Volatility and Skewness Transmission in International Stock Markets – A Comparison Study on ETFs and Their Underlying Indices

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Dec 8th, 2014

Abstract

This paper employs a VAR framework to investigate the differences between index tracking ETFs in Germany, Japan, UK and US and their underlying indices. Our paper investigates these differences in two different settings. First, we analyse the relationship between returns, volatilities and skewness in an intra-market setting, and compare the results for ETFs with those of their underlying indices. We then investigate the transmission of volatility and skewness between the four markets in our sample, again comparing the ETF results to the indices. The results from the intra-market analysis tell us that, although some differences exist, the ETFs do closely replicate the relationship exhibited by the underlying indices. However, in the transmission model we find significant differences between the ETFs and the indices.

Keywords: exchange traded funds, ETFs, volatility transmission, skewness transmission, upside volatility, downside volatility, VAR

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Acknowledgements

We are grateful to our tutor, Professor Halling who was very helpful in providing guidance and answering our questions. We also want to thank our families and friends for their support during the writing of this paper. . Finally, thanks to Kevin Sheppard at Oxford University, we are able to use MFE toolbox in MATLAB to facilitate our programming and modeling.

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1. Introduction

The importance of Exchange Traded Funds (ETFs) in today's financial markets is obvious, with ca. $2.5 trillion assets under management (AUM) and 3868 ETFs worldwide[1]. Numerous studies have been done on the tracking error of ETFs i.e. a comparison of their returns to the underlying indices. This tracking error can be both positive and negative. Management fees, transaction costs, rebalancing and capital flows, dividends and the bid-ask spread on ETFs exchange prices are all said to influence ETFs tracking error. Having established the importance of ETFs in today's markets our study aims to build on the previous literature in comparing four index tracking ETFs to their underlying indices. We will first do an intra-market analysis with a VAR framework regressing current returns, volatility and skewness on past returns, volatility and skewness. We will then compare the results we observe in the ETFs with the results we observe in the underlying indices. This first dimension in our paper aims to understand whether the relationship between past returns, volatility and skewness and current returns, volatility and skewness is the same for ETFs and their underlying indices.

A great deal of attention has been dedicated in recent years to volatility transmission across international markets, dealing mainly with equity and FX instruments[2]. It is usually assumed that the mean-variance investor chooses her optimal portfolio looking at the first two moments of returns. If this is the case, it is relevant to understand not only how returns (or their means) are correlated across markets, but also how risk, as expressed by the variance, spreads. A strong relationship among volatilities in different countries would reduce the possibilities of diversification, since when a shock occurs in one place, it is likely to have repercussions on returns in other locations as well. When correlations are large and positive, it becomes harder to get rid of the risk associated with a specific country by investing in other markets, and it becomes important, for investors who limit their asset range to domestic stocks, to understand how foreign markets influence the domestic one, so that they can hedge the risk.

Variance by itself is not completely a bad thing from an investor's point of view. If in a given period returns tend to be positive, having some variances on the upside might help make higher gains. For this reason the third moment of returns, skewness, which can be related to the difference between the probability mass that lies on the sides of the mode in a distribution, has become the focus of many empirical research papers. Intuitively, one might assume that investors should prefer positive skewness, which is related to upside volatility. This phenomenon resembles the outcome of buying a lottery ticket; there exists a relatively high probability of a small loss, but with some lower probability of a huge gain. Stock markets however seem to be on average negatively skewed, especially the US market. Therefore, one might hypothesize that inves-

[1] Sourced from ETF/ETP sponsors, exchanges, regulatory filings, Thomson Reuters/Lipper, Bloomberg, other publicly available sources, as at September 2014

[2] Following the methodology of Merton (1980) we essentially take the variance as our proxy for volatility, when this paper refers to volatility we are referencing our proxy for volatility i.e. variance

tors would look for opportunities to reduce negative skewness in their portfolios, by broadening the range of financial instruments and markets in which they are invested. However, if there exists some transmission mechanism for skewness across different markets, investors would find it harder to deal with this issue.

For this reason we believe that it is interesting to investigate to what extent different markets' asymmetries are correlated and whether one particular country is leading the others. If such a phenomenon is present, it should manifest itself clearly among developed markets. The second part of our analysis will address this issue. Specifically, we will analyse how much of the volatility and skewness we see in ETFs in one market can explain movements in ETFs in other markets– we will then again compare our findings to the results obtained by performing a similar analysis on the underlying indices that the ETFs aim to track. More explicitly this second part of our paper aims to answer the question: Is there transmission of skewness and variance between the different markets in our sample, and if so, do ETFs allow for more transmission of volatility and skewness between markets than what we would expect from analysing the transmission of volatility based on the market indices?

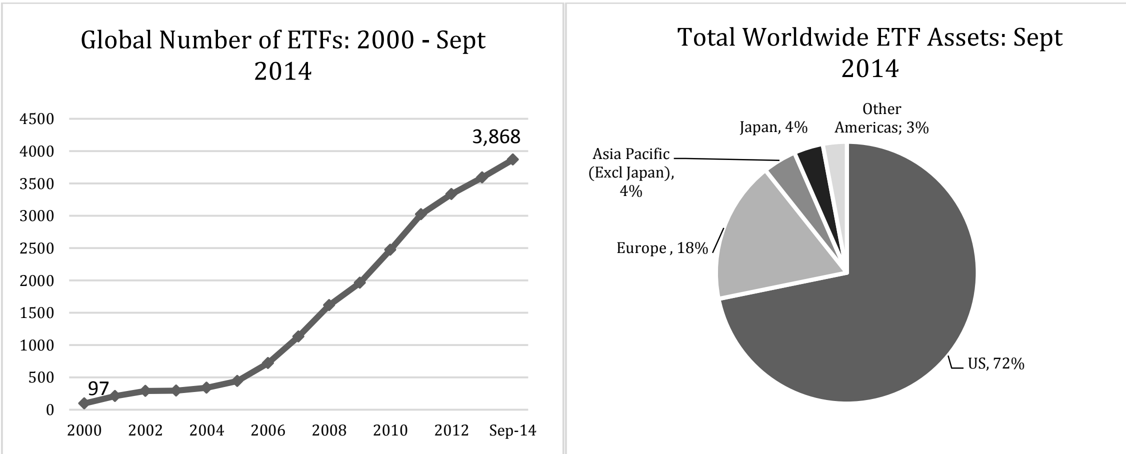
In the first part of our analysis, we found significant relationships between past returns, volatility and skewness and current returns, volatility and skewness. The relationships observed were broadly similar between ETFs and their underlying indices. In the second part of our analysis we observed volatility and skewness transmission between the markets in our sample. However, the transmissions observed differed between the ETFs and indices.

The layout of this paper is as follows: Section 2 deals with an introduction to exchange traded funds, their background and characteristics. Section 3 is a brief overview of past literature on the criticisms ETFs have received and on the topics of transmission of volatility between international stock markets and on the importance of attempting to measure skewness in returns. Section 4 details the different methodologies that we have applied in this study. Section 5 introduces the data in our sample as well as some statistics on this data. Section 6 covers the empirical results from our study. Section 7 details our interpretation of the results observed in the empirical analysis. Finally, Section 8 draws a conclusion and offers some possible implications for future research.

2. Exchange Traded Funds: Background and characteristics

The idea or concept behind Exchange Traded Funds (ETFs) was first introduced in the late 1980's by the Toronto Stock Exchange. It was a variation of an exchange traded product that allowed investors to track the largest stocks traded in Toronto and was known as the Toronto Index Participation Fund. The first ETF introduced to the US market was the Standard and Poors' 500 Depository Receipts (SPDRs), which began trading in 1993. This ETF is widely regarded as the true beginning of ETF history and is still trading today. This ETF tracked the S&P 500 Index and was the first ETF in this group of ETFs now referred to as SPDRs or "spiders". ETF's popularity has grown exponentially since the early 2000s. One hypothesis put forward to explain this growth is that the diversification offered to investors by ETFs became especially attractive after the bust of the dotcom bubble highlighted the importance of holding a balanced and diversified portfolio.

Figure 1



Source: ETF/ETP sponsors, exchanges, regulatory filings, Thomson Reuters/Lipper, Bloomberg, other publicly available sources
Note: Doesn't include other exchange traded products such as ETNs and ETCs

As of Sept 2014, the total net value of ETF's worldwide is ca. $2.5 trillion, with the United States holding the largest share of this market.

An ETF is similar to an index fund that represents a basket of stocks that in turn represent an underlying index. The primary difference between a mutual or index fund and an ETF is that an ETF trades throughout the day the same as an ordinary stock, therefore its price will change throughout the day as set by supply and demand in the market. Index funds, in contrast, cannot be bought and sold throughout the day but instead have a Net Asset Value (NAV) that is calculated at the end of each trading day. The main advantage of an ETF over an index fund is this extra liquidity that it provides to investors. The ability to trade ETFs throughout the day also makes them appealing to both long-term and short-term traders. In addition to the additional liquidity provided by ETFs, they also offer investors many varying investment opportunities. Examples of these include the investment opportunities offered by Leveraged and Inverse ETFs. Leveraged ETFs use financial derivatives and debt to amplify the returns of the underlying index. Inverse ETFs, again through the use of financial derivatives, aim to allow investors to profit from a decline in the underlying index. Essentially, an investment in an inverse ETF is akin to holding various short positions. Additional opportunities for investment provided by Exchange Traded Products include investment in commodities, foreign currencies and emerging markets. Appendix 1 includes a detailed discussion of these different products and the investment opportunities they provide.

3. Literature overview

Due to the scope of our topic, our literature review is divided into 4 separate sections: 3.1 deals with the various criticisms ETFs have received, 3.2 looks at papers written on the topic of transmission of volatility between international stock markets, 3.3 looks at the recent and growing interest that the literature has had in attempting to measure skewness in stock returns and finally 3.4 includes some stylized facts from previous research that we will look for in our results

3.1 ETFs

A number of papers have analysed the performance of ETFs, both in comparison to mutual funds and to their underlying indices. Guedj and Huang (2008) found that ETFs performed better over a longer investment horizon and therefore were better suited to investors with a longer term investment focus. Sventina and Wahal (2010) find that on average ETFs underperform their benchmark indices and are not immune from tracking error. Valle, Meade and Beasley (2014) also find that only 11% of the ETFs in their sample reproduce both the mean return and the volatility of their benchmark within 1% p.a.

As ETFs have increased their market share and taken a more prominent (and permanent) place in investor's portfolios, they have also attracted their fair share of criticism. Ramaswamy (2011) discusses ETFs contribution to a build-up of systematic risks in the financial system. Market regulators, such as the SEC in the US, have previously investigated the possible risks ETFs pose to investors[3]. One of the main advantages of ETFs mentioned in the previous section is the liquidity that they provide to investors. However, this liquidity translates into more price variation and therefore an increased volatility in the underlying basket of securities. Ben-David, Franzoni and Moussawi (2014) conclude that for S&P 500 stocks, a one standard deviation increase in ETF ownership is associated with a 21% increase in intra-day volatility. This volatility effect is also present in daily returns where the effect of a one standard deviation increase in ETF ownership is about 16% of a standard deviation of daily volatility[4]. They find that these effects are most significant for larger stocks. This finding is consistent with arbitrageurs concentrating on a subset of more liquid stocks in order to replicate the basket of securities underling an ETF. This extra volatility (especially short-term) is a concern for market regulators as it can potentially disadvantage long-term investors[5]. Bradley and Litan (2010) looks at the potential of ETFs to drain liquidity from stocks and commodities that are already illiquid, especially in the case of a short squeeze occurring when ETF sponsors rush to create new ETF shares. Madhavan (2011) links the Flash Crash of 2010 to market fragmentation in ETF trading. In

[3] See "SEC Reviewing Effects of ETFs on Volatility" by Andrew Ackerman, Wall Street Journal, 19 October 2011
[4] Based on intraday volatility that is calculated on second-by-second returns
[5] The SEC Concept Release No. 34-61358 states: "short-term price volatility may harm individual investors if they are persistently unable to react to changing prices as fast as high frequency traders. As the Commission previously has noted, long-term investors may not be in a position to assess and take advantage of short-term price movements".

their recent paper, Da and Shive (2013) find that ETF ownership positively affects the co-movement of stocks that are in the same basket. Another argument brought forward by critics of ETFs is that they encourage investors to trade more frequently; this frequent trading is thought to undermine the long-term investment philosophy that accompanies index investing[6].

If the results in the second part of our research show that index tracking ETFs allow for a greater amount of volatility and skewness transmission, it will therefore be harder for international investors to use these instruments to reduce their portfolio exposure to negative skewness.

3.2 Transmission of volatility between markets

Grubel (1968) and Levy and Sarnat (1970) both found empirical evidence to support the benefits and importance to investors of holding internationally diversified portfolios. Since these papers, a series of studies have examined the relationship among national stock markets. Despite using varying methods of empirical analysis, Granger and Morgenstern (1970), Ripley (1973), Lessard (1974), (1976), Panton, Lessig and Joy (1976), and Hilliard (1979) generally agreed that: (i) the correlations among returns in national stock markets was surprisingly low, and, (ii) national factors unique to each market played an important role in the return generating process. There were some researchers whose findings did not align with those mentioned above. For example, Agmon (1972), (1973), found a significant relationship among the four stock markets he chose to examine, Germany, Japan, the UK and the US. He found that stock prices in non-US markets responded to changes in prices in the US markets with no significant lags on a monthly basis. In a more recent study, Eun and Shim (1989) found that a substantial amount of multi-lateral interaction exists between national stock markets. Their study found the US market to have the most influence over other countries stock markets. Movements in the US stock market in their sample were found to be rapidly transmitted to other countries stock markets in a clear and identifiable pattern. However, their study also failed to find any single foreign market whose movements were transmitted in the same fashion to the US market. These findings support the notion of efficient international stock markets where information is processed and rapidly transmitted between markets. King and Wadhwani (1990) find that the stock market correlations between Japan, the US and the UK have increased since the stock market crash in 1987. Later studies, Lee and Kim (1993) and Longin and Solnik (1995) extend these studies to a wider range of countries. Despite these findings that indicate an increasing amount of correlation between international markets, a study by De Santis and Gerard (1998) indicates that the original benefits of international portfolio diversification expounded by the work of Grubel (1968) and Levy and Sarnat (1970) still exist.

[6] See "ETF Simplicity Betrayed by Volatility in Market Selloff", Bloomberg, 2013; this criticism was put forward by Jack Bogle, the founder of Vanguard Group. As of September 2014, Vanguard Group is one of the word largest ETF providers, responsible for 109 ETFs/ETPs, with a Net Asset Value of $395,750m.

More recent work in this field include Baele (2005), Fu, Holmes and Choi (2011) and Abbas et al. (2013): these papers employ multivariate time series models for returns, and then study conditional variance and covariance series in the BEKK framework. Aboura (2003) uses data on implied volatility derived from volatility indices, and estimates a VAR model for changes in these indices; the author finds that there are significant causality relations in the sense of Granger among implied volatilities in the USA, Germany and France, with the American market leading the way. Finally, different researchers have analyzed models that allow for jumps – Wagner and Szimayer (2004) – and studied the impact of crises in the transmission of volatility – Karunanayake et al. (2010). It appears that volatility shocks originate locally, and then propagate to other markets. For a more in depth review of papers on volatility transmission and on the different models employed see Soriano and Climent (2005).

3.3 Skewness

Starting from the Crash of October 1987, a significant amount of interest has been devoted to the third moment of returns, with various attempts to model conditional skewness and to measure realized skewness. It has been shown that skewness is intimately linked to the difference between upside and downside volatility. In our paper we build on these ideas by investigating the possible transmission of skewness, expressed as realized skewness, across the four markets in our sample. We then look to analyze whether this potential transmission of skewness is of the same magnitude for ETFs and their underlying indices.

Investors do attach different weights to volatility according to whether it is matched by positive or negative returns. Intuitively, investors should prefer to have more volatility on the upside, possibly leaving room for extreme positive events, and dislike downside risk, i.e. prefer positive skewness. Starting from Hansen (1994), several authors have tried to adapt the ARCH/GARCH framework to include terms that capture skewness, and to model conditional skewness. Among them we mention the work of Harvey and Siddique (1999), who use some adaptations of the GJR GARCH and of the exponential GARCH, and of León et al. (2004), who propose the NAGARCHS and the GARCHS models. These studies confirm the significance of skewness and its impact on variance persistence[7].

Skewness however appears to be an elusive concept as much as volatility is: Kim and White (2004) stress how measures of skewness based on the sample mean are extremely sensitive to outliers, and test the performance of robust measures of skewness, mainly based on quantiles.

Barndoff-Nielsen et al. (2010) introduce a new measure called Realized Semi Variance, which captures the downside volatility of high frequency returns. They show that using this measure in GARCH models gives better results than employing the traditional realized variance.

[7] See León et al.(2004). In particular conditional asymmetry as estimated in this paper can in part explain the leverage effect.

In their paper, the authors use returns at a very high frequency, and they also discuss the possibility of taking square returns to measure volatility. Indeed at such a frequency, some properties from continuous-time calculus can be applied. Feunou, Jahan-Parvar and Tédongap (2011 and 2013) extend this idea by arguing that the difference of the upside and downside realized semi-variances can be used as a proxy for skewness, and provide the link between downside volatility and conditional skewness, showing how the latter is a factor priced by investors. They also investigate which parametric model performs better in capturing conditional skewness, by relating the model-implied conditional skewness to realized skewness, and they find that a particular specification of the EGARCH is the one that works the best.

So far, few attempts have been made to investigate how skewness in stock returns can be transmitted across international markets. Ghysels et al. (2011) develop a quantile-based measure of conditional skewness employing the MIDAS quantile specification, and compute the correlation matrices among asymmetries in different sets of countries. Surprisingly they find that, in contrast with what happens for the first two moments, the correlation for skewness is low, and the more so between developed and emerging markets. Thus, they try to explain the level of skewness in one market with idiosyncratic characteristics of the market itself. Indeed they find that skewness is correlated with several financial and macroeconomic variables of each country such as the volatility of the stock market and the volatility of the GDP growth rate. Jondeau and Rockinger (2003), after having confirmed the relevance of higher moments in most instances for stock and FX returns, draw a correlation matrix for skewness, subdividing it into quartiles. They show that in general correlation of skewness seems to be higher during periods of market turbulence, i.e. when the most extreme values of skewness occur.

We build on these results to analyze whether and to what extent realized skewness in one country can influence realized volatility and skewness in another country. We also want to test in what magnitude realized volatility and realized skewness interacts with returns in a specific market.

3.4 Stylized facts

In our analysis we test for the presence of some established phenomena. The presence of these phenomena, in addition to the results of our statistical tests allows us to determine that our model is a realistic model. In particular, we test for the leverage effect and for volatility persistence, even at a monthly level. We will then look to analyze the differences in our index and ETF model.

The leverage effect refers to the generally negative correlation between an assets return and its changes in volatility. Black (1976) explains this phenomenon as a negative return implies a drop in the firm's equity value, which in turn causes the firms leverage to increase, this increase in leverage then leads to higher equity-return volatility. This effect and its leverage based explanation has been confirmed in a number of studies published subsequent to Black's paper, e.g. Christie (1982), Cheung and Ng (1992) and Duffee (1995). Volatility persistence or volatility clustering refers to the phenomenon of wide volatility swings across time periods. This is due to the fact that there is an observed pattern of volatility cycles, periods of low volatility and periods of high volatility. These periods are respectively known as "Calm" and "Wild" periods. The underlying logic for this effect is that a large shock in one direction, tends to be followed by a large shock in the other direction, or conversely a small shock in one direction is followed by a similarly small shock in the other direction. This effect is particularly evident at higher frequencies, but we will test to see if this effect is present at a monthly level.

4. Methodology

This comparison study aims to address the issue of the transmission of volatility and skewness from one market to another, with realized skewness being the measure for studying the upside and downside volatility. A variety of methodologies have been suggested and adopted in the literature for similar issues. Given the frequency of the data, we decide to study skewness at the monthly level, since we believe that transmission occurs in a short time span, and it would not make sense to consider lower frequencies. Detailed below are the different methodologies that are a best fit for our study.

4.1 Measure for volatility

Based on the previous work by Andersen, Bollerslev et al. (2002), the intra daily returns are prevalently constituted by noise (or innovation), so it is very convenient and straightforward to adopt the method from French, Schwert, and Stambaugh (1987), and take the square return as the measure for the volatility[8]. However, our data points for the four equity indices and ETFs in four different markets are all measured at a daily level. Thus, due to the limitation of the data frequency, we need to fit a model that removes serial correlation, and work with the residuals. By taking out the serial dependence, we follow the same logic as the literature and treat residuals as an innovation through time. First, we estimate the optimal ARMA (p, q) model for each return series of the four markets, from which we save the residuals. Then we take the square residuals as the daily unconditional variance of the return series. The study from French, Schwert, and Stambaugh (1987) suggests to include a term that accounts for serial correlation, but in our case we have already removed this effect, and hence we do not need to include the covariance term. Since we are studying the transmission at a monthly level, we use the approach from French, Schwert, and Stambaugh (1987) to scale the variance to the realized monthly variances, by adjusting for the trading days in the month. One issue that we have to address in our study is to obtain a measure of skewness that is not too sensitive to outliers in

[8] As we essentially take the variance as our proxy for volatility, when this paper refers to volatility we are referencing our proxy for volatility i.e. variance

the monthly subsamples. Since modeling conditional skewness would require more complex mathematical procedures, we stick to realized measures, rather than employing a GARCH specification that allows for skewness.

Conditional Mean Equations:

The mean equation of logarithm return series y_t is shown below:

$$y_t = \mathrm{E}(y_t|\psi_{t-1}) + \varepsilon_t \tag{1}$$

Where E (y_t |ψ_{t-1}) is the conditional mean of y_t given ψ_{t-1}. ψ_{t-1} is the information set at time t_{-1}. ARMA (p, q) model is used to fit the data to remove this linear dependence and get the residual ε_t that is uncorrelated (but not independent).

$$y_t = \mu \sum_{i=1}^{p} \hat{\phi}_t y_{t-i} + \sum_{j=1}^{q} \hat{\varphi}_t \varepsilon_{t-j} + \varepsilon_t \tag{2}$$

This ARMA (p, q) process is stationary when all the roots of

φ(z) =1−φ1z −φ2 z −....−φp z = 0 lie outside of the unit circle.

To specify the order of the ARMA process, we use Akaike Information Criterion (AIC) and the Bayesian Schwarz Criterion (BIC) to choose the ARMA term that minimizes the corresponding value of the criterions. After filtering our data with the ARMA process, we generate the variances as:

$$RV_t = \left\{ y_t - (\boldsymbol{\mu} \sum_{i=1}^{p} \hat{\phi}_t y_{t-i} + \sum_{j=1}^{q} \hat{\varphi}_t \varepsilon_{t-j}) \right\}^2 \tag{3}$$

4.2 Measure for skewness

It is often convenient to assume that the distribution of return series is normal. However, as Ghysels et al. (2011), Brooks et al. (2005), and Jondeau and Rockinger (2003) addressed in their studies, even in a large sample of financial time series, the conditional skewness does not vanish. So given the importance of skewness in financial time series, we try to employ a measure that is intuitive enough and that captures this feature efficiently. In this case, as for volatility, we do not have a set of data with observations frequent enough to allow us to directly calculate the realized monthly skewness for return series, so we follow the same methodology and treat residuals estimated from the ARMA (p, q) models as innovation and use them to study skewness. Based on the study by Feunou, Jahan-Parvar, and Tedongap (2013), skewness can be measured by the difference of upside and downside volatility. The difference in our case is that since the sample size for each monthly unit is small and usually we do not have a clear mode in a sample with average size of 22, we use zero as our threshold between upside and downside. We compare residuals with zero to determine whether it is in the downside or upside part. So when the residual is larger than zero, we save it and use the approach from French, Schwert, and Stambaugh (1987) to get the upside volatility. The same when the residual is negative, and we calculate the downside volatility. Given the fact that the distribution of logarithmic returns is unimodal, when the upside volatility is larger than the downside, we have a positive skewness; if they are equal, we have symmetry; if the upside volatility is smaller than the downside, the skewness of the distribution is negative. We follow the same logic as the study of Patton and Sheppard (2013) and we use upside volatility minus downside volatility to get the proxy for realized monthly skewness, which is our measure for skewness.

$$RV^{+} = \frac{J_t - 1}{J_t} * \sum u_t^2 \text{ ; for } (u_t > 0) \tag{4}$$

$$RV^{-} = \frac{J_t - 1}{J_t} * \sum u_t^2 \text{ ; for } (u_t < 0) \tag{5}$$

$$RA = RV^{+} - RV^{-} \tag{6}$$

Where Jt is the number of observations and ut is the residual derived from ARMA processes that we mentioned previously.

4.3 VAR framework

Based on the study of Aboura (2003), we use a VAR (p) model to analyze the relation among returns, volatility and skewness. A VAR (p) model can give us the statistical significance of each coefficient and show the magnitudes of the coefficients themselves. We have set the lags based on multivariate version of the Bayesian Schwarz Criterion (MBIC) in all cases, since we have these series of variables all in monthly level and it would be hard to interpret coefficients for many lags and the MBIC will add a punishment on the number of parameters. Indeed, in all the cases, the model suggested by the Bayesian information criterion contains only one lag. For complimentary analysis we have also looked at the VAR (p) model suggested by the multivariate version of the Akaike Information Criterion (MAIC). This was helpful in understanding the intra-market models, as it was possible to have a more realistic model by including more lags. However, for the cross-market VAR, we only used the MBIC as it is necessary to keep the number of lags constant over all markets.

The MBIC is defined as:

$$\mathrm{MBIC} = \ln\left|\hat{\Sigma}\right| + \frac{k' \ln \mathrm{T}}{\mathrm{T}} \tag{7}$$

The MAIC is defined as:

$$\mathrm{MAIC} = \ln\left|\hat{\Sigma}\right| + \frac{2k'}{\mathrm{T}} \tag{8}$$

Where $\hat{\Sigma}$ is the determinant of the variance-covariance matrix of residuals of the VAR model, k' is the total number of regressors in all equations, which will be equal to $g^2 * k + g$ for g equations, each with k lags of the g variables, plus a constant term in each equation. The values of the information criteria are constructed for 0, 1 ... lags (up to some pre-specified maximum $\bar{k}$).

The VAR (1) models will be defined as:

$$\begin{pmatrix} y_{1,t} \\ y_{2,t} \\ y_{3,t} \end{pmatrix} = \begin{pmatrix} \beta_{10} \\ \beta_{20} \\ \beta_{30} \end{pmatrix} + \begin{pmatrix} \beta_{11} & \alpha_{11} & \gamma_{11} \\ \alpha_{21} & \beta_{21} & \gamma_{21} \\ \alpha_{31} & \gamma_{31} & \beta_{31} \end{pmatrix} \begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \\ y_{3,t-1} \end{pmatrix} + \begin{pmatrix} \mu_{1,t} \\ \mu_{2,t} \\ \mu_{3,t} \end{pmatrix} \tag{9}$$

Our order for investigating the relationship of returns, volatility and skewness inside and across markets is as follows. Firstly, we build a VAR (p) model for each market. We want to see whether there is any meaningful relation among monthly returns[9], realized volatility and realized skewness. In particular we want to test whether skewness depends crucially on the other two variables, and whether it influences them in some way. Secondly, we build a VAR (p) including realized volatility and skewness in all markets. Thus, we can observe whether transmission of skewness exists across markets and if it does exist, which market is leading the others and what is the main driver for skewness transmission between the four markets in our sample. Even though it is not a crucial point in our paper, we can also observe whether there is a significant volatility transmission across markets at a monthly level, and which country exerts the most influence in this respect.

[9] Since we are dealing with log-returns, the monthly return is just the sum of the returns in the month.

We report the R^2 of the different VAR models, to have some understanding of whether realized volatility and skewness are better measured in an international or an intra-market framework.

4.4 Causality tests

Following the framework set by Aboura (2003), we include the results of a Granger causality test to measure the presence of transmission, even though, since in all cases we deal with a VAR (1) model, we expect the results to differ from what the VAR coefficients suggest due to higher frequencies tested in the Granger process.

Granger causality tests have been used frequently to investigate short run relationships among two or more variables of interest. A high degree of causality from one variable to another indicates that the two markets are integrated and that a change in the variable in one market tends to lead the change in the variable of the other market. The lead-lag relationships revealed by Granger tests allow an evaluation of which market may be dominant. The null hypothesis of no causality between 2 processes y_t and x_t is tested through the Granger causality bivariate expression:

$$\begin{aligned} y_t &= a_0 + a_1 y_{t-1} + \cdots + a_k y_{t-k} + b_1 x_{t-1} + \cdots + b_k x_{t-k} \\ x_t &= a_0 + a_1 x_{t-1} + \cdots + a_k x_{t-k} + b_1 y_{t-1} + \cdots + b_k y_{t-k} \\ &\text{With } H_0\colon b_1 = \cdots = b_k = 0 \end{aligned} \tag{9}$$

We also use the impulse response functions and include their plots, so that we can see how a shock in one variable might impact all the others, and for how long such effect is bound to last[10]. We can also extract a better understanding of the economic significance of each coefficient, by measuring the size of each effect.

[10] On the importance of using impulse response when dealing with more than two equations in a VAR framework, see also Lin, Jin-Lung, Notes on Testing Causality (2008).

5. Data description

5.1 Data overview

Our analysis looks at four stock markets; Germany, Japan, UK and US. The indices we chose to represent these markets are as follows: DAX 30 Performance - Price Index, Nikkei 225 Stock Average - Price Index, FTSE 100 – Price Index and the S&P 500 Composite – Price Index. The corresponding ETFs tracking these indices are: ISHARES DAX (DE), DAIWA ETF-Nikkei 225, ISHARES FTSE 100 UCITS ETF and ISHARES CORE S&P 500 ETF.

Within each of these markets our data includes closing prices for the selected indices and a corresponding ETF over the longest horizon available from January 2001 until November 2014 for Germany, July 2001 until November 2014 for Japan, May 2000 until the November 2014 for the U.K. and U.S. Therefore, our sample is comprised of 8 time series samples, including 3619 data points for Germany, 3481 data points for Japan, 3781 data points both for U.K. and the U.S. We have sourced all our data from Reuters DataStream.

For our cross-market VAR we cut the data horizon on all samples to align with that of the series with the least data points. This was necessary to ensure we had comparable horizons across our sample. As noted above, Japan had the shortest horizon in our sample, therefore our data horizon for cross-market VAR is from July 2001 until November 2014.

Our motivations for choosing these indices and corresponding ETFs is that we wanted to look at the indices of major developed markets that should have significant impact on each other. In addition, these more developed markets are also some of the markets where index tracking ETFs were first introduced. This allows us to include as many data points as possible and therefore increases the statistical quality of our results. Finally, since we are studying transmission between international markets, we choose 4 countries with different currencies as representative of different continents and regions i.e. Japan is representative of Asia, US of North America, Germany of the Eurozone and the UK of European countries outside of the Eurozone.

5.2 Data statistics

Table 1

Data Statistics – Indices (Daily Log Returns)	DAX 30	Nikkei 225	FTSE 100	S&P 500
Mean	0.00010	0.00009	0.00010	0.00003
Min	-0.09470	-0.12111	-0.08875	-0.09266
Quantile - 10%	-0.01346	-0.01699	-0.01719	-0.01290
Median	0.00027	0.00000	0.00048	0.00001
Quantile - 90%	0.01246	0.01721	0.01615	0.01236
Maximum	0.10957	0.13235	0.10797	0.09384
Variance	0.00016	0.00023	0.00024	0.00015
Standard Deviation	0.01253	0.01517	0.01538	0.01214
Skewness	-0.18124	-0.48222	-0.01284	-0.15275
Excess Kurtosis	11.78600	10.17200	7.88750	9.85570
Autocorrelations (r)				
$\rho(r_t, r_{t-1})$	-0.02	-0.03	-0.05***	-0.09***
$\rho(r_t, r_{t-2})$	-0.02	-0.03*	-0.04***	-0.04***
$\rho(r_t, r_{t-3})$	-0.03	-0.02*	-0.07***	0.01***
$\rho(r_t, r_{t-4})$	0.03*	0.00	0.07***	0.00***
$\rho(r_t, r_{t-5})$	-0.06***	0.02	-0.06***	-0.04***
Autocorrelations (r^2)				
$\rho(r_t^2, r_{t-1}^2)$	0,18***	0,17***	0,24***	0,20***
$\rho(r_t^2, r_{t-2}^2)$	0,26***	0,49***	0,30***	0,38***
$\rho(r_t^2, r_{t-3}^2)$	0,28***	0,17***	0,32***	0,21***
Jarque-Bera	12159.00***	7576.70***	3592.70***	7404.00***

Data Statistics – ETFs (Daily Log Returns)	DAX 30	Nikkei 225	FTSE 100	S&P 500
Mean	0.00010	0.00010	0.00007	0.00003
Min	-0.09612	-0.11255	-0.08895	-0.16231
Quantile - 10%	-0.01290	-0.01761	-0.01730	-0.01276
Median	0.00041	0.00000	0.00039	0.00000
Quantile - 90%	0.01237	0.01705	0.01580	0.01235
Maximum	0.10525	0.11363	0.11792	0.09292
Variance	0.00015	0.00023	0.00023	0.00016
Standard Deviation	0.01236	0.01515	0.01503	0.01267
Skewness	-0.17045	-0.60981	0.00059	-0.67190
Excess Kurtosis	10.89300	9.60890	8.38460	18.20300
Autocorrelations:				
$\rho(r_t, r_{t-1})$	-0.02	-0.03**	-0.05***	-0.09***
$\rho(r_t, r_{t-2})$	-0.02	-0.03**	-0.04***	-0.04***
$\rho(r_t, r_{t-3})$	-0.03	-0.02*	-0.07***	0.01***
$\rho(r_t, r_{t-4})$	0.03*	0.00*	0.07***	0.00***
$\rho(r_t, r_{t-5})$	-0.06***	0.02	-0.06***	-0.04***
Autocorrelations (r^2)				
$\rho(r_t^2, r_{t-1}^2)$	0,16***	0,19***	0,21***	0,29***
$\rho(r_t^2, r_{t-2}^2)$	0,26***	0,51***	0,36***	0,17***
$\rho(r_t^2, r_{t-3}^2)$	0,24***	0,19***	0,21***	0,14***
Jarque-Bera	9814.10***	6534.40***	4360.90***	36630.00***

*** Significantly different from zero at the 1 % level, ** at the 5% level and * at the 10% level.

As we can see from Table 1, the means of the log returns are close to zero, as are the medians. Out of the markets in our sample, we observe the highest variances and standard deviations in the FTSE 100 and Nikkei 225. This is true in both ETFs and indices. The minimum values for all the time series are approximately -0.1. However, we observe an extreme value in the S&P 500 ETF of -0.16 on October 15th 2008. This corresponds to the day in which the S&P 500 Index experienced the single biggest drop in returns[1]. The extremity of the ETF return is far greater than that observed in the index. All markets except FTSE 100 ETF display negative skewness. In contrast, the FTSE 100 ETF displays positive skewness. In the indices, the most negative value is observed in the Nikkei 225. In the ETF sample, it is the S&P 500 ETF that displays the most negative skewness. Also, all markets have positive excess kurtosis (i.e. a leptokurtic distribution). In the data for the indices, DAX 30 and Nikkei 225 have the highest values while the S&P 500 ETF has the largest excess kurtosis among the four markets. The differences observed between the data statistics for the ETFs and the indices indicate that we will most likely expect some differences when we run our VAR models.

As expected, the Jarque-Bera test rejects normality at 1% level as we can see from the distribution graphs in Figure 2. Based on the Ljung-Box test, we see that for both of the English speaking markets autocorrelation starts from the first lag, significant at least at the 1% level. For the German market, the autocorrelations start to appear in the 4th lag at 10% level and become significant at 1% from 5th lag. And there is no difference between indices and ETFs. As for the Japanese market, in the index the autocorrelations appear for the 2nd and 3rd lags but are less significant than the other three markets and the autocorrelations start to disappear in the 5th lag. However, for the Nikkei 225 ETF, the autocorrelations are significant for the 1st and 2nd lags at 5% level as well.

According to Merton (1980), a simple way to approximate the instantaneous volatility is to take the squared or absolute value of returns. This enables us to detect if there is some non-linear or quadratic dependence in returns, which yields to see if there are some patterns in conditional volatility. We can note the strong linear dependence between second moments as the first, second and third order auto-correlation.

From the data statistics, the 3rd and 4th moments (skewness and kurtosis) observed for the ETFs in our sample are quite different from their underlying indices. However, our paper will exclusively focus on skewness and the differences we find in the transmission mechanism of this variable.

[1] The biggest ever single-day crash on Sept. 29, 2008, came after the U.S. House of Representatives rejected the government's $700 billion bank bailout plan.

Table 2

Correlations - Indices				
	t			
t	DAX 30	Nikkei 225	FTSE 100	S&P 500
DAX 30	1.000	0.123	0.617	0.547
Nikkei 225		1.000	0.255	0.293
FTSE 100			1.000	0.824
S&P 500				1.000

Correlations - ETFs				
	t			
t	DAX 30	Nikkei 225	FTSE 100	S&P 500
DAX 30	1.000	0.137	0.649	0.506
Nikkei 225		1.000	0.216	0.291
FTSE 100			1.000	0.711
S&P 500				1.000

Table 2 shows us that the log returns of FTSE 100 and S&P 500 indices are highly correlated. However the level of correlation is slightly less for the comparable ETFs. Germany is also highly correlated with the U.K. and U.S. markets. The Japanese market appears to be more isolated than the other three markets i.e. its relative level of correlation is much lower. However, it appears to be more correlated to the DAX 30 and less to the FTSE 100 in term of ETFs.

Figure 2

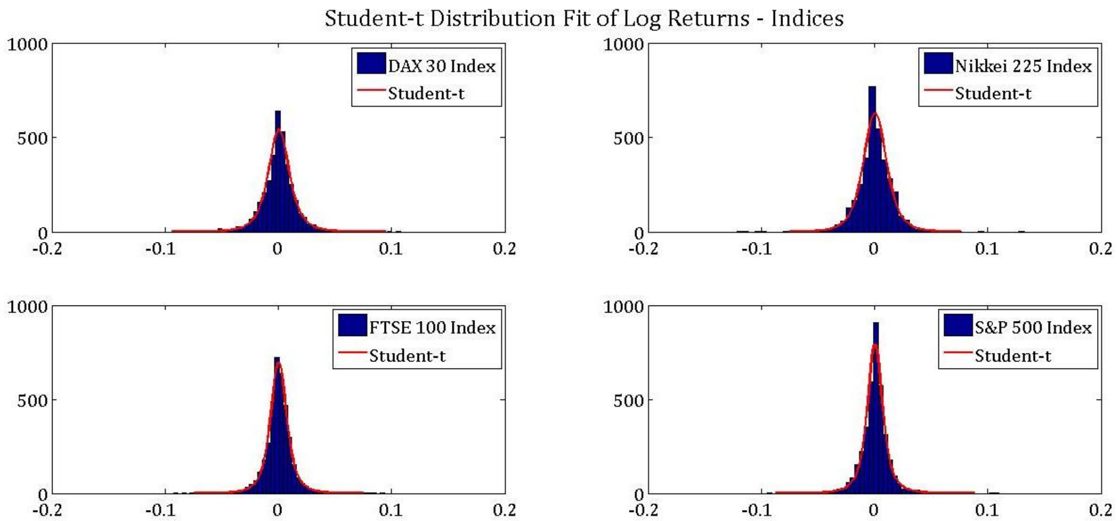
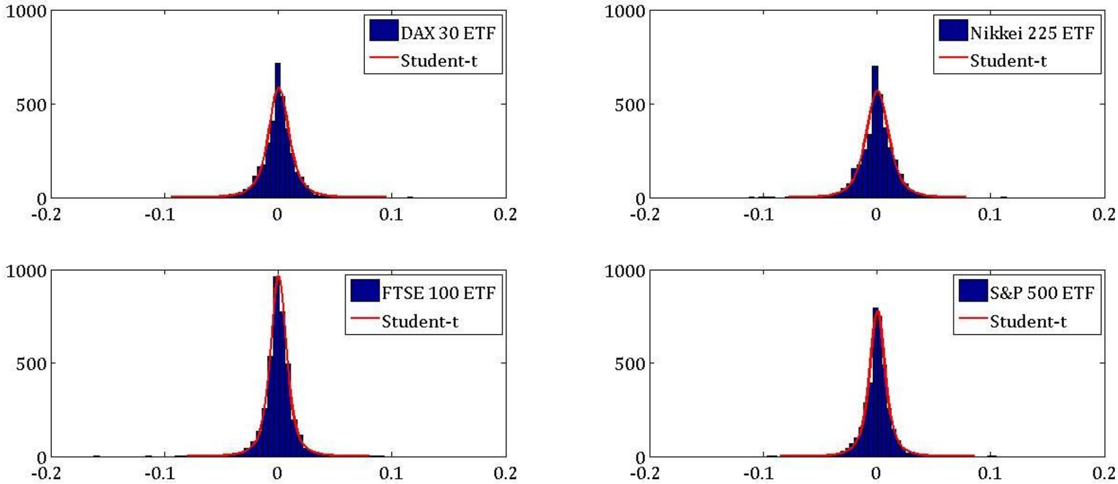


Figure 3

Student-t Distribution Fit of Log Returns - ETFs



As we can see from Figures 2 & 3, a generalized student-t distribution is a good fit for all four markets, especially for the FTSE 100. This is due to the fact that the generalized student t-distribution allows for excess kurtosis in the data. For DAX 30, Nikkei 225, and S&P 500, there are extreme sample values beyond the distribution fit and there is an obvious fat tail in the DAX 30. For S&P 500 log returns series, there are large outliers around +/- 0.1 in both sides of the tails. The distribution of the ETFs and indices is the same for all four markets.

Figure 4

Time Plots of Index Daily Log Returns

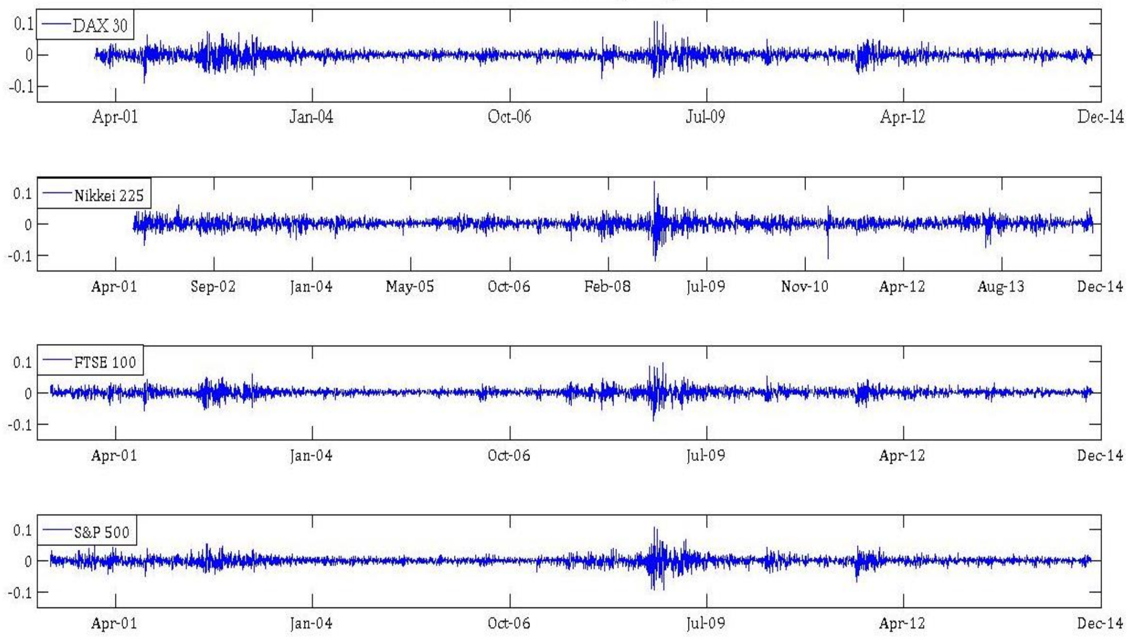
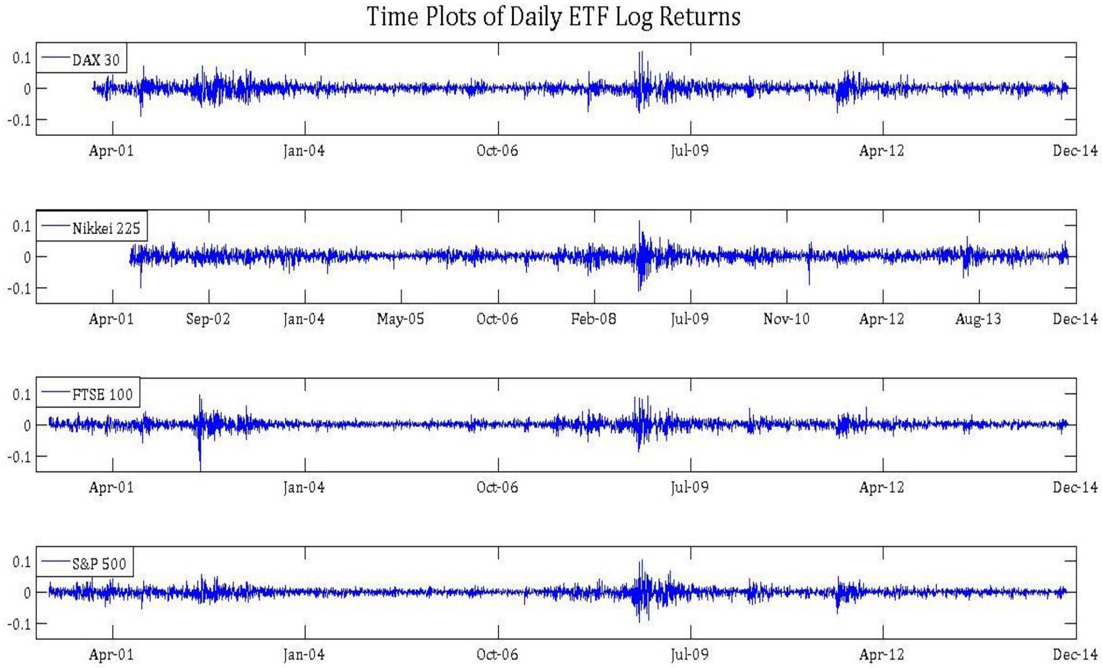


Figure 5



In Figures 4 & 5, we observe all four developed markets exhibiting a similar pattern of log returns. This is true for both the indices and the ETFs. From the previous plots it is clear that all log returns are stationary series and therefore suitable for the ARMA process. The U.K. and U.S. stock markets have the smoothest pattern of the returns, while the Japanese stock market shows a noisier pattern. The Japanese pattern is quite distinct in comparison to the other markets with the exception of the period during the 2008 financial crisis. As for the German stock market, we see noisier pattern during the early 2000s. This is slightly different from the other two western markets, the UK and the US. This shows the presence of a specific pattern for Germany compared to the other two western markets. This extra noise present in the German market during early 2000s could be related to the introduction of the physical Euro and fluctuations in the currency's value.

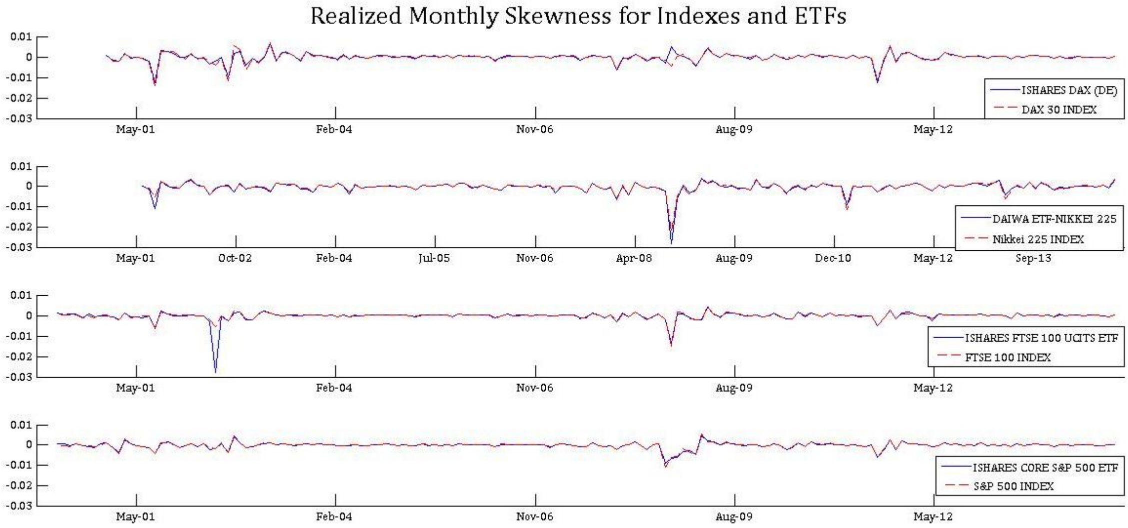
One obvious difference we noted between the ETFs and the indices was the presence of extreme values during 2002-2003 in the FTSE 100 ETF which were not present in the index. The most extreme divergence occurred during August 2002.

6. Empirical Results

To specify the order of the ARMA process, we use Akaike Information Criterion (AIC) and the Bayesian Schwarz Criterion (BIC) to choose the ARMA term which will minimize the corresponding value of the criterions. In general, we prefer to use BIC since it will give us a stable model with less parameters. We then test the filtered model for sample autocorrelations and partial autocorrelations. We employ the following models in removing the serial correlation: ARMA (1, 1) model for DAX 30 Index, ARMA (4, 4) model for Nikkei 225 Index, ARMA (1, 3) for the FTSE 100 Index, and an ARMA (1, 1) for the S&P 500 Index. By using the same methods, we employ an ARMA (2, 2) model for DAX 30, an ARMA (1, 1) model for Nikkei 225, an ARMA (1, 1) for the FTSE 100 ETF and an ARMA (1, 1) for S&P 500 ETF. A detailed description of the ARMA process is included in appendix 2.

6.1 Time plots of realized variance

Figure 6



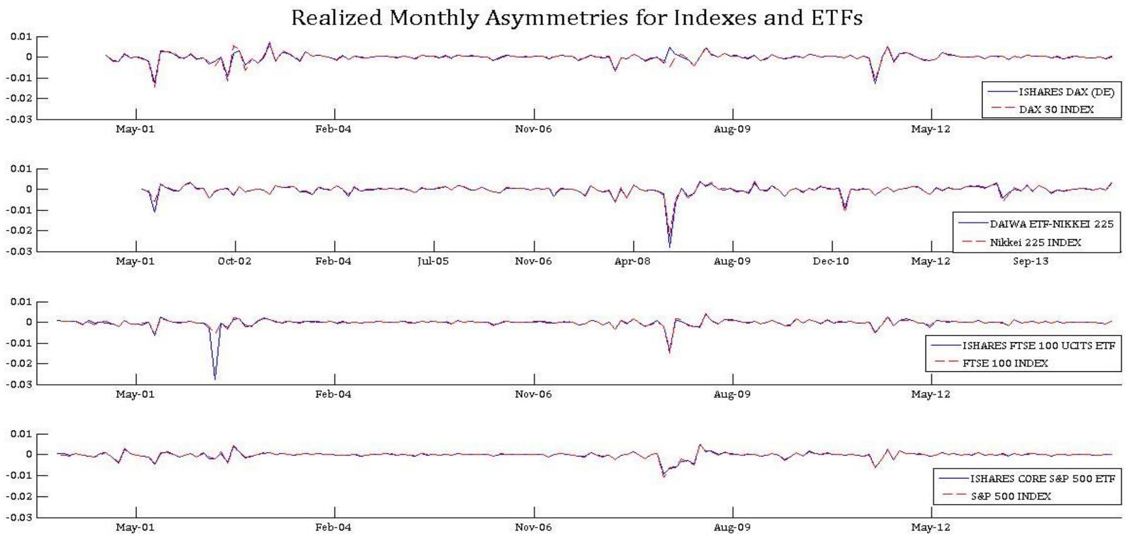
We observe two main spikes in realized volatility occurring during the early 2000s (at the time of the end of the tech bubble) and during the 2008 financial crisis. As one might expect, the terrorist attacks of 9/11 2001 had a big impact on the S&P's volatility as well as on FTSE's. In the recent period we see a peak that might be related to the uncertainty surrounding the Eurozone, starting from the summer of 2011. The Japanese market is the one that has seen the highest volatility throughout the period. This can be attributed to the turbulent times that its economy has experienced since the beginning of the 1990's. Moreover, since Japan faces a more complicated political environment in the Asia-Pacific region, especially with respect to its relationship with China and the U.S., its idiosyncratic risk might be related to political developments. The low or negative infla-

Note: Enlarged figures shown in appendix 3 tion that the country has been experiencing, together with the slowness in reacting to the growth slowdown are all factors that could influence this volatility. In the German market we observed a similar pattern to the UK and US expect during the early 2000s where we noticed an increase in volatility not observed in the other markets. This may due to the instability at the early stage of the Eurozone.

In general, for all four markets, the ETFs track the variance of the indices quite closely. This is especially true for the US market, as we notice very little divergence between the index and ETF. However, for the other three markets we notice significant tracking errors when there are peaks in variance. This is especially obvious during the early 2000s and for a period after 2009 when the Eurozone was experiencing economic difficulties. We notice the most significant divergence in Aug 2002 between the FTSE 100 ETF and its index. However, during the 2008 financial crisis, the FTSE 100 ETF didn't show significant divergence from its index while both DAX ETF and NIKKEI 225 showed divergence from their respective indices. These divergences may be due to the facts that the liquidity is low during that time and thus the variance of the ETFs are not enough to closely track the indices.

6.2 Time plots of realized skewness

Figure 7



Note: Enlarged figures shown in appendix 4

In terms of the indices, we see that realized skewness has been close to zero for the majority of the time covered in our sample. The Japanese market displays the most skewness out of all four markets. In the German market, we again observe a different pattern from the other three markets. We also see significant skewness persistence during the early 2000s which is only present in the German market. The instability of the Eurozone during the early 2000s which caused fluctuations in the value of the Euro could be a contributing factor to this anomaly. We observe a similar pattern during 2008 financial crisis, where Germany experiences much less negative skewness in comparison to the other three markets. Again in 2011, we observe negative skewness in the German market. This is not present to the same extent in any of the other markets. What can be said about volatility can be repeated here: the most noticeable events are usually those that bring negative skewness into the market. Indeed most of the deviations occur on the negative side. This corroborates the idea that the study of downside volatility is of particular interest in understanding financial markets[2].

For all four markets, ETFs ability to track skewness is worse than its ability to track variance. This is most prominent in a divergence of the FTSE 100 ETF and the FTSE 100 Index during August 2002. This may lead to the differences in our cross-market VAR transmission models. However, for the other three markets Germany, Japan and U.K., the tracking errors in skewness are similar to the tracking errors of the variances. We notice the tracking errors of skewness are more extreme in the case of negative skewness, while the tracking errors happen more frequently for positive skewness which is less commonly observed than negative skewness.

6.3 Intra-market VAR results

Table 3

Intra-market - VAR Regression Results: Indices

DAX 30

t	t-1 Return	t-1 Volatility	t-1 Skewness
Return	0,60***	0,82	-13,52***
Volatility	-0,05*	0,47***	0,58
Skewness	0,03***	0,08*	-0,60***

NIKKEI 225

t	t-1 Return	t-1 Volatility	t-1 Skewness
Return	0,05	-0,51	-0,36
Volatility	-0,04*	0,42***	0,81*
Skewness	0,00	-0,03	0,03

FTSE 100

t	t-1 Return	t-1 Volatility	t-1 Skewness
Return	0,01	0,28	-0,36
Volatility	-0,05*	0,63***	0,96
Skewness	0,02	-0,04	-0,48

S&P 500

t	t-1 Return	t-1 Volatility	t-1 Skewness
Return	-0,16	-0,35	8,67
Volatility	0,01	0,49***	-1,60
Skewness	-0,01	-0,07**	0,25

Intra-market - VAR Regression Results: ETFs

DAX 30- ETF

t	t-1 Return	t-1 Volatility	t-1 Skewness
Return	0,53***	1,40	-12,50***
Volatility	-0,04**	0,44***	0,11
Skewness	0,02***	0,10***	-0,40***

NIKKEI 225- ETF

t	t-1 Return	t-1 Volatility	t-1 Skewness
Return	0,20	-1,72	-5,94
Volatility	-0,05*	0,63***	1,43*
Skewness	0,01	-0,12	-0,31

FTSE 100 - ETF

t	t-1 Return	t-1 Volatility	t-1 Skewness
Return	-0,01	0,11	0,06
Volatility	-0,07***	0,69***	1,38**
Skewness	0,02	-0,07	-0,24

S&P 500- ETF

t	t-1 Return	t-1 Volatility	t-1 Skewness
Return	-0,15	-0,30	8,51
Volatility	0,00	0,45***	-1,37
Skewness	-0,01	-0,06*	0,35

*** Significantly different from zero at the 1 % level, ** at the 5% level and * at the 10% level.

[2] See Barndorff-Nielsen et al. (2008).

Before running our model it is important to ensure that the data in our time series is stationary. A non-stationary series is characterized by a drift parameter that increases with time, which make the computation of its mean difficult and even if it was possible, as the number of observations would increase, the mean of the sample would not converge toward a same value. The variance and covariance would also not be stable through time. We want to check if the drift is stochastic or deterministic. To test for this we focus on the existence of a unit root through the Augmented Dickey-Fuller (1981) test. Our test result shows that all realized variances and asymmetries are stationary. The results of the test are shown in appendix 5.

From the Intra-market VAR models estimated by taking monthly returns, realized variance and realized skewness we can observe that there is a strong evidence of volatility persistence or volatility clustering. In particular, the coefficient on the first lag of variance is positive and significant at 1% level in all the four markets in the equation that describes variance. This is the case for both indices and ETFs. Therefore, for all the four markets, variance in the previous month positively influences variance in the current month. The coefficients are also very similar in size between indices and ETFs. These findings are consistent with the realized variances we observed previously. Therefore, the ETFs covered in our sample do a good job of tracking the variances of their respective indices. However, for the Japanese market, we see that the coefficient of the ETF model is larger than the index model i.e. the effect of variance clustering in the ETF model is more significant than in the index. Again, this is consistent with the patterns observed in the realized variances.

When we investigate quantitatively the so-called "leverage effect," which corresponds to a negative correlation between previous returns and current variance, we see this effect at a monthly level in all 3 markets except the US market both for the indices and ETF models (when we refer to the VAR (5) US model, suggested by MAIC, we found leverage effects significant for the 3rd and 4th lags). While the coefficients remain similar across the indices and ETFs, the ETF models show more significant leverage effects (in terms of confidence level). The closeness of the ETF results to that of those observed in the underlying indices allows us to infer that over the horizon in our sample the ETFs do a good job representing the variance that is seen in the underlying indices. However, there do exist some tracking errors in terms of variance.

Distinct from what we find in the other markets, in the Nikkei 225 we see that variance in the current month is also influenced by skewness in the previous month. We can see that the coefficient is positive and significant at the 10% level in both the Nikkei Index and its corresponding ETF. We also see this effect in the FTSE 100 ETF tracking the FTSE index but not in the FTSE index itself. In this case, some of the variance in the current month can be explained by skewness in the previous month but only in the ETF model. This leads us to the conclusion that there is some difference in the realized skewness of the ETF and the underlying index, which is consistent with our observation in the data statistics.

For skewness, the US, UK and Japan all have a negative relationship with variance in the previous month, however this is only significant in the US market at a 10% level. According to our results, the previous month's variance in the US market will be negatively correlated with skewness in the current month, however the co-efficient is very small so we can expect the effect to be very weak. The effect is similar across ETFs and the indices. One possible explanation for a negative coefficient is that one might expect a higher variance to push down skewness. This is because more uncertainty in the market might make it more likely to see large negative realizations, as investors might be sensing that something bad – a tail event – is going to happen. On the other hand, this also means that a lower variance in the previous month will cause a rise in the current month's skewness. If we follow the same logic, then investors should expect a good event to happen after a lower variance month, however, this may not be true since a low variance could also signal a frozen market that has little liquidity. This contradict could be used as a possible explanation for the weak relationships.

The results for the German market seem quite different from what we see in the other three markets, which is consistent with the different patterns observed in the German markets (discussed in 5.2 Data Statistics, 6.1.1 Time plots of realized variances and 6.1.2 Time plots of realized skewness). For instance, we see a positive correlation between this month's returns and the previous months. This shows an autocorrelation of the log returns of the DAX 30 Index/ISHARE DAX (DE) ETF. This is not unheard of and is consistent with previous findings on studies of the US market. In a study of US stock prices at a daily and monthly level, both Mandelbrot 1963 and Fama 1965 found some serial correlation in the stock returns i.e. large changes tended to be followed by large changes and conversely small changes tended to be followed by small changes. This could be interpreted as evidence of semi-strong form of the efficient market hypothesis (EMH) in the German market.

In the equations for monthly returns for S&P 500, FTSE 100 and Nikkei 225 we see that (except for skewness in the S&P 500) no single coefficient is significant at the 10% level. Apparently, monthly returns are not driven by either realized variance or skewness in the past month. This allows us to draw a similar conclusion to what French, Schwert and Stambaugh (1987) found; there exists no clear risk premium attached to the previous period's variance[3].

Furthermore, except for what we observed in DAX 30, monthly returns seem to have no serial correlation at the first lag, which is different from what has been observed among daily returns in our sample.

3 French, Schwert and Stambaugh (1987) use both monthly realized measures of variance, and conditional variance from a GARCH in mean model.

6.4 Cross–market VAR results

Table 4

VAR Regression Results: Indices

		Volatility (t-1)				Skewness (t-1)			
		DAX 30	Nikkei 225	FTSE 100	S&P 500	DAX 30	Nikkei 225	FTSE 100	S&P 500
Vol.(t)	DAX 30	0.41**	-0.20	0.54	-0.03	-0.13	0.30	0.48	-1.74*
	NIKKEI 225	-0.57*	-0.03	1.70*	-0.26	0.73	0.34	1.10	-3.37**
	FTSE 100	-0.16	-0.20*	0.82*	0.07	0.06	-0.04	0.33	-1.33*
	S&P 500	-0.18	-0.09	0.68	0.26	0.39	0.08	0.22	-1.77**
Ske.(t)	DAX 30	0.01	0.06	0.14	-0.09	-0.25	0.11	0.20	0.36
	NIKKEI 225	0.21**	0.02	-0.56**	0.13	-0.16	-0.11	-0.31	0.84**
	FTSE 100	0.08	0.07*	-0.17	0.03	-0.21*	0.04	-0.14	0.73***
	S&P 500	0.11*	0.00	-0.10	-0.10	-0.09	0.11	-0.10	0.11

*** Significantly different from zero at the 1 % level, ** at the 5% level and * at the 10% level.

VAR Regression Results: ETFs

		Volatility (t-1)				Skewness (t-1)			
		DAX 30	Nikkei 225	FTSE 100	S&P 500	DAX 30	Nikkei 225	FTSE 100	S&P 500
Vol. (t)	DAX 30	0.31*	-0.14	0.67**	-0.05	-0.52	0.25	1.08*	-1.63*
	NIKKEI 225	-0.41	0.07	1.09*	-0.02	0.02	0.13	1.98*	-3.12
	FTSE 100	0.02	-0.25	0.52*	0.14	-0.31	-0.37	0.84	-1.47
	S&P 500	-0.15	-0.12	0.56*	0.35	0.11	-0.03	0.99*	-1.96**
Ske. (t)	DAX 30	0.07	0.07	0.10	-0.13	-0.08	0.12	0.18	-0.03
	NIKKEI 225	0.18**	0.00	- 0.43**	0.08	-0.03	-0.03	-0.74*	1.07*
	FTSE 100	0.06	0.14**	-0.10	-0.01	-0.12	0.21	-0.17	0.69**
	S&P 500	0.13**	0.05	-0.06	-0.17**	-0.10	0.19*	-0.14	0.18

*** Significantly different from zero at the 1 % level, ** at the 5% level and * at the 10% level.
Note: P-values are included in appendix 6

We will discuss the results found in our cross-market VAR following a clockwise approach from the top-left quadrant i.e. the description of the results will be detailed as follows: 1) the impact of previous volatility on current volatility; 2) the impact of previous skewness on current volatility; 3) impact of previous skewness on current skewness; 4) the impact of previous volatility on current skewness.

In our cross-market VAR model, we again observe volatility persistence in the DAX 30 and the FTSE 100 in both the index and ETF model. Contrary to what we observed in the intra-market model, we do not observe volatility persistence in the Nikkei 225 ETF or index. We do however observe relationships between volatility in Japan and past volatility in the UK and US markets. This is consistent with the theory that Japan tends to follow western markets and our inclusion of other markets better explain current volatility in the Nikkei 225. When we look at the countries that do display volatility persistence we can see that the effect is not as strong as it was in the intra-market VAR results, both in terms of significance and the size of the coefficient. This effect might be attributed to two different causes: either the coefficient loses significance once we include other markets in the regression, as these additional factors may better explain the current realization of the variance, or the meaningful relationship that we found before depends crucially on the inclusion of returns in the model. However, if we combine this information with the results from our R^2 analysis in 6.5, we believe it is more likely to be the former case.

In our regression on the indices we observe transmission of volatility from the previous month of DAX 30 to current month of Nikkei 225. We also observe transmission from the FTSE 100 to Nikkei 225. The converse of this relationship is also significant i.e. there seems to be a feedback mechanism between the Nikkei 225 Index and the FTSE 100 index. In the ETF model we only see this transmission from the FTSE 100 to the Nikkei 225. This allows us to make the assumption that it is the FTSE leading the transmission of volatility between this markets. In addition to this, we also see transmission from FTSE 100 to DAX 30 and S&P 500 in the ETF model, whereas this relationship doesn't exist in the index model.

When we look at the effect of previous monthly skewness on current variances, we observe different patterns for the indices and the ETFs. Dealing with the index model, we only find the previous monthly skewness of S&P 500 Index has significant impact on the current variances of all markets, including itself. This result is within our expectations, since previous trends in the U.S. market hold important information for investors in the other markets. This finding is also consistent with what has been found in a previous study by Eun and Shim (1989). In comparison to the indices, we found a different transmission pattern in the ETFs. We see the FTSE 100 ETF impacting current monthly asymmetries of DAX ETF, NIKKEI 225 and S&P 500 ETF, whereas these relationships don't exist in the index model. In addition, we see the S&P 500 skewness only affecting DAX 30 and itself, as opposed to all markets as in the index model.

Looking at possible channels for transmission of asymmetries, again, we found that the monthly skewness of the German market is not explained by the previous monthly skewness any of the four markets in our sample, including the German market itself. As for the Japanese market, the current monthly skewness is positively influenced by the previous monthly skewness of the U.S. market. This holds both for the index model and the ETF model. However, in the ETF model, we also found that NIKKEI 225 ETF to be negatively related to the FTSE 100 ETF. We observe larger coefficients in the ETF model and therefore can infer that the Japanese ETF is affected more by the FTSE 100 ETF and S&P 500 ETF. As for the U.K. market, we found skewness to be positively related to the previous monthly skewness of the U.S. market. We see this in both the ETF and index model. In addition, we also found that the skewness of U.K market is also affected by the German market in the index model, while this is not true for the ETF model. Finally, we didn't find any skewness transmission from the other markets to the U.S. in the index model. This is reasonable since the skewness of the U.S. market seems to be the one of the main drivers for the skewness in the Japanese market and the U.K. market. However, for the ETF model, we found that there is skewness transmission from the Japanese market to the U.S. market which is less expected. The coefficient of this effect is also really small compared to the coefficient of the skewness transmission from the U.S. to Japan. Therefore, we might interpret this as a weak feedback mechanism. This is similar to the results found by Becker, Finnerty and Gupta (1990), where they found US stocks to have a large impact on Japanese stocks, while Japanese stocks were found to have a much smaller impact on US stocks. However, there study was done on stock prices at a daily level.

Looking at possible channels for transmission of realized volatilities on realized asymmetries, we found that the German market is not affected by the other three markets, nor does the previous monthly skewness in the German market affect current skewness. This holds for both the indices and ETFs. This is consistent with the intra-market German models, since current monthly skewness of the German market is well explained by its previous monthly returns. As for the other three markets, we found that the current monthly skewness of Japanese market is affected by previous monthly volatility of both the German market and the UK market. The current monthly skewness of the UK market is also affected by the previous monthly volatility of the Japanese market. This effect is present in both models. Finally, the U.S. market is affected by the previous monthly volatility of the DAX 30. This is also present in both models. We also see S&P 500 volatility affecting current skewness in the ETF model, a relationship not present in the index model. There is no significant difference in the coefficients, except for the FTSE, where we observe a weaker relationship in the ETF model.

An interesting point is that we observe the DAX 30 to have a negative impact on skewness in all other markets. However, this relationship is only significant in the index model for the FTSE 100. We also see this negative impact from the FTSE on all markets except for Germany. Overall, the results from our cross-market VAR model lead us to wonder about the differences in transmission attributes between ETFs and their underlying indices. Put differently, from these observations it appears that there may be a greater degree of interdependence between the ETFs than is present among the underlying indices.

6.5 Analysis of Adjusted R^2

Table 5

Intra-market Adjusted R^2: Indices

t	DAX 30 (t-1)	NIKKEI 225 (t-1)	FTSE 100 (t-1)	S&P 500 (t-1)
Return	6.5%	-0.2%	-0.9%	3.3%
Volatility	46.7%	11.7%	43.2%	61.9%
Skewness	10.3%	0.2%	7.0%	10.4%

Intra-market Adjusted R^2: ETFs

t	DAX 30 (t-1)	NIKKEI 225 (t-1)	FTSE 100 (t-1)	S&P 500 (t-1)
Return	4.8%	0.4%	-1.0%	3.2%
Volatility	41.6%	16.6%	30.8%	56.0%
Skewness	6.3%	1.0%	3.7%	10.9%

Table 6

Cross-Market VAR Model Adjusted R^2: Indices		
	t-1	
t	Volatility	Skewness
DAX 30	59.2%	6.9%
NIKKEI 225	59.1%	32.9%
FTSE 100	55.5%	37.6%
S&P 500	68.6%	20.9%

Cross-Market VAR Model Adjusted R^2: ETFs		
	t-1	
t	Volatility	Skewness
DAX 30	57.7%	3.5%
NIKKEI 225	48.8%	30.2%
FTSE 100	32.7%	13.0%
S&P 500	63.9%	22.4%

From the Adjusted R^2 results, we observe that the cross-market VAR model does a better job at explaining the variation in realized skewness than the intra-market models for all the three countries except for Germany. In Germany, we observe a slightly lower R^2 for the skewness variable in the intra-market VAR for both the ETF and the index. This could be explained by the fact that returns are excluded in the cross-market VAR, and this impacts the fit of the model (the R^2 observed for returns in Germany's intra-market model was much higher in comparison to the other countries). The explanation of the monthly returns are significantly higher than the other three markets.

The cross-market VAR model does a better job in all the four countries at explaining volatility since the R^2 increased significantly in our transmission models. Thus, in terms of R^2 our cross-market models seem to be a better fit than the intra-market models in terms of explaining both the volatilities and asymmetries.

In comparing the R^2 in the cross-market VAR models we are able to make a more direct comparison between the indices and ETF model as the increase in R^2 can be attributed directly to a better fit. In terms of volatility, the cross-market index model is a better fit than the cross-market ETF model; we observe a greater R^2 for all the four countries. However, this is not the case for asymmetries, the cross-market index model has a better explanation for the skewness in the U.S. market with a R^2 of 35.85% that is significantly higher than the R^2 of 13.22% in the ETF model. However, for the skewness in the U.K. market, the cross-market ETF model has a lower R^2.

Overall the models allow to capture different aspects, and, as we see, give different significant coefficients. In particular, the inclusion of returns in the intra-market models, especially for the DAX 30 Index/ETF and Nikkei 225 Index/ETF, allows us to capture persistence in skewness, whereas for the S&P 500 Index, we capture this effect only in the VAR (1) transmission model.

6.6 Granger causality test

Table 7

Cross-market VAR - Granger Test: Indices

		Volatility				Skewness			
		DAX 30	Nikkei 225	FTSE 100	S&P 500	DAX 30	Nikkei 225	FTSE 100	S&P 500
Vol.	DAX 30	313.35***	121.16***	126.28***	12.31***	23.51***	45.04***	45.20***	4651.57***
	Nikkei 225	392.84***	0.47	356.90***	26.66***	201.19***	11.68***	155.08***	2982.24***
	FTSE 100	139.33***	481.01***	1280.82***	232.04***	0.07	6.50**	111.69***	5872.38***
	S&P 500	157.13***	33.71***	400.00***	314.90***	175.59***	7.99***	21.90***	4431.20***
Ske.	DAX 30	0.06	32.77***	14.22***	25.48***	52.56***	13.96***	22.05***	275.76***
	Nikkei 225	127.37***	0.36	106.56***	30.28***	18.82***	3.59*	31.90***	449.93***
	FTSE 100	80.65***	139.29***	47.15***	8.03***	180.21***	9.44***	34.01***	2113.23***
	S&P 500	355.42***	0.00	14.38***	115.66***	39.91***	32.05***	17.84***	23.57***

*** Significantly different from zero at the 1 % level, ** at the 5% level and * at the 10% level.

Cross-market VAR - Granger Test: ETF

		Volatility				Skewness			
		DAX 30	Nikkei 225	FTSE 100	S&P 500	DAX 30	Nikkei 225	FTSE 100	S&P 500
Vol.	DAX 30	208.06***	31.59***	1054.88***	2.13	162.51***	24.87***	501.51***	1643.13***
	Nikkei 225	302.31***	8.15***	2451.87***	1.63	0.08	1.75	1414.26***	1286.15***
	FTSE 100	0.09	192.18***	1108.67***	85.59***	296.48***	101.33***	1323.67***	1310.14***
	S&P 500	118.02***	55.41***	1440.97***	1013.49***	37.03***	0.27	1627.84***	4041.28***
Ske.	DAX 30	29.01***	40.54***	39.24***	83.38***	7.47***	18.93***	78.82***	0.02
	Nikkei 225	122.12***	2.29	531.55***	19.62***	0.66	0.72	619.81***	539.88***
	FTSE 100	26.43***	285.95***	231.40***	0.05	36.42***	93.44***	136.00***	963.13***
	S&P 500	295.43***	28.12***	36.43***	244.83***	56.45***	86.18***	108.49***	68.18***

*** Significantly different from zero at the 1 % level, ** at the 5% level and * at the 10% level.

We want to stress the fact that the Granger causality test does not allow us to gauge neither the size of the impact that one variable has on the others, nor the specific point in time at which the spillover effect occurs. Thus, we see that the picture given by the Granger causality test is considerably different from what the p-values of the coefficients in the VAR tell us for both indices and ETFs. Indeed, most relations seem to be significant at the 1% level. For both the index and the ETF, it appears that FTSE 100 variance and skewness Granger-cause all other variables. However, we do note some differences between the two. For example, the S&P 500 ETF appears to Granger-cause less variables in comparison to the S&P 500 index, where variance and skewness Granger-cause all other variables.

We also find more evidence of spillover. The UK market seems to Granger cause the variables in the other markets in the most significant way through its realized skewness. This holds true for both the index and ETF model. We also see that almost all other markets in turn influence the FTSE 100, in both volatility and skewness. Interestingly, in our ETF model realized volatility in the US seems not to Granger cause realized volatility in the UK but it does in the index model[16].

We notice that these results from the Granger causality test depend on the fact that we are using the Likelihood ratio specification: the Wald test specification would instead point to weaker relations among the variables, in a similar way to what the p-values for the VAR do. This happens because of different assumptions made by these tests with respect to the variance-covariance matrix of residuals, which enters in the calculation of the statistic. In particular, the Wald test starts from assuming that the alternative hypothesis holds, and then considers improvements towards the null[17]. The Likelihood ratio test compares the two hypotheses directly. Asymptotically they should give the same results, but sometimes they can disagree. In our case we believe that since residuals from the VAR (1), in many cases, show a large correlation, a relation among the variables of interest exists in reality. Since intuitively transmission should not occur at very low frequencies, i.e. we should not be able to find a better evidence of transmission by extending our VAR model to more lags, it must be that the relation occurs contemporaneously. Therefore, we believe that it would be interesting to investigate contemporaneous transmission on a monthly level by means of a structural VAR model.

We include the results of the Granger causality test for the intra-market VAR in appendix 7.

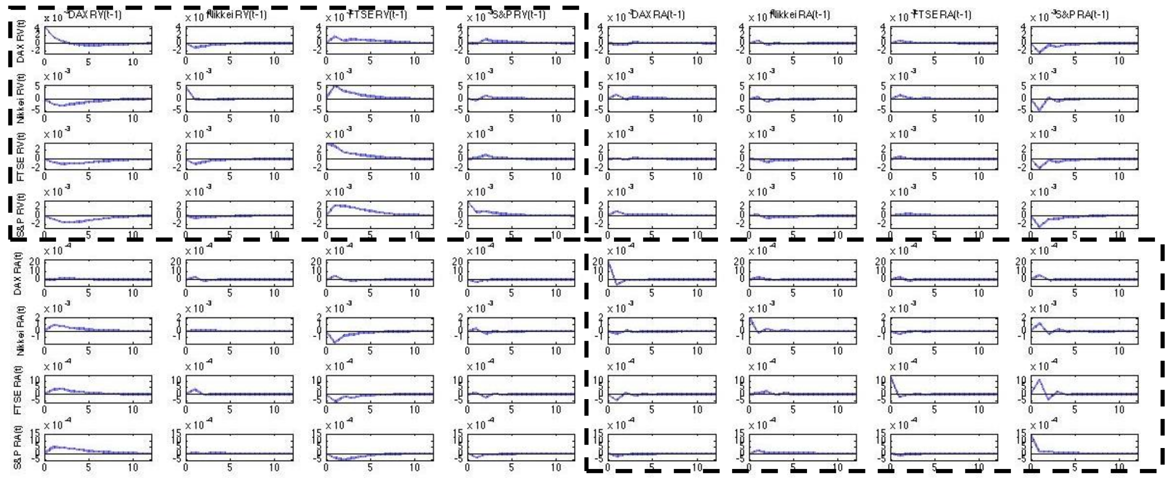
[16] However, realized volatility in the FTSE 100 Granger causes realized volatility in the S&P 500.
[17] Engle, Robert F.: Wald, Likelihood Ratio, and Lagrange Multiplier Tests in Econometrics, Handbook of Econometrics Vol II, Elsevier Science Publishers 1984.

6.7 Impulse response functions

To better investigate the transmission channels suggested by VAR models for all markets, we study the plots of the impulse response functions. These figures help us gauge the size and duration of the impacts of the relations we have found with our VAR models.

Figure 8

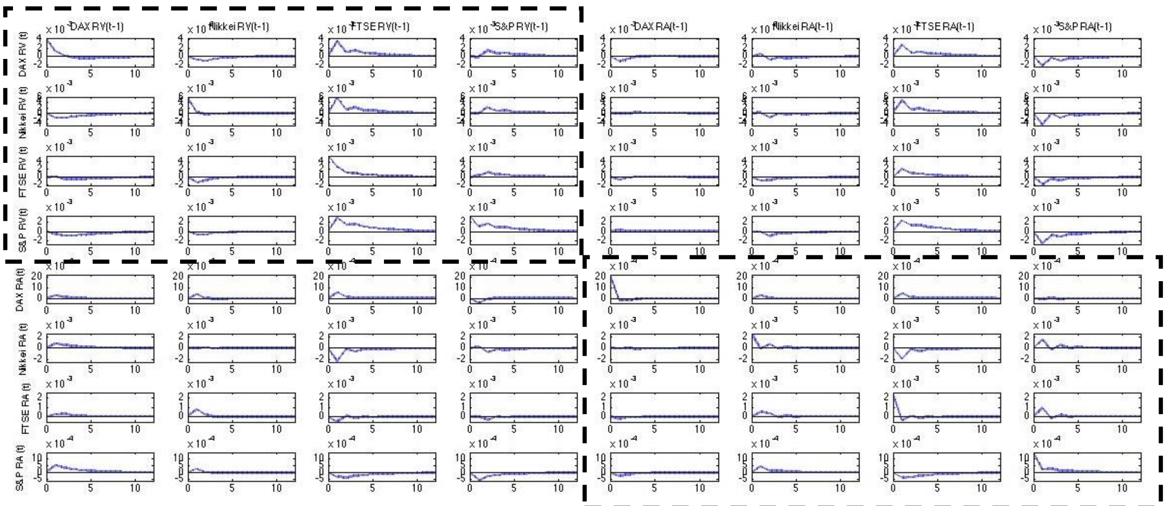
Impulse Response: Indices



Note: Enlarged figures shown in appendix 8

Figure 9

Impulse Response: ETF



Note: Enlarged figures shown in appendix 9

We will discuss the results found in the impulse response function following the same clockwise approach as before, starting from the top-left quadrant i.e. the description of the results will be detailed as follows: 1) the impact of previous volatility on current volatility; 2) the impact of previous skewness on current volatility; 3) impact of previous skewness on current skewness; 4) the impact of previous volatility on current skewness.

Interestingly, we can tell from the impulse response that the previous monthly volatility in the German market negatively impacts realized volatilities in the other three markets. These impacts last for more than 10 lags, which makes the DAX 30 ETF a good choice to diversify the idiosyncratic risk of the investors who invests in the other three markets. Similarly, previous month's volatility in the Japanese market also has negative impacts on the other three markets, but of a lesser magnitude. Again, the U.K. market has positive impacts on the volatilities in the other markets. We see the same pattern in the US market, but the impacts of the UK are stronger and longer. Finally, we don't observe any significant differences between the ETF model and the Index model. An interesting point is that at 0 lags we notice that all four markets exhibit significant volatility persistence in both models. This is consistent with volatility persistent existing contemporaneously.

We can observe that the skewness in German market and Japanese market do not have a strong impact on the volatility in all four markets. The skewness in S&P 500 shows a large and lasting negative impact on the volatility in all four markets. This is reasonable since the performance of the U.S. financial market is the key indicator of all the four financial markets, and investors will trade more often during a downside trend while stay still in a upside trend. This is because our measure of positive skewness could be qualitatively interpreted as an uptrend, vice versa for negative skewness. Results for ETFs and indices are the very similar except for the case of FTSE 100. FTSE 100 ETF has significant positive lasting impacts on all markets volatilities. This is in comparison to the index system where almost no impacts are present.

In general, we see that shocks on skewness tend to die out quickly. We didn't find any significant transmissions from Germany to any other market, except for impacts on itself and this impact also dies out quickly after 1 lag. In the index model for the Japanese market we find similar patterns. However, in the ETF model we found skewness transmission from Japan to the U.K. and U.S. This is different from the results of the Index model where we observed no such impacts. In the index model for the U.K. market we again found a similar pattern to Germany and Japan. However, in the ETF model, we found skewness transmission to all the four markets including the U.K. itself. As for the U.S. market, we see a significant impact on all the three markets except for Germany since the skewness of the German market is mostly explained by itself. The results for the US are consistent across both models.

We observe volatility in the German market having a large, lasting and positive impact on skewness in all three other markets, while only slightly impacting the German market itself. We also find that previous monthly volatility in the Japanese market has an impact on the current monthly skewness in the U.K. market. Additionally, we can also see that the volatility in U.K. market has a clear impact on skewness in all four markets. Finally, we don't observe any significant differences between the ETF model and the Index model.

Overall the analysis of impulse response functions highlights some results that we could already see from the coefficients in our models. Specifically, we see that in many cases, a shock from the U.S. market, seems to have an impact that is relatively large in magnitude. Broadly speaking the results are consistent across the ETF and index model, with the exception of the FTSE ETF where we notice significant differences with regards skewness transmission.

7. Interpretation of results

7.1 Interpretations from intra-market VAR

In the individual country VAR models volatility persistence at a monthly level is observed in all four markets in both indices and ETFs. However, in the case of the Nikkei 225 when we run the cross-market VAR model, we do not observe volatility persistence. Whereas we do see it in both the FTSE and DAX, again this holds true for both ETFs and Indices. This might be because the coefficient loses significance once we include other markets in the regression i.e. these additional factors may better explain the current realization of the variance. Our impulse response function reveals strong volatility persistence at lower lags. Therefore, we can assume if we ran a contemporaneous cross market VAR we would observe this effect for all markets.

Looking at the VAR models for individual countries, we find evidence of the leverage effect in all 3 markets except for the US: we see that what has been proved to hold for daily returns, i.e. that volatility is higher following negative returns, holds also at a monthly level. This is true for both the ETFs and the indices. On a monthly level, this phenomenon might also be connected to seasonal effects, since in some cases there exist some patterns in the way monthly returns behave over the course of one year; therefore it might be interesting to analyze the connection with volatility patterns in different months more in depth in the future[18].

For both Nikkei 225 and FTSE 100 ETFs we see that previous month's realized skewness has a positive and significant impact on the current month's volatility. This is not surprising. Volatility seems to increase following periods of positive skewness. This may happen because, if we assume that inside a month, the average return is zero, a positive skewness would imply that there is a larger probability mass to the left of the mean. This means that, on average, there exists a higher probability of negative returns. If one assumes that investors are loss-averse rather than risk-averse, they may actually dislike such a situation, and try to avoid it by trading more[19]. This effect is also observed in the index model of the Nikkei 225 but not in the FTSE index model. For both markets this coefficient is larger in the ETF model, showing a stronger relationship. However, we observe that the significance of such relation disappears once we estimate the cross-market VAR, this is true for both indices and ETFs. Compared to the intra-market VAR model, the cross-market VAR

[18] For example it might be interesting to see how much the "January effect", i.e. positive returns on average in January, is linked to lower volatility in February.

[19] A behavioral explanation on why investors might prefer negative skewness is suggested in Taleb (2004).

model assumes that domestic realized volatility is not only influenced by domestic realized skewness, but also affected by the same variables in the other three foreign markets. Therefore, the positive and significant impact of domestic skewness on domestic volatility is relaxed once the domestic market is exposed to the international markets. This phenomenon may be due to a transmission mechanism that will offset the investors' reactions to positive skewness that we discussed before. We believe that this topic deserves future investigation.

7.2 Interpretations from cross-market VAR model

In our sample, the evidence for outright volatility transmission is weak. This leaves us doubtful about the real economic relation. In particular we would expect, as it has been found by other authors, the American market to lead the way in variance transmission. In the impulse response function (measured at a monthly level) the only evidence that we can find is that a shock in the UK is in many cases the one with the largest impact on other markets. Therefore, we suspect that variance transmission occurs mainly on a daily, if not on an intra-daily, basis among international markets, and that the relation becomes weaker as we reduce the frequency of the observations. As the Granger causality test points out, there are probably some relevant relations in the series, even though they do not necessarily occur in the first monthly lag. As a result, a VAR model with contemporaneous terms would probably be suited to investigate the ways in which realized monthly volatilities are related across different markets.

Our cross-market VAR model of the indices finds evidence of past lags of skewness in the US market explaining volatility in all four markets. We observe a negative relationship in all four cases. Interestingly, we do not observe the same significant relationship in our ETF model. We see a relationship between S&P 500 and volatility in DAX 30 and volatility in S&P 500, but not for the other two markets. We also observe differences in the UK market between the index and ETF. In the FTSE 100 index we observe no relationship between skewness and current volatility. However, in the ETF model we see it affecting all markets volatility except itself. One possible explanation for the differences between the results for the FTSE is the outliers we observed in the FTSE ETF. This is consistent with Kim and White (2004) findings that measures of skewness based on the sample mean are extremely sensitive to outliers.

For skewness transmission the results are mixed. If we rely on our VAR transmission model we find very few significant coefficients; the size and the analysis of the impulse response function reveal that the magnitude of this effect is limited. On the other hand, when we run a Granger causality test, we find many significant relations. Therefore, we believe that the link occurs simultaneously rather than with a one-month lag, and that our VAR models could be refined to better capture the underlying patterns. However, we do observe significant skewness spillover from the US market to both the Nikkei 225 and FTSE 100. We observe this in both models. In fact, we would expect the UK market, which lies between the other two developed markets from a geographical point of view, to be influenced by both DAX 30 and the S&P 500. This should happen because of the UK's strong economic bounds with the other countries through its financial system. On the other hand, one might expect the US market to be the initial source of the spillover effect, because of the large economy that lies behind it, and because of the political influence that the US exert in different parts of the world. The strong correlation found between this three markets also adds weight to this expectation.

While we understand that the Granger causality test has definite limitations i.e. it does not allow us to gauge the size of the impact that one variable has on the others, nor the specific point in time at which the spillover effect occurs. We do believe that the evidence pointed out by our Granger causality test suggests some interesting relations, which require an economic interpretation. In particular, we see that the FTSE 100 is deeply interconnected with global markets, something that makes sense because the UK has a large financial system, whose developments both influence and depend on what happens in other parts of the world. This relationship also holds true for both the index and ETF models.

In addition, we see that both the Nikkei 225 Index Granger causes the outcomes in terms of volatility and skewness in most other markets. This might be due to the earlier market opening time, even though we believe that on a monthly level this effects should not matter much. Indeed, if we assume that our Granger causality test works as an approximation for the presence of a contemporaneous relation, what we can extract from it is that there exists a network of links, rather than a unidirectional influence. Therefore, the result might be due to the fact that the Japanese markets acts as a proxy for Asia as a whole, and given the increasing economic clout that the region has on global markets, we might well expect to see some spillover effects originating from there. However, to better understand if this is the true cause behind the phenomenon, one should study how the relation among Asian and Western markets has developed over time in terms of correlation of returns, volatility, and skewness. Finally, it is not surprising to see how volatility and skewness in the US and German market are Granger caused by realizations in other markets, since we know that many companies of the S&P 500 and DAX 30 are multinationals, with operations all over the globe. Therefore, their share price is probably affected by information from many different countries. However, the results observed in the ETF model are different from the indices, since the Nikkei 225 ETF has less impact on the other markets.

The most significant differences we observe are the differences between the FTSE ETF and underlying index. We also notice the most differences occurring between the ETFs and indices in the skewness term. We see this in both the effect of skewness on volatility in the intra market models and again in differences in transmission in the cross market VAR. The most likely explanation for these differences is the fact that an index represents a paper portfolio which assumes a passive benchmark strategy can be instantaneously implemented without cost - however due to market frictions this is not the case. This is discussed in detail in the paper by Frino and Gallagher (2001, 2002). Another possible explanation is that it is possible that many diversified investors will hold position in a number of ETFs at the one time. This could lead to a difference in transmission between ETFs and the indices. Finally, these differences may also be connected to the different liquidity levels in the ETFs and their underlying stocks.

8. Conclusion and implications for further research

This papers examines the differences observed between ETFs and their underlying indices in two different settings. In the first part, we build an intra-market VAR model to study the relationship among returns, volatility and skewness inside each market. We perform this analysis at a monthly level on both the indices and ETFs. In our analysis, we examine for established effects such as volatility persistence and the leverage effect. Broadly speaking, we find the results very similar for ETFs and the underlying indices that they aim to track. However, we do notice some differences in the relationship between past skewness and the current returns, volatility and skewness, this is especially noticeable in the FTSE 100.

In the second part of our analysis, we construct a cross-market VAR model. We include the four markets in our sample with a variance and skewness variable for each market. The purpose of this model is to try to observe transmission of volatility and skewness between the different markets in our sample. We notice that some of the relationships observed in our intra-market VAR model become weaker when we run this cross-market VAR, which doesn't include returns in the regression. We again run this analysis at a monthly level on both the indices and ETFs. In this model the differences in the results are more pronounced. We notice differences in transmission of volatility and skewness for all markets. These difference are again most obvious in the FTSE model.

When we consider the intra-market results alone we find that there exists some differences between the volatility and skewness observed in the ETFs and their underlying indices. These differences then become more pronounced when we look at how the ETFs interact with each other across the markets. In the previous section we discuss some possible explanations for these differences.

As we noted earlier in our paper, some of the interactions may have been obscured by the frequency of our observations, so it could be interesting to run this analysis at a daily or intra-day level we would expect to observe more significant differences between ETFs and their underlying indices. However, when analyzing the empirical results and drawing conclusions considerations for time differences must be included. A study done at the daily frequency would also allow the inclusion of more markets in the study – by using daily data it will be possible to look at markets where ETFs have been introduced more recently. It might also be interesting to run a similar analysis that includes a specific comparison study between ETFs and other open-ended index tracking funds. This study could help determine whether other open-ended index tracking funds offered better opportunities to diversify and reduce exposure to negative skewness than ETFs. We also believe that it could be interesting to run a similar analysis on non-traditional ETFs, such as leveraged ETFs. These non-traditional ETFs are discussed in more detail in appendix 2. Finally, we also think that it might be of interest to include some emerging markets in the analysis, as it would be interesting to note the relationship that they have with the more developed markets.

One of the main drawbacks of our paper is the inability of our models to observe contemporaneous relationships. As pointed out earlier, we believe, in the light of economic theory, that there should exist a contemporaneous relation – at a monthly level - among volatility and skewness in the different markets. Therefore, we acknowledge that a better model, perhaps a structural VAR would be better suited to study this phenomenon. We also believe that the ideal time unit to study transmission would be at a daily frequency. In today's deeply interconnected financial markets information spreads quickly, and it might happen that the overreaction that occurs in one market following a specific event, such as an unemployment or inflation report, spreads almost immediately to other countries. On a monthly level, on the other hand, we expect these effects to correct, and the transmission of volatility and skewness should depend more on broader economic trends, and on investors' long run views.

9. References

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10. Appendices

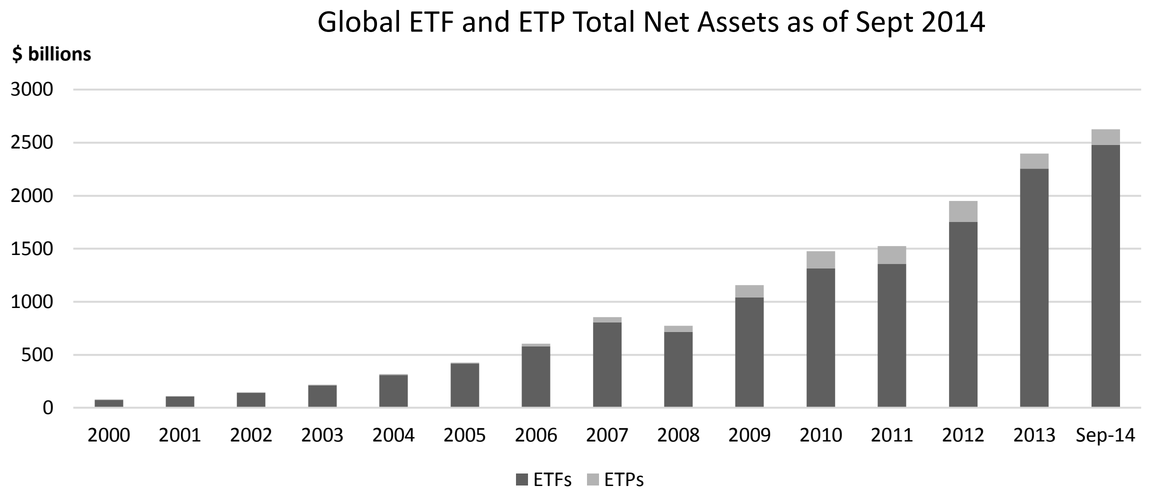
Appendix 1: Non – traditional ETFs and other Exchange Traded Products or ETPs

We will define traditional ETFs as the plain vanilla exchange traded fund described in the previous section. These ETFs are physically backed meaning that the fund manager has bought each individual constituent of the underlying index. However, there is a portion of these ETFs that are not physically backed, and are instead created synthetically. This means that the returns that the fund generates do not come from the basket of underlying securities, instead they come from a swap agreement with a counterparty. When creating these synthetic ETFs, instead of buying the constituents of the index they are tracking, the fund manager will place the investors' cash into a basket of collateral whose returns are swapped with a counterparty for the returns of the target index. One issue with this "synthetic" form of ETF, is that they expose investors to counterparty risk i.e. the event when the counterparty defaults. In this case the investor will be left holding the basket of goods that was used as collateral which may be completely different from the underlying index the ETF purposed to be tracking. Regulators worry that sometimes fund managers or ETF providers may be dumping their illiquid assets into these baskets of collateral and then getting funding on the back of these assets through the sale of the ETF. However, in markets not easy accessible, "synthetic" ETFs can have an advantage over physically backed ETFs. In addition, "synthetic" ETFs generally have a lower tracking error and reduced costs.

Other examples of non-traditional ETFs are leverage ETFs and Inverse ETFs. Leverage ETFs employ financial engineering methods to magnify the returns of the particular benchmark that they are following. These ETFs use derivatives, futures or forwards, and equity swap contracts with an aim to amplify the returns of the particular benchmark they track. For example, a 2x Leveraged ETF tracking an index that gains 10% in one day will aim to generate a return of 20%, conversely if the index drops by 10% in one day, the 2x Leveraged ETF aims to generate a loss of 20%. Inverse ETFs employ the same financial engineering methods described above but instead aim to generate returns when the index they are tracking falls. As mentioned earlier, they are similar to taking various short positions. However, the difference between inverse ETFs and actually taking various short positions, is that Inverse ETFs do not require investors to hold a margin account, however an investor taking a traditional short position will be required to hold a margin account.

The term ETC refers to Exchange Traded Commodities or Exchange Traded Currencies. Exchange Traded Commodities are listed securities that are backed by a commodity – either physical commodities or commodity futures (ETCs are generally only physically backed for precious metals and a small number of industrial metals). This innovation provides investors would much easier access to investment opportunities in the commodity markets. Exchange Traded Currencies offer investors exposure to foreign exchange movements by tracking indices on currency pairs.

Exchange traded notes or ETNs are generally senior, unsubordinated debt instruments issued by a single bank and listed on an exchange. The bank that underwrites these instruments agrees to pay the return of the specific benchmark that the ETN relates to (minus fees). In the case that the ETN is uncollateralized, the investor is taking on counterparty risk i.e. they are assuming direct exposure to the credit risk of the underwriter. Therefore, the credit rating of the underwriter is one factor that can affect the pricing of an uncollateralized ETN. The graph below shows the development of the split in Net Asset Value of ETFs and ETPs traded globally.



Source: ETF/ETP sponsors, exchanges, regulatory filings, Thomson Reuters/Lipper, Bloomberg, other publicly available sources

Appendix 2: ARMA process

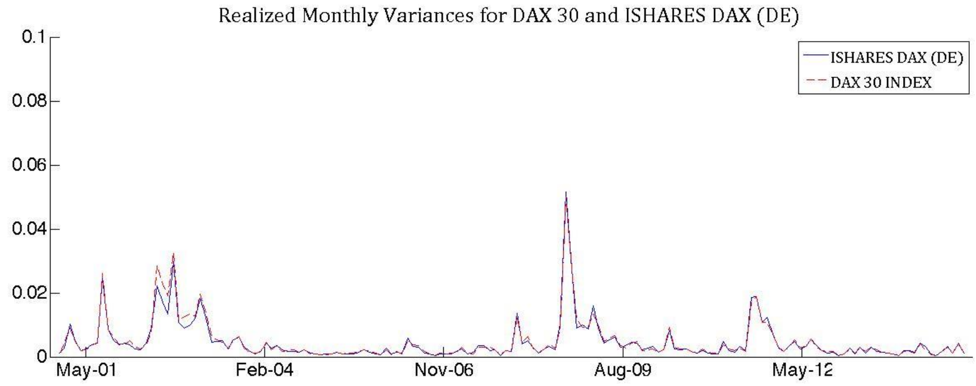
Note: We used MATLAB R2013a on Mac system; it is slightly different from the Windows version. In our codes, the only differences appear in the 'import data' section. In the Mac version the code' xlsread ()' will import both texts and numbers while in the Windows version it only reads numbers. Thus, the row/column selection in generating the dates and log returns will be different since the first 6 rows of our data include text information; this is the same for the dates. We also utilized the MFToolbox supplied by Kevin Sheppard at Oxford University (http://www.kevinsheppard.com/MFE_Toolbox).

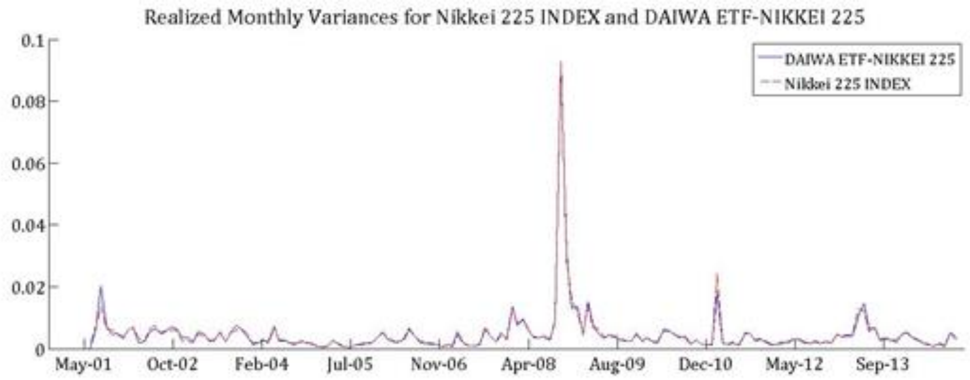
Please contact the authors for access to the data series and more codes used in our analysis.

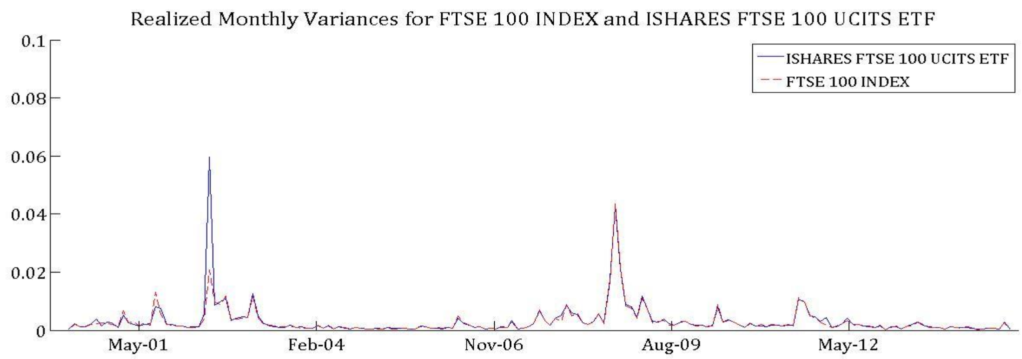
```
%%An example of the FTSE 100 Indices
%import data
G=xlsread('newdata.xlsx',1);%Germany
N=xlsread('newdata.xlsx',2);%Japan
F=xlsread('newdata.xlsx',3);%U.K.
S=xlsread('newdata.xlsx',4);%U.S.
%the first 6 rows are headers, the dates starts at 7th rows and since
%we will take the difference of the log prices,there will be one date
missing
dateE=F(8:end,1);dateN=N(8:end,1);dateG=G(8:end,1);
%Calculate log returns
Fret=diff(log(F(7:end,2)));Nret=diff(log(N(7:end,2)));Sret=diff(log(S(
7:end,2)));Gret=diff(log(G(7:end,2)));
clear F N S G
%%
%Plot the returns of daily log returns
%Analysis on the underlying assets
figure;
subplot(4,1,1);
plot(Gret);title('Log returns of DAX 30 Index');
axis([0 4000 -0.12 0.12])
subplot(4,1,2);
plot(Nret);title('Log returns of NIKKEI 225 Index')
axis([0 4000 -0.12 0.12])
subplot(4,1,3)
plot(Fret);title('Log returns of FTSE 100 Index');
axis([0 4000 -0.12 0.12])
subplot(4,1,4);
plot(Sret);title('Log returns of S&P 500 Index');
axis([0 4000 -0.12 0.12])
%%
% estimating the best model ARMA model; note: we prefer the BIC to the
AIC
n=8;
% UK model
 AIC_F = zeros(n,n);%pre-define the space for AIC
 BIC_F = zeros(n,n);%pre-define the space for AIC
 %Loops to filter the ARMA models
 for i=1:n;
     for j=1:n;
     [~,~,~,~,dia]=armaxfilter(Fret,1,1:i,1:j);
     AIC_F(i,j)=dia.AIC;
     BIC_F(i,j)=dia.SBIC;
     end
```

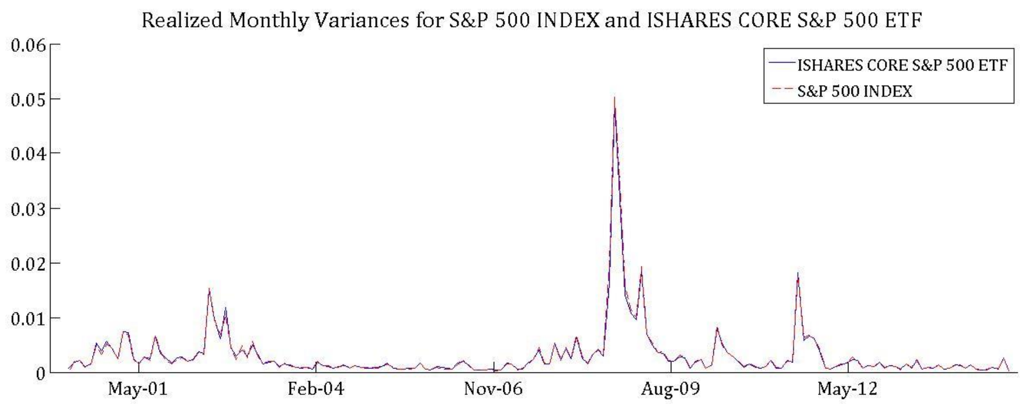
```
 end
 %%
 %generate the p/q with the minimum value of BIC elements
index= find(BIC_F==min(min(BIC_F)));
R = rem(index,n);
if R==0
    i=n;j= fix(index./n);
else
    i=R;j= fix(index./n)+1;
end
i_F=i, j_F=j
%includes constant in the model (furthur explanantions)
%To include or not to include the CONSTANT?
% Most multiple regression models include a constant term (i.e., the
intercept), since this ensures that the model will be unbiased--i.e.
the mean of the residuals will be exactly zero. (The coefficients in a
regression model are estimated by least squares--i.e. minimizing the
mean squared error. Now, the mean squared error is equal to the vari-
ance of the errors plus the square of their mean: this is a mathemati-
cal identity. Changing the value of the constant in the model changes
the mean of the errors but doesn't affect the variance. Hence, if the
sum of squared errors is to be minimized, the constant must be chosen
such that the mean of the errors is zero.) In a simple regression mod-
el, the constant represents the Y-intercept of the regression line, in
unstandardized form. In a multiple regression model, the constant rep-
resents the value that would be predicted for the dependent variable
if all the independent variables were simultaneously equal to zero----
a situation which may not physically or economically meaningful. If
you are not particularly interested in what would happen if all the
independent variables were simultaneously zero, then you normally
leave the constant in the model regardless of its statistical signifi-
cance. In addition to ensuring that the in-sample errors are unbiased,
the presence of the constant allows the regression line to "seek its
own level" and provide the best fit to data, which may only be locally
linear.
%%
%INDEX ARMA(1,3) - BIC by dia chosen
%INDEX ARMA(6,8) - AIC by dia
% [coeff_F,~,eps_F]=armaxfilter(Fret,1,1:i_F,1:j_F);
%We include a constant in our model
%([PARAMETERS]=armaxfilter(Y,CONSTANT,P,Q))
[coeff_F,~,eps_F]=armaxfilter(Fret,1,1,1:3);%ARMA(1,1) model
%%
%Plots of ACF/PACF of ARMA model residuals
sacf(eps_F,15,0,1)
title('Sample autocorrelation function for FTSE 100 residuals')
spacf(eps_F,15,0,1)
title('Sample partial autocorrelation function for FTSE 100 residu-
als')
%taking squared residuals
sq_res_F=eps_F.^2;
%%
% looking at autocorrelation/partial autocorrelations of squared re-
siduals
sacf(sq_res_F,12,0,1)
title('Sample autocorrelation function for FTSE 100 squared residu-
als')
spacf(sq_res_F,12,0,1)
title('Sample partial autocorrelation function for FTSE 100 squared
residuals')
```

Appendix 3: Enlarged plots of realized monthly variances



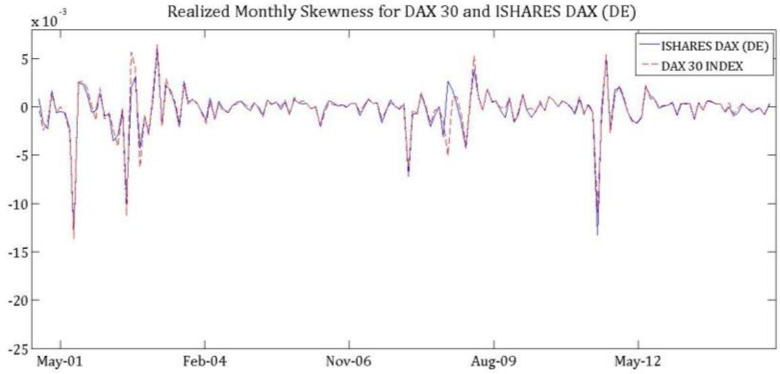




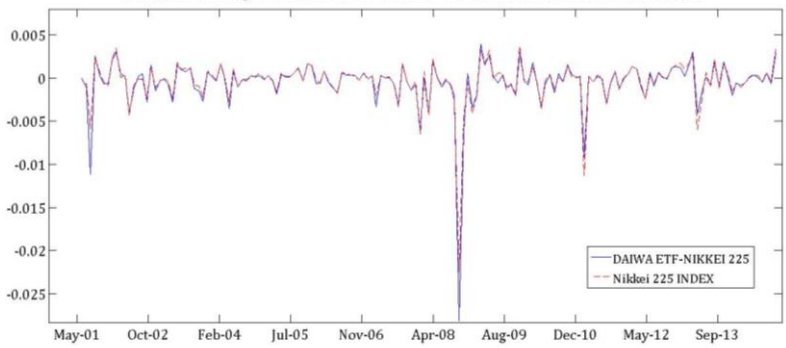


Appendix 4: Enlarged plots of realized monthly skewness

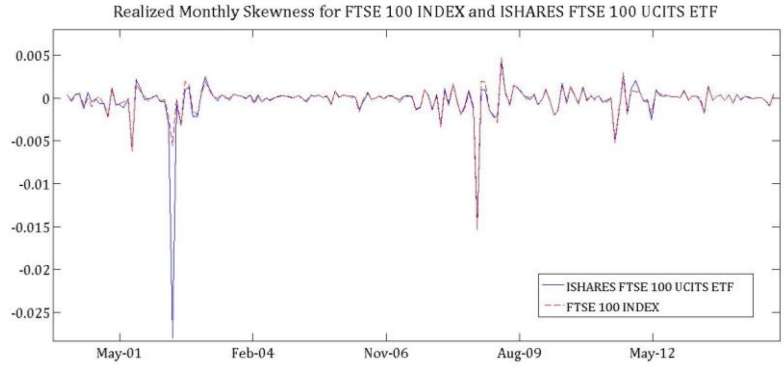
Realized Monthly Skewness for DAX 30 and ISHARES DAX (DE)



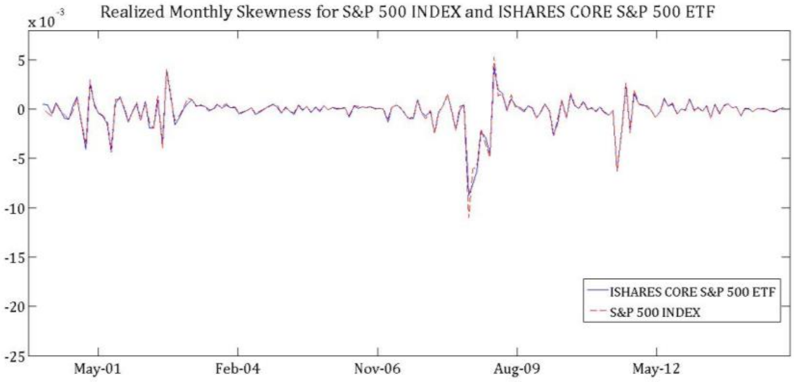
Realized Monthly Skewness for Nikkei 225 INDEX and DAIWA ETF-NIKKEI 225



Realized Monthly Skewness for FTSE 100 INDEX and ISHARES FTSE 100 UCITS ETF



Realized Monthly Skewness for S&P 500 INDEX and ISHARES CORE S&P 500 ETF



Appendix 5: Augmented Dicky Fuller test

Augmented Dicky Fuller Test: Indices Realized Variance				
	DAX 30	Nikkei 225	FTSE 100	S&P 500
Stats	-4.364	-8.860	-3.771	-4.519
Lags	2	0	4	2
P-value	0.000	0.000	0.006	0.000

Augmented Dicky Fuller Test: ETF Realized Variance				
	DAX 30	Nikkei 225	FTSE 100	S&P 500
Stats	-4.561	-8.594	-8.513	-5.879
Lags	2	0	0	0
P-value	0.000	0.000	0.000	0.000

Augmented Dicky Fuller Test: Indices Realized Skewness				
	DAX 30	Nikkei 225	FTSE 100	S&P 500
ADF	-10.802	-10.919	-5.030	-5.597
Lags	1.000	0.000	5.000	5.000
P-value	0.000	0.000	0.000	0.000

Augmented Dicky Fuller Test: ETF Realized Skewness				
	DAX 30	Nikkei 225	FTSE 100	S&P 500
ADF	-7.434	-10.976	-12.292	-5.549
Lags	3.000	0.000	0.000	5.000
P-value	0.000	0.000	0.000	0.000

Appendix 6: P-values of Intra-market & cross-market VAR

Intra Market - Var Regression P-values: Indices			
DAX 30		ARMA(8,4)	
	Return	Volatility	Skewness
Return	0.10%	42.36%	0.36%
Volatility	5.52%	0.00%	41.36%
Skewness	0.15%	8.99%	0.48%
NIKKEI 225			
Return	72.33%	57.74%	93.59%
Volatility	8.80%	0.00%	6.68%
Skewness	93.51%	35.13%	86.22%
FTSE 100			
Return	92.47%	80.58%	93.78%
Volatility	7.61%	0.28%	20.73%
Skewness	18.60%	60.64%	24.96%
S&P 500			
Return	27.59%	65.18%	9.82%
Volatility	65.32%	0.00%	12.92%
Skewness	13.80%	1.59%	19.98%

Intra Market - Var Regression P-values: ETFs			
ISHARES DAX ETF			
	Return	Volatility	Skewness
Return	0.06%	10.45%	0.03%
Volatility	5.63%	0.00%	89.57%
Skewness	0.80%	0.62%	0.56%
DAIWA ETF-NIKKEI 225			
Return	34.25%	31.69%	42.00%
Volatility	10.76%	0.02%	9.13%
Skewness	46.92%	21.69%	52.53%
ISHARES FTSE 100 UCITS ETF			
Return	91.54%	96.81%	99.72%
Volatility	0.60%	0.12%	1.73%
Skewness	18.06%	65.91%	43.80%
ISHARES CORE S&P 500 ETF			
Return	28.98%	65.80%	12.20%
Volatility	79.89%	0.00%	17.71%
Skewness	13.90%	1.18%	12.81%

Cross-market Var Regression P-values: Indices

		Volatility				Skewness			
		DAX 30	NIKKEI 225	FTSE 100	S&P 500	DAX 30	NIKKEI 225	FTSE 100	S&P 500
Volatility	DAX 30	4.2%	19.3%	27.5%	94.2%	77.7%	31.1%	49.5%	4.1%
	NIKKEI 225	9.5%	89.7%	5.6%	62.5%	17.3%	28.3%	19.9%	3.8%
	FTSE 100	33.6%	9.8%	6.3%	81.1%	85.0%	86.0%	54.1%	8.3%
	S&P 500	25.7%	44.0%	12.7%	38.3%	17.4%	68.4%	68.0%	1.0%
Skewness	DAX 30	94.8%	43.8%	40.6%	47.1%	11.2%	32.1%	43.0%	12.0%
	NIKKEI 225	3.3%	74.8%	4.1%	33.6%	29.5%	39.7%	31.2%	2.8%
	FTSE 100	20.4%	9.1%	26.0%	71.2%	5.0%	58.5%	47.7%	0.2%
	S&P 500	7.6%	93.6%	50.0%	28.6%	37.7%	21.6%	57.9%	54.3%

Cross-market Var Regression P-values: ETFs

		Volatility				Skewness			
		DAX 30	NIKKEI 225	FTSE 100	S&P 500	DAX 30	NIKKEI 225	FTSE 100	S&P 500
Volatility	DAX 30	5.3%	35.1%	3.7%	84.6%	12.0%	27.3%	7.7%	6.4%
	NIKKEI 225	13.4%	73.7%	6.9%	95.3%	96.3%	69.1%	7.3%	10.1%
	FTSE 100	93.1%	11.6%	10.5%	63.0%	27.3%	27.0%	15.1%	11.5%
	S&P 500	26.5%	33.0%	5.4%	18.8%	65.9%	87.0%	6.2%	2.4%
Skewness	DAX 30	50.8%	18.7%	39.4%	26.5%	54.1%	31.1%	36.6%	90.3%
	NIKKEI 225	4.7%	96.4%	3.7%	54.1%	83.6%	83.7%	5.1%	7.2%
	FTSE 100	55.5%	3.8%	35.5%	91.0%	25.9%	20.0%	40.7%	1.4%
	S&P 500	3.6%	24.3%	49.5%	1.7%	32.3%	5.7%	31.3%	32.3%

Appendix 7: Granger Test: Intra-market

Intra Market - Granger Test for Indices

DAX 30

	Return	Volatility	Skewness
Return	71.00***	5.62**	62.36***
Volatility	14.04***	81.28***	2.14
Skewness	78.99***	30.93***	70.45***

Nikkei 225

	Return	Volatility	Skewness
Return	1.08	1.52	0.05
Volatility	19.81***	67.05***	11.00***
Skewness	0.11	5.76**	0.36

FTSE 100

	Return	Volatility	Skewness
Return	0.02	0.60	0.16
Volatility	188.28**	528.50**	112.66***
Skewness	165.53**	20.33***	173.23***

S&P 500

	Return	Volatility	Skewness
Return	8.94***	1.53	33.30***
Volatility	1.77	79.21***	20.85***
Skewness	17.15***	31.72***	21.94***

Intra Market - Granger Test for ETF

DAX ETF

	Return	Volatility	Skewness
Return	72.41***	15.34***	82.00***
Volatility	10.07***	85.78***	0.081
Skewness	65.64***	58.95***	80.37***

Nikkei 225 - ETF

	Return	Volatility	Skewness
Return	12.25***	13.85***	14.59***
Volatility	33.27***	103.55**	29.09***
Skewness	25.72***	48.46***	24.61***

FTSE 100 - ETF

	Return	Volatility	Skewness
Return	0.097	0.036	0.005
Volatility	198.19**	148.17**	149.92***
Skewness	86.63***	8.26***	15.52***

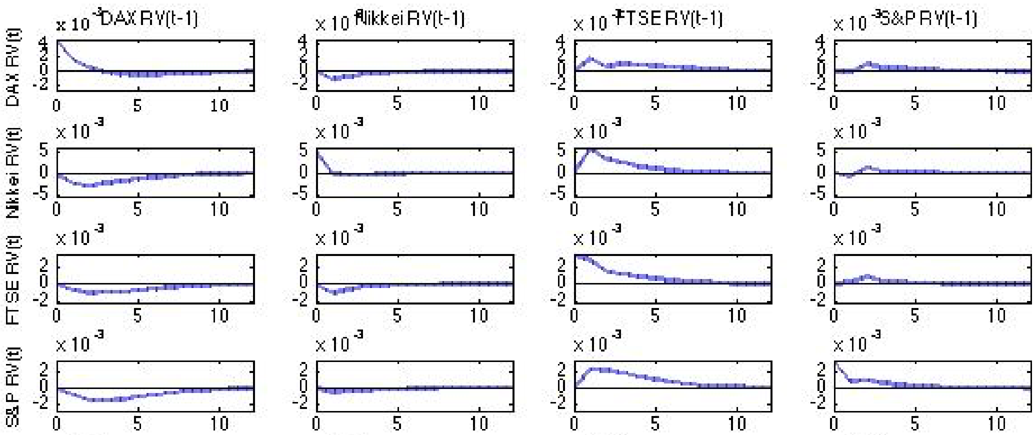
S&P 500 - ETF

	Return	Volatility	Skewness
Return	6.28**	0.697	22.00***
Volatility	0.046	80.58***	19.97***
Skewness	17.44***	16.66***	36.97***

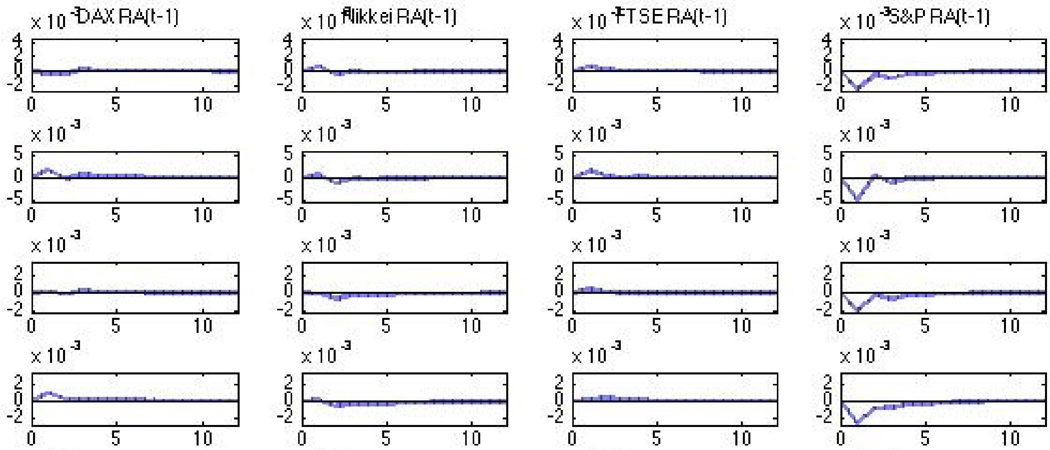
*** Significantly different from zero at the 1 % level, ** at the 5% level and * at the 10% level.

Appendix 8: Impulse response function – Indices

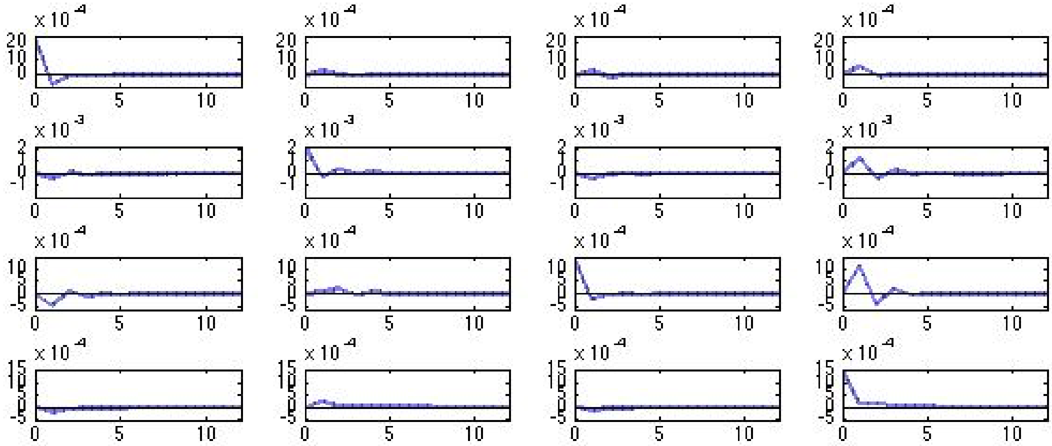
1) Current Realized Variances Impacted by Previous Realized Variances



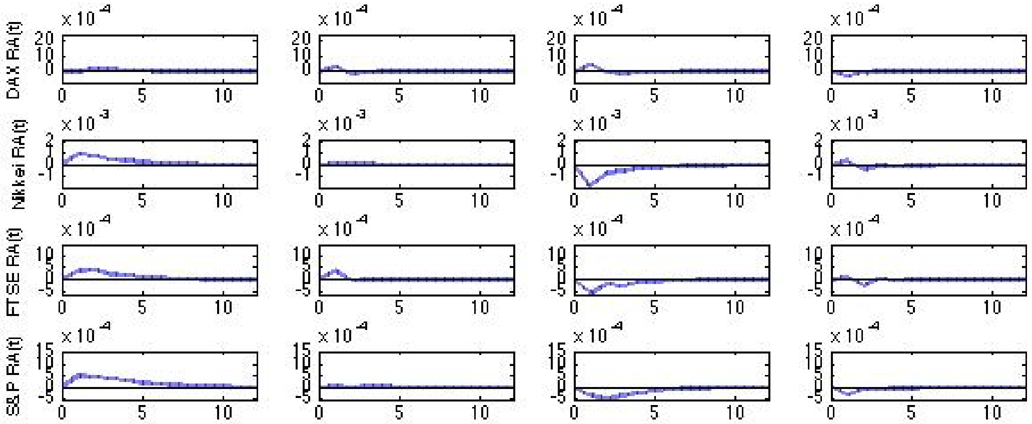
2) Current Realized Variances Impacted by Previous Realized Skewness



3) Current Realized Skewness Impacted by Previous Realized Skewness

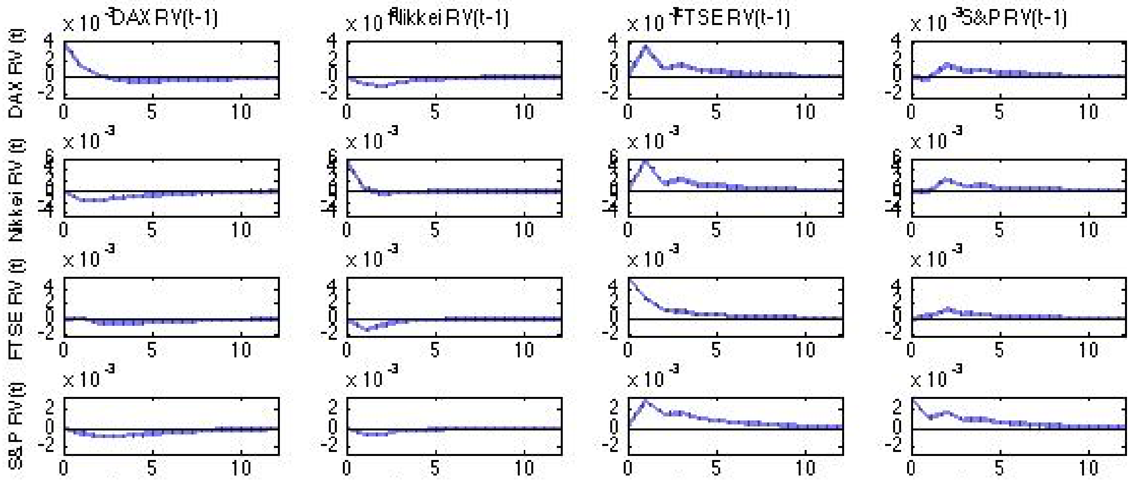


4) Current Realized Skewness Impacted by Previous Realized Variances

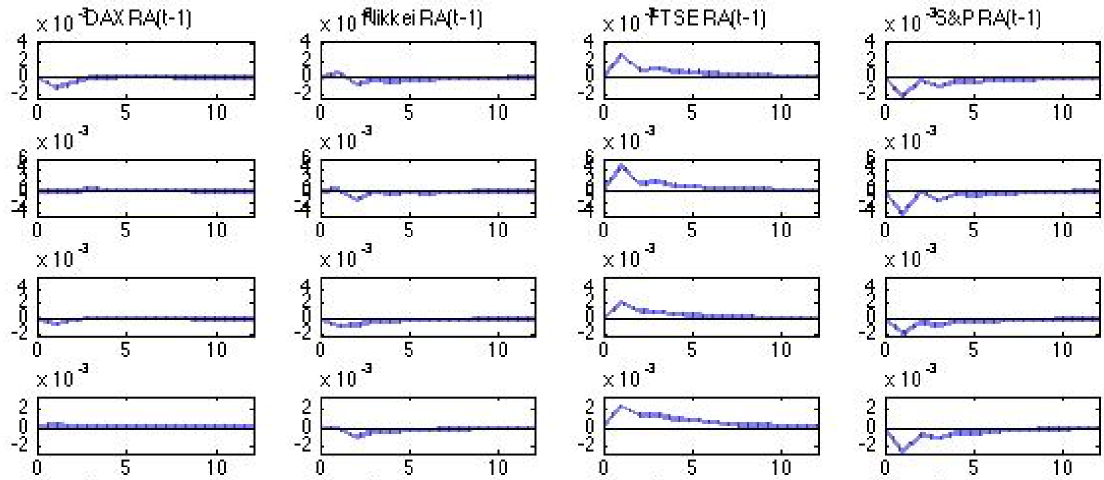


Appendix 9: Impulse response function – ETF

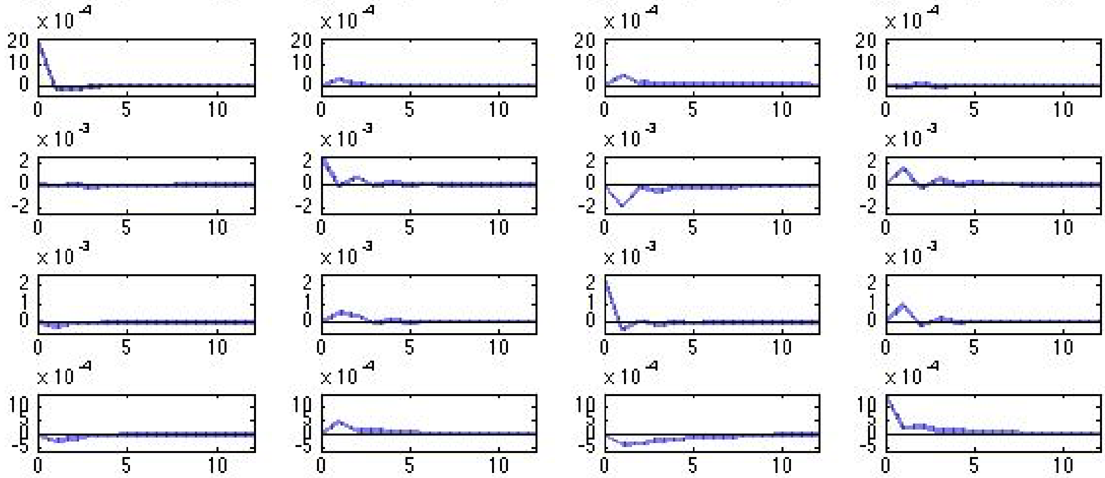
1) Current Realized Variances Impacted by Previous Realized Variances



2) Current Realized Variances Impacted by Previous Realized Skewness



3) Current Realized Skewness Impacted by Previous Realized Skewness



4) Current Realized Skewness Impacted by Previous Realized Variances