is not evident in the Granger causality test, i.e., Table 3. Regarding the spillover from the UK non-overlapping/overlapping trading period on the US non-overlapping trading period, we find that $RV_t^{UK^0,S}$ spillover is 0.29, greater than the $RV_t^{UK,S}$, with the value about 0.17, i.e., in line with the findings of Table 3. These results imply the existence of strong contemporaneous effects that are transmitted in the same day with risk management and international portfolio diversification implications for both countries. A shock occurring in the US stock market is automatically transmitted to the EU stock market in the same day. As such, investors and risk managers who do not pay attention to the contemporaneous effects may assess inaccurately the uncertainty exposure, i.e., the evaluation of risk is mislead. Practically, based on a traditional VAR they assume the risk transmission is with one day lag, instead we prove that the risk is transmitted in the same day when there is simultaneous trading. Consequently, the Granger causality tests and the dynamic reduced form VAR effects do not capture the contemporaneous effects between our stock markets, both analyse the causality/dynamics based on $\mathbf{\Phi}(\mathbf{L})^*$ which is a combination of the dynamic and the contemporaneous effects.

INSERT TABLE 5 HERE

II. Dynamic Relationship

Having the total spillover, i.e., matrix $\mathbf{\Phi_1^*}$ and understanding how much of spillover is due to the contemporaneous interactions, i.e., matrix $\mathbf{A}$, we are able to explore the dynamic linkages. Table 6 presents the findings for dynamic relations, matrix $\mathbf{\Phi_1}$ as given in Equation (1) alongside with the bootstrap results. We find there is no significant dynamic spillover from ${RV_{t-1}}^{US^0,S}$ to $RV_t^{UK,S}$ and $RV_t^{US,S}$, suggesting the incorporation in the same day of the spillover effect. There is, however, a positive dynamic spillover from ${RV_{t-1}}^{US,S}$ of 0.21 to the UK equity market, as well as both UK/US overlapping trading periods with the values of 0.16/0.25. These relationships reveal the importance of taking into account the contemporaneous spillover effects, i.e., the next day are transmitted only the effects due to non-overlapping trading.

When comparing the dynamic SVAR effects, in Table 6 with the dynamic reduced form VAR effects, in Table 4, we observe they lead to different conclusions. As can be seen, a 1% increase in ${RV_{t-1}}^{UK^0,S}$ causes an increase in $RV_t^{US,S}$ equal to 0.09% in the reduced form, versus a decrease of -0.04% in the structural form. These relationships are essential when implementing global hedging strategies. For example, knowing the previous reduced form dynamics one would take a long position into options to reduce the risk of adverse price movements. However, the structural form dynamics demonstrate that actually we increase the risk, i.e., a 1% increase in UK overlapping will lead to a decrease of -0.04% in the US. Looking at the spillover from ${RV_{t-1}}^{US,S}$ to both UK/US overlapping periods we find a suggestive positive relationship of 0.21/0.31 in the reduced form VAR, respectively a lower positive relationship of 0.16/0.25 in the structural form. Similarly, an investor would take a options long position based on the reduced form results ending up in increasing the risk instead of reducing it. Only by applying a SVAR to identify the contemporaneous and dynamic effects separately we are able to reduce the risk. Therefore, the dynamic linkages based on the reduced form VAR and the SVAR lead to various findings concerning the direction and magnitude of the spillover.

INSERT TABLE 6 HERE

III. Impulse response functions

Knowing matrix **A** containing the contemporaneous effect, we can determine the contemporaneous reactions of structural shocks to ε_t given by $\mathbf{A^{-1}}$. Therefore, Table 7 and Figure 2 presents the estimates of the SVAR impulse responses. Examining the first column of Table 6, i.e., the long run impact of $RV_t^{UK,S}$, $RV_t^{UK^0,S}$, $RV_t^{US^0,S}$ and $RV_t^{US,S}$ to a unit shock in $RV_t^{UK,S}$ we notice the impact is insignificant. Hence, there is no long-run effect of volatility spillover from any of the realized variances to the UK stock market. When we explore the impulse responses of the overlapping trading periods to a unit shock in all other realized variances we observe suggestive interactions. For instance, a unit shock in $RV_t^{UK^0,S}/RV_t^{US^0,S}$ induces an increase in both overlapping periods of approximately 10.31/9.12 units with respect to first shock, respectively 5.70/7.96 units to the second shock. This implies strong volatility spillover between the UK and the US stock markets during simultaneously trading.

INSERT TABLE 7 HERE

In Figure 2, we plot the structural impulses 250-day ahead for the four series. Panel A, B, C and D shows the responses of each series to a structural unit shock in $RV_t^{UK,S}$, $RV_t^{UK^0,S}$, $RV_t^{US^0,S}$ and $RV_t^{US,S}$. As can be seen most of the structural impulse responses converge within 75 days, where they stabilize around the value zero.

INSERT FIGURE 2 HERE

IV. Variance Decomposition

Having analysed the contemporaneous relationships, dynamic effects and the long-run impulse response, i.e., Table 5, 6 and 7, we turn our attention to the overall significance of each series in the system. In essence, the share of the variance of each asset that is explained by the structural shocks occurring in foreign markets and domestic market. Consequently, we compute the 250-day ahead forecast error variance decompositions which are presented in Table 8.

INSERT TABLE 8 HERE

Each element gives the percentage contribution of the structural shocks, i.e., ${\varepsilon_t}^{\mathrm{UK,S}}$, ${\varepsilon_t}^{\mathrm{UK^0,S}}$, ${\varepsilon_t}^{\mathrm{US^0,S}}$ and ${\varepsilon_t}^{\mathrm{US,S}}$ in clarifying the share of the total variance of each equity. Observing the diagonal of Table 8, we notice that the highest share of variance is due to the own structural shocks, ranging between 36% and 62%. The spillovers to the UK stock market are especially strong: structural shocks to US overlapping/non-overlapping explain on average 33%/30% of the UK overlapping/non-overlapping variances. A large share of the US stock movements are due to the UK stock market, i.e., near 26%/30% of the US overlapping/non-overlapping variances are defined by the UK overlapping shocks. The main finding is that a large share of the interactions in the equity markets are justified by simultaneously foreign asset prices.

6 Conclusion

In this paper, we analyze the total spillover distinguishing between the dynamic and contemporaneous spillover effects in the UK and the US stock markets. By using the high frequency data split in overlapping and non-overlapping periods we are able to explain the complexity of these relationships at volatility level.

We observe that the opening of the NYSE induces a higher contemporaneous spillover to the UK stock market. When comparing the spillover from the UK non-overlapping/ overlapping trading period to the US stock market, we notice the last one leads to a higher increase. The structural dynamic effects, as well as the contemporaneous effects suggest that the information is transmitted in the same day when we have overlapping trading and only the remaining spillover into the next day. We show the implications of our model by comparing the structural with the reduced form dynamic effects. The results show that the bi-directional dynamic relationships between the US and simultaneous trading periods are overestimated in the traditional VAR. Furthermore, we show the direction of causality, magnitude of the spillover and the overall importance by generating the structural impulse-responses, respectively the variance decomposition.

Our results have major implications for international diversification, risk management and hedging strategies. Investors and risk managers who do not pay attention to the contemporaneous effects may inadequately evaluate the risk, i.e., based on traditional VAR the risk is transmitted with one day lag, instead we demonstrate that the transmission is within the same day when simultaneous trading occurs. The implementation of hedging strategies concentrating on the reduced form results carry an increase in our risk exposure. We establish that only by identifying the contemporaneous and dynamic effects separately we are able to reduce the risk of adverse price movements. All in all, our estimates confirm the relevance of taking into account the simultaneous information.

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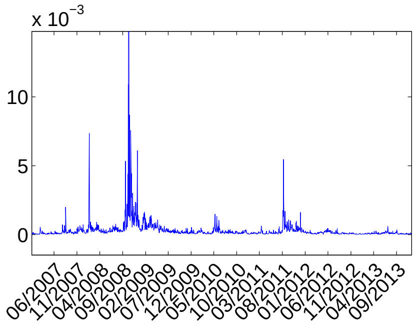
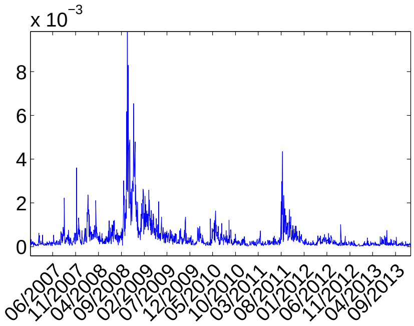
Figure 1: Realized variances

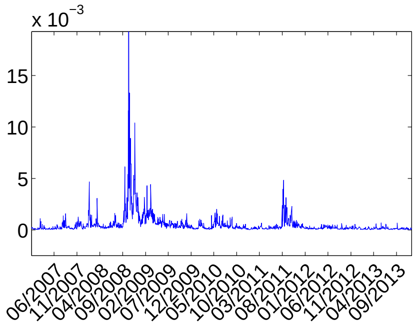
(a) Equity in UK



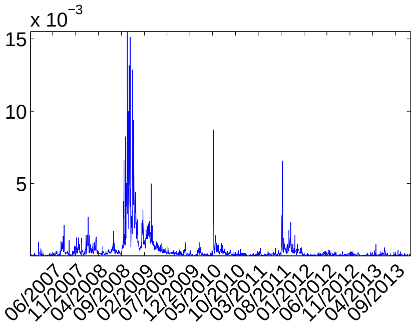
(b) Equity in UK^0



(c) Equity in US^0



(d) Equity in US



Note: This Figure shows the time series plot of the equity markets in all trading periods, over the sample January 3, 2010 to December 31, 2013.

Table 1: Summary Statistics

	Mean	Max	Min	Std.Dev.	Skew.	Kurt.	ADF
$V_t^{UK,S}$	0.0147	0.1874	0.0042	1.07e-04	0.0104	5.46	-6.36^*
$V_t^{UK^0,S}$	0.0182	0.1215	0.0037	1.23e-04	0.0111	2.46	-5.00^*
$V_t^{US^0,S}$	0.0191	0.1863	0.0043	1.69e-04	0.0130	3.49	-5.61^*
$V_t^{US,S}$	0.0159	0.1245	0.0031	1.80e-04	0.0134	3.30	-4.98^*

Note: This Table reports summary statistics for the equity volatilities in four trading periods. ADF is the t-statistics for the Augmented Dicky-Fuller test. * denote the significance at the 1% level.

Table 2: Correlation Matrix

	UK^S	UK_0^S	US_0^S	US^S
UK^S				
UK_0^S	0.8472			
US_0^S	0.8203	0.9088		
US^S	0.8160	0.8306	0.8553	

Note: This Table reports the correlation between equity in UK, UK^0, US^0 and the US.

Table 3: Granger Causality for Realized Variances

Null Hypothesis	5 lags	
	F-statistics	P-value
UK_0^S does not Granger Cause UK^S	36.28^{***}	2.E-35
UK^S does not Granger Cause UK_0^S	7.85^{***}	3.E-07
US_0^S does not Granger Cause UK^S	20.25^{***}	1.E-19
UK^S does not Granger Cause US_0^S	6.71^{***}	3.E-06
US^S does not Granger Cause UK^S	44.36^{***}	5.E-43
UK^S does not Granger Cause US^S	2.92^{**}	0.01
US_0^S does not Granger Cause UK_0^S	2.29^{**}	0.04
UK_0^S does not Granger Cause US_0^S	6.55^{***}	5.E-06
US^S does not Granger Cause UK_0^S	25.79^{***}	4.E-25
UK_0^S does not Granger Cause US^S	7.18^{***}	1.E-06
US^S does not Granger Cause US_0^S	47.26^{***}	94.E-46
US_0^S does not Granger Cause US^S	5.07^{***}	0.001

Note: This Table reports the results for the Granger causality tests on the reduced-form VAR. The reduced-form VAR is estimated using 5 lags. We present F-statistics and their associated P-values. ***, **, * denote significance at the 1%, 5%, 10% levels, respectively.

Table 4: The 1^{st}order Reduced Form Effects between Realized Variances

	UK^S	UK_0^S	US_0^S	US^S
UK^S	0.2101	0.2225	-0.0637	0.2114
UK_0^S	0.1017	0.2320	-0.0538	0.2191
US_0^S	0.0087	0.0727	0.1848	0.3164
US^S	-0.0248	0.0996	0.0451	0.3949

Note: This Table reports the dynamic relationship, matrix $\mathbf{\Phi_1^*}$ as given in Equation (4). The vector of variables is $RV_t = \left(RV_t^{UK,S} \quad RV_t^{UK^0,S} \quad RV_t^{US^0,S} \quad RV_t^{US,S}\right)'$.

Table 5: Contemporaneous Relationship between Realized Variances

	Parameter estimates	Bootstrap	
		Mean	Confidence Intervals
α_{21}	0.1393^{***}	0.1379	[0.1133, 0.1583]
α_{23}	-0.2533^{***}	-0.2530	[-0.2632, -0.2420]
α_{31}	-0.1197^{***}	-0.1225	[-0.1479, -0.1156]
α_{32}	-0.1796^{***}	-0.1805	[-0.1931, -0.1762]
α_{41}	-0.2286^{***}	-0.2279	[-0.2384, -0.2137]
α_{42}	-0.2935^{***}	-0.2934	[-0.3040, -0.2822]
α_{43}	-0.3663^{***}	-0.3659	[-0.3754, -0.3556]

Note: This Table reports the contemporaneous relationship, matrix $\mathbf{A}$ as given in Equation (7). We present coefficients together with their associated mean and 95% confidence intervals obtained in a bootstrap. Judging through the p-value from bootstrap all coefficients are significant at the 1% level. The vector of variables is $RV_t = \left(RV_t^{UK,S} \quad RV_t^{UK^0,S} \quad RV_t^{US^0,S} \quad RV_t^{US,S}\right)'$.

Table 6: The 1^{st}order Dynamic Effects between Realized Variances

	Parameter estimates	Bootstrap	
		Mean	Confidence Intervals
Panel A: Dynamic transmission to $RV_t^{UK,S}$			
ϕ_{11}	0.2101^{***}	0.2096	[0.1535, 0.2671]
ϕ_{12}	0.2225^{***}	0.2219	[0.1735, 0.2676]
ϕ_{13}	-0.0637^{**}	-0.0623	[- 0.1338, 0.0057]
ϕ_{14}	0.2114^{***}	0.2112	[0.1664, 0.2564]
Panel B: Dynamic transmission to $RV_t^{UK^0,S}$			
ϕ_{21}	0.1287^{***}	0.1300	[0.0614, 0.1992]
ϕ_{22}	0.2446^{***}	0.2405	[0.1814, 0.2952]
ϕ_{23}	-0.1095^{**}	-0.1071	[- 0.1885, -0.0265]
ϕ_{24}	0.1684^{***}	0.1682	[0.1154, 0.2210]
Panel C: Dynamic transmission to $RV_t^{US^0,S}$			
ϕ_{31}	-0.0348^{**}	-0.0342	[- 0.0828, 0.0167]
ϕ_{32}	0.0044^{**}	0.0050	[- 0.0362, 0.0463]
ϕ_{33}	0.2021^{***}	0.2009	[0.1372, 0.2664]
ϕ_{34}	0.2517^{***}	0.2511	[0.2114, 0.2887]
Panel D: Dynamic transmission to $RV_t^{US,S}$			
ϕ_{41}	-0.1058^{***}	-0.1042	[- 0.1755, -0.0314]
ϕ_{42}	-0.0460^{**}	-0.0458	[- 0.1035, 0.0153]
ϕ_{43}	0.0078^{**}	0.0083	[- 0.0868, 0.0944]
ϕ_{44}	0.1664^{***}	0.1645	[0.1088, 0.2177]

Note: This Table reports the dynamic relationship, matrix $\mathbf{\Phi_1}$ as given in Equation (1). We present coefficients together with their associated mean and 95% confidence intervals obtained in a bootstrap. ***, **, * denote significance at the 1%, 5%, 10% levels, respectively, judged through the p-value from bootstrap. The vector of variables is $RV_t = \left(RV_t^{UK,S} \quad RV_t^{UK^0,S} \quad RV_t^{US^0,S} \quad RV_t^{US,S} \right)'$.

Table 7: Long-Run Impact Matrix

	$\varepsilon_t^{UK,S}$	$\varepsilon_t^{UK^0,S}$	$\varepsilon_t^{US^0,S}$	$\varepsilon_t^{US,S}$
$RV_t^{UK,S}$	4.6064	9.2541	5.1448	7.7242
$RV_t^{UK^0,S}$	2.8408	10.3146	5.7098	7.8440
$RV_t^{US^0,S}$	2.8235	9.1267	7.9639	8.4564
$RV_t^{US,S}$	3.6169	11.1779	8.0760	11.4418

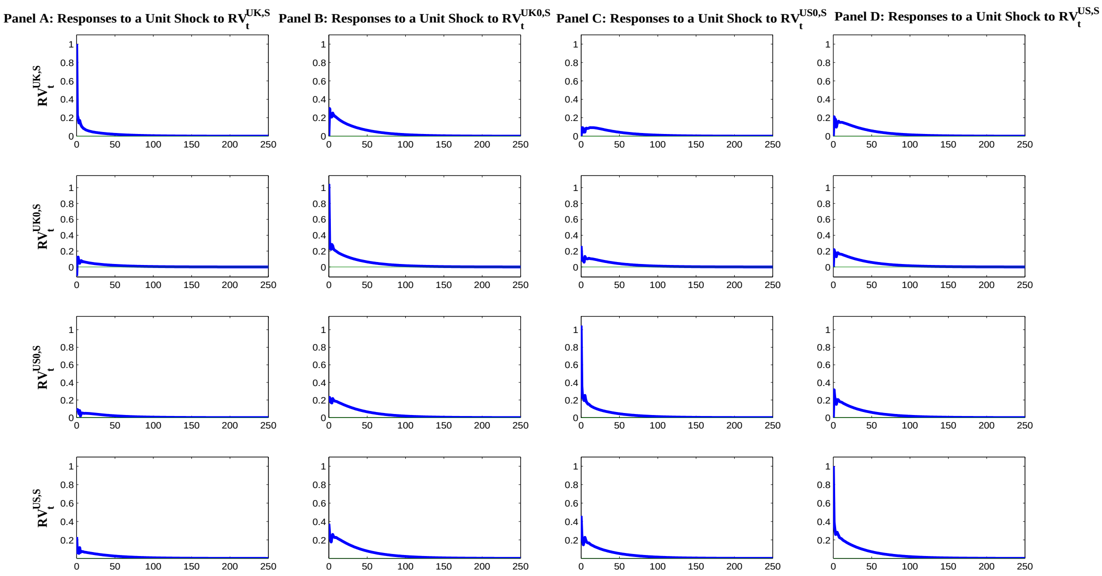
Note: This Table reports the long-run impact matrix of structural VAR. The impacts are computed at the 250-day ahead response to a unit structural shock.

Table 8: Variance Decomposition

	$\varepsilon_t^{UK,S}$	$\varepsilon_t^{UK^0,S}$	$\varepsilon_t^{US^0,S}$	$\varepsilon_t^{US,S}$
$RV_t^{UK,S}$	36.24%	33.72%	8.63%	21.41%
$RV_t^{UK^0,S}$	3.90%	62.85%	11.70%	21.55%
$RV_t^{US^0,S}$	2.63%	26.15%	46.83%	24.39%
$RV_t^{US,S}$	3.74%	30.14%	18.91%	47.21%

Note: This Table reports the share of the variance of each equity that is explained by the structural shocks. The variance decomposition are computed at the 250-day ahead response to a unit structural shock.

Figure 2: Structural Form Impulse-Response



Note: This Figure shows the equity impulse response functions of the structural VAR. Panel A, B, C and D presents the responses to a structural unit shock in $RV_t^{UK,S}$, $RV_t^{UK^0,S}$, $RV_t^{US^0,S}$ and $RV_t^{US,S}$, respectively. The x-axis is the 250-day ahead responses and the y-axis is the non-accumulated response.