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Applications of High-Order Realized Moments in Financial Market Linkages

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This project is entirely the original work of student registration number 28959302. I declare that this dissertation is my own work, and that where material is obtained from published or unpublished works, this has been fully acknowledged in the references. *This dissertation may include material of my own work from a research proposal that has been previously submitted for assessment for this programme.*

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Abstract

Understanding the financial market linkages attracts a significant attention from both investors and academics. For this reason, asset market relations have been usually examined in terms of return and volatility level. However, dynamic relations via skewness and kurtosis level draw less attention. Therefore, this dissertation investigates stock and foreign exchange market linkages among developed countries via realized volatility, skewness and kurtosis. High order realized moments of major stock indices and foreign exchange rates are calculated by employing 5-minute intradaily data. The first section examines the joint dynamics of stock-FX market linkages within the same economy via higher moments. In the second section, the associations of high order measures between the S&P 500 index and the other stock indices in developed countries are investigated. Within the VAR framework, Impulse Response Analysis and Granger Causality tests are applied to explain the dynamic relations in both sections. Empirical results support the evidence of unidirectional volatility spillovers from stock markets to exchange rates. Similarly, positive unidirectional volatility spillovers from the US stock markets to other developed economies. Moreover, positive skewness spillovers run from the USA to the other major stock markets whereas there are unidirectional Granger causalities from all of the selected stock indices to S&P 500. Lastly, empirical findings exhibit positive kurtosis spillovers between stock-FX markets and from S&P 500 to other major stock indices. Overall, skewness and kurtosis are able to explain financial market linkages similarly to realized volatility.

Key words: High frequency data, VAR, spillover effect, high-order realized moments, Granger causality, stock market.

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1. INTRODUCTION

1.1 Theoretical Background

The last wave of globalization era which starts in 1980s have made the major financial markets connected by allowing free capital mobilization and foreign investments. Meanwhile, financial market linkages increasingly transformed into a complicated network around the world. Asian financial crisis in 1997 and global financial crisis of 2007-2008 clearly demonstrate how the world's financial system can affect each other. For this reason, understanding the relationship between financial markets is crucial for risk management and international portfolio allocation. Investors and policy makers attempt to take their financial decisions by considering the current and future circumstances in major markets. Therefore, stock and foreign exchange (FX, hereafter) markets successfully describe how financial relations evolves between countries.

The relationship between stock and FX markets draw a significant amount of attention in many aspects by both investors and financial analysts. In addition to cross market, co-movements between these markets within the same economy is crucial at the national level. One strand of previous literature heavily works on the stock and FX returns via return and volatility connections between markets. Return level financial linkages were attempted to explain within the causality framework. Dornbusch and Fisher (1980) asserted that the FX rates are the main determinant of stock prices. In other words, the causality runs from FX rates to stock markets. On the other hand, 'stock-oriented' approach emphasized that transmission mechanism runs from stock markets to FX rates. Despite controversial results, both theoretical approaches reveal significant implications. Another strand of literature concentrates on volatility dynamics across FX and stock markets. Engle *et al.* (1990) came up with a new terminology in which defines volatility behaviours. *Heat waves* is the type of volatility in a country in which a function of its own previous volatility. Conversely, *meteor shower* defines the volatility of a country which is affected by other countries. A vast number of studies investigate volatility patterns based on these hypotheses. Despite the contradictive results, heat waves hypothesis is the more pronounced in recent studies. Also, more recent papers try to explain volatility linkages by focusing on the contagion during crisis periods (Forbes and Rigobon, 2002) or constructing novel measures such as spillover index (Diebold and Yilmaz, 2009). To sum up, current literature on the return and volatility level linkages have been growing in many aspects.

In contrast to return and volatility linkages, high order moments such as skewness and kurtosis draw less attention in the literature. In addition to return and volatility level linkages, skewness and kurtosis can provide novel aspects for stock and FX markets. Skewness is a measure of asymmetry in return distribution. Specifically, it can be positive or negative based on whether one tail of distribution is relatively greater or not. Meanwhile, kurtosis is a measure that shows the frequency extreme events in return distribution. According to previous studies (Rubinstein, 2006 and Del Brio *et al.,* 2017) investors frequently consider skewness and kurtosis in portfolio allocation. They demand assets that have high and positive skewness and low kurtosis. Thus, the measure of skewness and kurtosis need a special attention in the context of international portfolio management. Do *et al* (2015, 2016) and Del Brio (2017) find evidence on the existence of spillover effects via skewness and kurtosis among financial markets. This dissertation attempts to provide an evidence of realized skewness and kurtosis I financial market linkages.

1.2 Research Objectives

In this research, financial market linkages are investigated via their high order moments, namely volatility, skewness and kurtosis. As suggested by Andersen *et al.* (2001a, 2001b) and Amaya *et al.* (2011); realized volatility, skewness and kurtosis are calculated based on 5-minute intradaily return data. Intradaily returns of major stock market indices and FX rates against the US Dollar (USD) are employed to measure weekly realized higher moments with non-parametric fashion.

This dissertation involves two main research objectives. Two designated sections analyse financial market linkages in particular aspects.

The first objective is to investigate the joint dynamics of stock and FX market linkages in the same economy via higher moments. Stock indices of Germany, the UK, Japan, Canada and their national currencies against USD are applied to construct a number of bivariate Vector Autoregressive (VAR) models. Further procedures such as Granger Causality and Impulse Response Functions are used to determine spillover effect in higher moments.

In a similar fashion, the second section evaluates major stock market indices in five countries, namely France, Germany, the UK, Japan, Switzerland and Canada. Bivariate VAR models attempt to explain the effect of US stock markets to selected stock markets. Each VAR model includes S&P 500 index as an indicator of US stock market and one other stock index from selected countries. Impulse Analysis and Granger Causality in the VAR model are used to explain the dynamic relations.

This research simply focuses on advanced economies due to following reasons. Firstly, the majority of transactions in stock and FX market transactions are occurred in the advanced countries. According to World Federation Exchanges (WFE), selected stock markets have 62.5% of market capitalization in the world (world-exchanges.org, 2017) Secondly, these financial markets do not experience any external interventions. In other words, asset prices can fully reflect market conditions. Finally, these financial markets provide accurate and continuous intradaily data for the time period.

1.3 Structure

This research consists of five chapters. The first chapter briefly introduce the background and clarify the research objectives. In the second chapter, previous studies are discussed in detail. Modelling and measuring high order moments and their applications to the financial market linkages are briefly described. The third section demonstrates how the sample data are selected and transformed. Then, VAR framework and model construction is proposed in the chapter 4. Chapter five evaluates the empirical results in two sections. The last chapter provide a brief conclusion and address the limitations of the research.

2. LITERATURE REVIEW

In this chapter, relevant previous studies are reviewed in some aspects. The first section involves major works on modelling and measuring volatility. Two approaches in volatility modelling, namely ARCH-family models, and realized volatility are discussed. The second section provides an extensive literature about how researchers construct linkages between financial markets via return, volatility and further high order moments.

2.1. Modelling and Measuring Volatility

2.1.1. ARCH Family Models

Modelling volatility plays a crucial role on option pricing, hedging decisions and portfolio allocation. For this reason, a vast number of econometric models try to estimate volatility deviation. However, classical linear models fail to capture the variance due to some stylized facts of financial data. Mandelbrot (1963) described volatility clustering as a common property of financial data that indicates that large price changes are likely to be result of large fluctuations whereas small changes followed by small changes. Another key feature of financial data is its leptokurtic distribution. It reveals heavy tails and high peak in the mean. Again, Mandelbrot (1963) emphasized that the normal distribution is not sufficient enough to characterize leptokurtic distribution. The third property of financial time-series data is leverage effect. Black (1976) noticed that volatility increases when asset prices tend to fall but the volatility does not increase when prices start to increase. As a result, volatility behaviour of returns shows unstable deviations. These properties of asset returns are observed in the majority of markets and their instruments. A significant literature on financial econometrics concentrates on constructing models that captures time-varying variance.

The first studies on time-varying variance treat volatility as an unobserved (latent) factor. Specifically, ARCH (autoregressive conditional heteroscedasticity) models firstly obtain the conditional variance implicitly. Engle (1982) constructed the ARCH model based on time-varying variance that depend on lagged squared error terms. Unique specification of ARCH allows us to detect non-linear relationship between current and past conditional variances. Nevertheless, the ARCH specification has some drawbacks in practice. First, determination of optimum number of lags used in ARCH models is not clear. Several information criteria often show different lags to be chosen. Moreover, number of lags can substantially reduce the degrees of freedom in case information criteria points high. (Brooks, 2014). As a result, Bollerslev (1986) introduced “generalized” ARCH model. GARCH specification suggest that variance does not only depend on lagged squared error terms, but also past values of variance itself. Bollerslev’s study showed that GARCH (1, 1) process is parsimonious alternative of infinite ARCH (q) specification. However, the pure GARCH model has two major drawbacks: the restriction in which explanatory variables in the variance equation cannot be negative (Nelson and Cao, 1992) and responses against positive and negative shocks are asymmetric which known as leverage effect (Engle and Ng, 1993). Several extensions to pure GARCH model evolve to solve these limitations. Asymmetric GARCH models such as E-GARCH (Nelson, 1991), GJR-GARCH (Glosten *et al.*, 1993), T-GARCH (Zakoian, 1994) are able to capture the leverage effects. In brief, one strand of the literature is constructing volatility as a latent factor through ARCH-type models and the scope of this literature have been still growing along with more complex models.

2.1.2 Realized Volatility and Other Realized Measures

Availability of intradaily data allows us to understand financial volatility mechanism and risk components more precisely. Recent developments in empirical finance highlight the measure of realized volatility which exploits high frequency returns via non-parametric procedures. The idea of realized volatility goes back to Merton (1980). He implied that if there exist enough number of sampling frequencies, summing the squared returns leads to obtain precise volatility estimates. Building on this earlier intuition, Schwert (1990), Hsieh (1991), Taylor and Xu (1997) employ intradaily returns to generate volatility measures. These papers set up a theoretical background of realized measures. Therefore, Andersen *et al.* (2001b) and Barndorff-Nielsen and Shephard (2002) introduced the realized volatility and theorized its statistical properties with a model-free manner. It is measured by summing up intradaily squared returns over a fixed time interval (e.g day, week). If intraday returns have adequate frequency, realized volatility generates a precise estimate of underlying integrated volatility. Hence, realized volatility is theoretically justified as an observable measure.

The procedure had a great impact on modelling volatility literature. Many studies examined realized volatility from different aspects. At first, researchers evaluated the statistical properties of realized volatility based on different stock and foreign exchange (FX) markets. Based on return volatilities of individual stocks in Dow Jones Industrial Average, Andersen *et al.* (2001a) showed that realized volatilities and covariances are highly right-skewed and possess long memory process. Also, individual realized volatilities are strongly related with corresponding stock correlations. Similarly, Andersen *et al.* (2001b) explained both conditional and unconditional distributions of realized volatility by exploiting Deutschemark and Japanese yen (JPY) returns against the USD. They find that volatility distributions and their covariance are positively skewed, leptokurtic and appear to be fractionally integrated. Therefore, it is concluded that multivariate linear Gaussian long memory models could perform well on predicting and forecasting. Areal and Taylor (2002) examined the distributional and autocorrelation properties FTSE 100 index-futures volatility and FTSE 100 index realized volatility. It is found that the realized volatility contains non-normal distribution and long memory process. In conclusion, realized volatility possess long memory process as well as the common properties of financial time series.

Although high frequency data reveal significant explanatory power in asset returns, it might bring along some unfavourable statistical circumstances. The major setback is that realized volatility might contain microstructure noise component depending on sampling frequency. It yields a bias problem and instability in realized volatility. Microstructure noise might arise from trading process such as bid-ask bounces, discreteness of price changes, latency, differences in trade size, etc. (Ait-Sahalia and Yu, 2009). Martens (2002) evaluated realized volatility and market microstructure noise using S&P 500 index-futures contracts. Results showed that overnight future returns cause microstructure noise component in volatility. Andersen *et al.* (2001b) demonstrated that the theory of quadratic variation suggests very high frequency sampling whereas, ‘too frequent’ data induce microstructure noise. As a result, 5-minute return frequency should be exploited to reduce microstructure frictions. Further studies attempted to distinguish microstructure noise from aggregate volatility (Bandi and Russell, 2006) and proposed a bias correction method to reduce the mean squared error of realized volatility (Hansen and Lunde, 2004).

Another strand of literature has focused on forecasting techniques which are exploiting realized volatility. Volatility forecasting literature substantially changed after realized volatility. In the spirit of non-parametric procedure, Andersen *et al.* (2003) estimated a fractionally integrated vector autoregression (VAR) model using FX rates. Results showed that the simple VAR model provides better forecast results among other forecast models. In response, Andersen *et al.* (2004) provided analytical expressions for integrated volatility forecasting in stochastic volatility models such as GARCH. For those models, reduced-form procedures perform well in terms of forecasting. Several studies proposed alternative approaches to improve forecasting performance. Corsi (2004) introduced a parsimonious model named 'heterogenous autoregressive model of realized volatility' (HAR-RV) which is successfully captures the properties of time-series data (fractionally integration, leptokurtic distribution etc.). Forecast results on USD/CHF rates outperforms the standard models. Andersen *et al.* (2007) showed that separating the rough jump moves from aggregate volatility improves the forecasting performance. In addition, Liu and Maheu (2005) suggested that realized power variation can improve modelling and forecasting volatility. In conclusion, it should be noted that realized volatility has become a benchmark measure among the volatility forecasting models.

Further important realized measures are introduced to capture risk components and volatility forecasting. Firstly, Barndorff-Nielsen *et al.* (2008) proposed a new risk measure called realized semivariance. They noticed that realized variance ignore whether high frequency returns move upward or downward. In other words, it does not tell us anything about asymmetric behaviour of financial time series. For this reason, downside realized semivariance 'bad volatility' is introduced as the sum of squared negative movements in intradaily returns. Downside realized semivariance is more predictive than realized volatility. Secondly, model-free nature of realized volatility can be applied into third and fourth-order realized moments. Amaya *et al.* (2011) constructed realized skewness and realized kurtosis in order to apply portfolio allocations. Realized skewness gauge the asymmetry of intradaily return distribution. Positive skewness can be interpreted as fatter right tail distribution which is desirable for investors. Similarly, negative skewness defines the opposite. In a similar fashion, realized kurtosis is constructed to measure the extremes of return distribution involving forth moment. As extreme movements occur in intradaily returns, it will directly increase realized kurtosis. However, few studies have employed higher realized moments cross market linkages, forecasting and portfolio management. Amaya *et al.* (2011) constructed portfolios based on realized volatility, skewness and kurtosis. Results provide significant insight about the association between high order moments and cross-section of stock returns. They demonstrated that using realized skewness in portfolio applications help to produce higher weekly returns. Also, Nolte and Xu (2014) implied that realized measures can improve portfolio allocation. In addition to portfolio applications, higher moments can be applied into volatility forecasting. Based on HAR-RV framework introduced by Corsi (2004), Mei *et al.* (2017) found that the realized skewness improves forecast accuracy whereas realized kurtosis has little power on forecasting volatility. Finally, Do *et al.* (2015, 2016) applied realized skewness and kurtosis to assess the link between asset markets. They found negative bidirectional skewness spillovers between stock and FX markets while FX markets are linked via realized kurtosis in developed economies.

2.2 Linkages between Stock Markets and FX Rates

2.2.1 Return Level Linkages

Financial globalization has yielded strong economic linkages between countries especially via stock and foreign FX markets. There is a long tradition in the literature which investigates the relationship within or between stock and FX markets. A major part of studies evaluates stock market - FX rate return relation by applying causality techniques. However, results are quite controversial. Traditional *(flow-oriented)* approach asserts that FX rates affect directly stock prices. The causality runs from FX rates to stock market (Dornbusch and Fisher 1980). Specifically, a depreciation in the national currency strengthen the international competitiveness structure of the exporting firms. As a result, stock prices positively affected by this change. On the other hand, *stock-oriented* approach claims that FX rates are also be affected by stock market. For instance, an increase in equity prices leads to enhance the wealth of investors, and then raise money demand and interest rates. Consequently, higher interest rates lead to capital inflows that depreciates the FX rates. In the opposite case, decreasing stock prices drive investors to change their portfolios and concentrate on foreign assets (Gavin, 1989). To sum up, FX rates can be negatively influenced by stock price changes.

Empirical studies reveal controversial results on the causality of the relationship. Some papers found unidirectional causality from FX rates to equity markets observed in Asian emerging markets (Abdalla and Murinde, 1997; Pan *et al.,* 2007; Wongbangpo and Sharma, 2002), and in developing European countries (Murinde and Poshakwale, 2004), and in Eurozone countries (Ehrmann *et al.,* 2011; Alagidede *et al.,* 2011). On the other hand, there are many empirical studies that advocate the stock-oriented approach. Smith (1992) found that stock prices have a significant effect on Deutschemark/USD and JPY/USD rates. This result is also consistent with Yang and Doong's study (2004) in which validates this approach for France, Italy, Japan and USA in G-7 countries. Ajayi and Mougoue (1996) showed that stock prices are inversely related with domestic currency value in short term while there is a positive relation in the long run. In conclusion, all studies have their own justification since this association is examined for a wide variety of countries, data frequencies and time periods.

2.2.2 Volatility Level Linkages

A vast number of studies investigates the volatility transmission between FX markets. Ito (1987), Ito and Roley (1987) were the first studies that examine the volatility transmissions from one region to another via 24-hour time intervals. The former paper demonstrated that positive surprises in U.S cause appreciation in USD against JPY, whereas positive announcements in Japan did not have the same impact in JPY/USD. Also, Ito and Roley (1987) pointed out that FX rate volatilities mainly respond to the news about economic fundamentals rather than currency market interventions held by monetary authorities. Based on these seminal papers, Engle *et al.* (1990) defined the volatility spillover behaviours in two ways: heat waves and meteor showers. *Heat waves* occur where the volatility in a country is a function of its own previous volatility. Conversely, *meteor shower* defines a volatility of a country that is affected by other countries. Seminal work of Engle *et al.* (1990) examined the sources the volatility clustering in FX rates using intradaily data. The results indicate a meteor shower. On the contrary, Baillie and Bollerslev (1990), Hogan and Melvin (1994) supported the heat wave hypothesis in FX markets. Conflicting results might be due to different sampling frequencies and different time periods. Apart from previous works, Melvin and Melvin (2003) investigated volatility spillovers of Deutschemark/USD and JPY/USD across regional markets using realized volatility. Volatility patterns exhibits both meteor shower and heat waves, but they favour heat waves pattern. Similarly, Cai *et al.* (2008) found that both effects occur in EUR/USD and JPY/USD markets. However, the economic significance of heat waves effect is greater than meteor shower effect in terms of volatility. In addition, Clements *et al.* (2015) investigated the volatility transmission in bond, equity and FX markets using high frequency data. Volatility patterns possess a mixture of heat waves and meteor showers. Meteor shower between regions exist in the same trading day while heat waves is significant in all markets.

Besides direct measures, indirect econometric techniques such as dynamic correlations applied to understand cross market linkages. Hamao *et al.* (1990) is the first study that proves the return and volatility spillovers in stock markets using GARCH model. They found stock market volatility spillovers from the USA and the UK stock markets to Japanese stock market. Using the same methodology, Lin *et al.* (1994) decomposed the intradaily return data into daytime and overnight returns to identify global and local factors. Contrary to the former paper, they found bidirectional return and volatility interdependence between New York and Tokyo stock markets. Also, cross market connections rise after a shock to one country. Following the same approach, subsequent studies found strong volatility spillover effects between financial markets (see, e.g Baur, Jung (2006); Savva *et al.* (2009). Dimpfl and Jung (2012) indicates that the USA is major transmitter in terms of volatility spillovers. Similarly, Jung and Maderitsch (2014) proved that the global financial crisis leads to contagion in 2007 due to spillover effects. Unlike the approach mentioned above, Diebold and Yilmaz (2009) suggested a new measure to determine interdependence via return and volatility linkages. In this seminal paper, distinguished forecast error variances by variance decompositions allow us to obtain a ratio, namely spillover index. This index enables to find particular spillover effects between countries through variance decomposition. Based on the empirical analysis, return spillovers exhibit a moderate increase in time whereas volatility spillovers occurs in bursts. Further studies detected these patterns in Eastern Asian stock markets (Yilmaz, 2010), and in Latin American economies (Diebold and Yilmaz, 2011). Moreover, they introduced measures of total and directional volatility. They showed that volatility spillovers across equity, FX, commodity and bond markets are at moderate levels whereas the spillovers rise significantly (Diebold and Yilmaz, 2012).

Financial market volatilities during crisis period have drawn a special attention in empirical and behavioural finance due to its importance for institutional or private investors. Therefore, one strand of literature has attempted to measure volatility spillovers using correlation-based measures focusing on contagious behaviour of financial markets. General definition of contagion is defined as a significant increase in the co-movements between markets during crisis in one or more countries. King, Wadhwani (1990) and Lee, Kim (1993) investigated the effect of market crash of 1987 across 12 national stock markets. There is a significant evidence that high level of volatility exists in the period of shocks. This contagious behaviour of markets intensified substantially during 1987 crash and continue to exist for subsequent periods. Subsequent studies indicated that simple correlation measures might have some drawbacks. Forbes and Rigobon (2002) emphasize that highly correlated market movements may not always be the case of contagion. Specifically, high market co-movements are considered as contagion only when the relation of markets increase *significantly* after a shock. Otherwise, this strong linkage between markets can only be seen as interdependence. Based on the new definition, contagion effect does not exist during 1987 market crash, 1997 Asian crisis, and 1994 Mexican devaluation. This important evident shows that previous correlation-based studies can lead to wrong conclusions due to heteroscedasticity problem.

2.2.3. Skewness and Kurtosis Level Linkages

Although the majority of literature concentrates on cross-market relations based on their first and second moments, recent literature investigates the association using high-order moments such as skewness and kurtosis. Do *et al.* (2015) examined realized spillover effects between FX and stock markets by employing realized measures. They found positive and bidirectional spillovers in realized volatility for all financial markets. Negative and bidirectional skewness spillovers occur only in emerging regions while developed regions do not have evidence of skewness spillover effect. Similarly, Do *et al.* (2016) extended their analysis and investigate realized spillover effects between and within stock and FX markets. In general, volatility spillovers in developed countries are stronger than the spillovers in emerging markets. Interestingly, realized skewness spillovers between countries (through stock and FX markets) are negative whereas they are positive within the same economy. Furthermore, the spillover effects via the fourth moment reveals positive correlation both within and between developed countries. On the other hand, Del Brio *et al.* (2017) employ conditional measures of volatility, skewness and kurtosis to construct dynamic linkages between regional markets. Analogous to the previous works, they found positive correlation via conditional volatility and kurtosis while conditional skewness was negatively correlated between regions. In addition to higher measures, realized semivariance proposed by Barndorff-Nielsen *et al.* (2008) is successful to detect asymmetries in volatility. Barunik *et al.* (2016) investigated 'good' and 'bad' volatility spillovers by employing realized semivariance is USA stocks. Results showed that negative spillovers are greater than positive spillovers in terms of magnitudes and total transmissions intensify substantially during global financial crisis.

3. DATA

3.1 Data Selection

This study employs 5-minute high frequency data of major stock indices and FX rates. Since the dissertation contains two distinct sections, time periods for corresponding data sets are different. The first section investigates the joint dynamics of stock and FX markets and exploits 5-minute intradaily data from June 1, 2012 to June 30, 2017. The second section evaluates the relations between S&P 500 and other major stock market indices. Time period is between January 4, 2010 and Jun 30, 2017. Stock market data in both sections is obtained from high frequency databases of Esignal Trading Platform. FX rates is provided by Dukascopy Bank Historical Data Feed. Data range for both sections is determined due to the availability of data. In this study, I exclude data on weekends, public holidays and the days that have extremely low volume.

Intradaily stock market data includes major stock indices for developed countries, namely Canada, Germany, Japan, the United Kingdom (UK) and the United States (USA). I choose the most widely quoted stock market indices for corresponding countries. Selected indices can be seen as a benchmark for the countries because they capture the majority of aggregate market capitalization in the stock market. One of the common characteristics of these indices is that they can perform as an accurate indicator for corresponding countries. Table 1 shows relevant individual indices and further details such as notations and trading hours.

Table 1. Data Description for Stock Markets

Countries	Index Notation	Trading Hours (GMT)	DST
France	CAC 40	08:00-16:30	07:00-15:30
Germany	DAX	08:00-16:30	07:00-15:30
Canada	S&P/TSX (TSX)	14:30-21:00	13:30-20:00
United Kingdom	FTSE 100	08:00-16:30	07:00-15:30
Japan	NIKKEI 225	00:00-06:00	-
Switzerland	SMI	08:00-16:30	07:00-15:30
United States	S&P 500 (SPX)	14:30-21:00	13:30-20:00

Note: DST shows the adjusted trading hours based on daylight saving time.

This research employs intraday exchange rates in four major FX rates namely, Euro, Japanese Yen, British Pound, and Canadian Dollar against the US Dollar. FX rates are calculated as the average of bid and ask prices. These currency pairs capture the majority of global FX turnover. Meanwhile, it should be noted that FX markets work 24 hours per day due to overlapping trading hours. Unlike stock markets, FX rates exhibits 5-minute data for 24 hours and they do not have either daily open or close prices. However, continuous trading hours might lead to false measurement of individual market volatilities. For this reason, data sample concentrate on three FX market centres such as London, New York and Tokyo. Each FX pair is calculated by considering their trading hours. Table 2 summarizes selected market hours for each FX pairs and further details. In this study, it is assumed that FX markets have trading hours as described in Table 2.

Table 2. Data Description for FX Markets

FX Market Centres	Notation	Trading Hours (GMT)
London/Europe	GBP/USD	07:00-15:00
Frankfurt/Europe	EUR/USD	07:00-15:00
Tokyo/Asia	USD/JPY	00:00-08:00
Canada/ North America	USD/CAD	12:00-20:00

3.2 Computing Realized Moments

Constructing realized measures requires a number of transformations on the high frequency data. Firstly, intraday log returns for both stock and FX markets are calculated based on the following formula:

$$R_{t,i} = \ln P_{t,i} - \ln P_{t,i-1} \quad (1)$$

$R_{t,i}$ denotes *ith* intraday log return and $\ln P_{t,i}$ represents the natural logarithm of *ith* intradaily data on day t. In this study, 5-minute closing price data are used to obtain high frequency returns. For instance, there are 78 five-minute returns during a trading day (6.5 hours) in US. Main reason to choose 5-minute interval is to avoid market microstructure noise as suggested by Andersen *et al.* (2001a).

Secondly, following realized methodology that suggested by Andersen *et al.* (2001a, 2001b), daily realized volatility is calculated by summing 5-minute returns during the day as shown below:

$$RV_t = \sum_{i=1}^{N} R_{i,t}^2 \tag{2}$$

where RV_t refers to realized volatility on day t and *N* is the number of 5-minute data during a trading day. One should note that *N* can be different due to the working hours of stock markets.

In addition to realized volatility, I calculate high order moments of returns such as realized skewness and realized kurtosis as suggested by Amaya *et al.* (2011). Realized skewness on day t (RS_t) can be computed as the third order moment of return based on the formula below:

$$RS_t = \frac{\sqrt{N}\sum_{i=1}^{N} R_{i,t}^3}{RV_t^{3/2}} \tag{3}$$

Similarly, realized kurtosis (RK_t) is computed as the fourth moment as follows:

$$RK_t = \frac{N\sum_{i=1}^{N} R_{i,t}^4}{RV_t^2} \tag{4}$$

where $R_{i,t}^3$ and $R_{i,t}^4$ are the *ith* returns on day t with third and fourth power, respectively.

Model-free fashion of realized volatility allows us to calculate daily realized volatilities for our sample set of data. However, daily data contain some unfavourable statistical properties. As mentioned in the literature section, daily realized volatility contains non-normal distribution and long memory process (see, e.g Areal and Taylor (2002), Andersen *et al.*, (2001a, 2001b). Moreover, it leads to heteroscedasticity and autocorrelation which makes the coefficients of regressions unreliable. For this reason, I transform the data in two steps. At first, following the same method with Amaya *et al.* (2011), weekly realized volatility is computed by summing 5-minute returns between Monday to Friday. Then, I transform weekly realized volatility into natural logarithmic form as suggested in Do *et al.* (2015, 2016). Thus, the sample data does not have fractional integration and heteroscedasticity.

3.3 Descriptive Statistics

Descriptive statistics summarize the main statistical properties of data used in this study. Following the same procedure, two descriptive statistics is shown for Stock – FX dynamic relations and the relationship across stock markets. Table 3 exhibits weekly realized volatility, skewness and kurtosis for stock and FX markets (section 1). There are 265 weeks of observations within the period June 1, 2012 to June 30, 2017.

As shown in Panel A, realized volatility estimates are normally distributed for 5 of 8 indices. All variables have a negative mean around -8. Results mostly represent leptokurtic distribution for realized volatility.

On the other hand, realized skewness in Panel B are normally distributed in all cases. Skewness and kurtosis values are close to zero and three, respectively. Realized skewness distributions are normal.

Panel C illustrates that realized kurtosis is not normally distributed in all cases. They have a positive mean around 4 and excess kurtosis.

Table 3. Descriptive Statistics on Stock - FX Dynamics

Panel A: Realized Volatility						
Stock Index	**Mean**	**Median**	**Std. Dev.**	**Skewness**	**Kurtosis**	**p-value**
DAX	-7.8898	-7.9532	0.8596	-0.0049	4.3692	0.0000
FTSE 100	-8.4755	-8.4989	0.7794	0.4487	4.4649	0.0000
NIKKEI 225	-7.6462	-7.6187	0.9093	0.0398	2.8980	0.9118
S&P/TSX	-8.9152	-8.9754	0.8449	-0.3126	3.1724	0.1956
EUR/USD	-9.2787	-9.2451	0.8138	-0.1335	3.0509	0.6651
GBP/USD	-9.3744	-9.3670	0.8191	0.5065	6.0699	0.0000
USD/CAD	-9.4054	-9.3225	0.7539	-0.3533	3.2029	0.0506
USD/JPY	-9.1884	-9.1677	0.9445	-0.0188	3.0802	0.9576
Panel B: Realized Skewness						
DAX	1.1472	1.1522	5.0667	-0.0549	3.1625	0.8086
FTSE 100	0.8877	1.0922	4.8438	-0.1415	2.9008	0.6087
NIKKEI 225	1.9432	1.5422	7.0054	0.1228	3.0014	0.7168
S&P/TSX	1.4649	1.2058	5.7525	0.0551	3.5787	0.1472
EUR/USD	0.5855	0.4366	5.8778	0.1126	3.0948	0.7192
GBP/USD	0.4318	0.2816	5.7764	0.0704	2.8099	0.7343
USD/CAD	0.1642	0.2825	6.0240	-0.0982	3.2493	0.5733
USD/JPY	2.5877	2.0590	9.8346	-0.0070	2.6008	0.4144
Panel C: Realized Kurtosis						
DAX	3.9434	4.0194	0.6643	-0.9216	4.8521	0.0000
FTSE 100	3.9380	3.9492	0.6645	-0.6379	3.9539	0.0000
NIKKEI 225	4.2170	4.3146	0.5441	-1.0088	4.6918	0.0000
S&P/TSX	3.9223	4.0120	0.6048	-0.5765	3.3286	0.0004
EUR/USD	4.1194	4.2460	0.6543	-1.0102	4.7845	0.0000
GBP/USD	4.0555	4.1712	0.6688	-0.9276	4.3444	0.0000
USD/CAD	4.0593	4.1622	0.6533	-0.9955	4.5769	0.0000
USD/JPY	4.7933	4.8941	0.5721	-1.2016	5.3318	0.0000

Note: Realized volatility and realized kurtosis are shown in natural logarithmic form. P-values denotes Jarque-Bera normality test results.

Table 4 shows the summary statistics for realized measures used in the second analysis (section 2). 391 weeks of observations are between January 4, 2010 and Jun 30, 2017. Again, both realized volatility and kurtosis have the mean around -8 and 4, respectively. Realized skewness has a normal distribution whereas realized volatility and kurtosis indicate non-normal distributions.

To sum up, descriptive statistics in Table 3 and 4 usually exhibit common properties of financial time-series data. Specifically, all distributions do not have zero mean and realized volatility and kurtosis indicate leptokurtic distributions due to excess kurtosis and non-zero skewness. However, realized skewness is normally distributed in most cases.

Table 4. Descriptive Statistics on Stock Markets

Panel A: Realized Volatility						
Stock Index	**Mean**	**Median**	**Std. Dev.**	**Skewness**	**Kurtosis**	**p-value**
CAC 40	-7.6544	-7.7431	0.8561	0.2217	3.5037	0.0255
DAX	-7.7241	-7.7877	0.9095	0.0324	4.4541	0.0000
FTSE 100	-8.2656	-8.3218	0.8614	0.1957	3.8553	0.0007
NIKKEI 225	-7.6397	-7.6179	0.8730	-0.1913	3.6995	0.0056
SMI	-8.3094	-8.3966	0.8516	0.6078	4.6885	0.0000
S&P/TSX	-8.7020	-8.7360	0.9001	0.1702	4.0041	0.0001
S&P 500	-8.5036	-8.5802	1.0250	-0.0573	4.3313	0.0000
Panel B: Realized Skewness						
CAC 40	0.8297	0.6284	4.4721	0.1436	3.0143	0.5101
DAX	1.0796	0.9779	4.8821	0.0995	3.2561	0.4247
FTSE 100	0.8476	0.6627	4.7941	0.1001	3.5032	0.0917
NIKKEI 225	1.6811	1.6984	7.1375	-0.0625	2.7846	0.6032
SMI	1.0975	0.9157	5.1058	0.2256	3.7305	0.0025
S&P/TSX	1.5619	1.3581	5.3928	-0.0163	3.2825	0.5175
S&P 500	1.2699	0.8828	5.2408	0.2268	3.5368	0.0179
Panel C: Realized Kurtosis						
CAC 40	3.8955	3.9580	0.5925	-0.3607	3.1866	0.0109
DAX	3.9507	4.0273	0.6080	-0.6106	3.3167	0.0000
FTSE 100	3.9395	4.0298	0.6466	-0.7262	3.6103	0.0000
NIKKEI 225	4.2383	4.3412	0.5857	-1.5272	6.4944	0.0000
SMI	3.9435	3.9939	0.6504	-0.8574	4.4617	0.0000
S&P/TSX	3.9791	4.0505	0.5905	-1.0431	5.2316	0.0000
S&P 500	3.9390	3.9898	0.6140	-0.9706	5.2272	0.0000

Note: Realized volatility and realized kurtosis are shown in natural logarithmic form. P-values denotes Jarque-Bera normality test results.

3.4 Correlation Matrices

Due to its simplicity, correlation measures generally provide limited information about the associations between variables. Nevertheless, it gives a brief notion about stock markets relations without causal relations.

Table 5 shows the cross-market dependence based on simple correlation measures. As it clearly shown in Panel A, stock markets are positively correlated with each other. Furthermore, the stock markets within the same region have higher correlations relatively to the others. In other words, European stock indices are highly correlated with each other while USA and Canada have a strong correlation. Japanese stock market is the least correlated with other stock markets in terms of realized volatility.

Panel B and Panel C indicate that the correlations in further moments follows a similar pattern as it shown in realized volatility but the degree of correlations are lower. Again, high regional correlations exist in both skewness and kurtosis correlations.

Table 5. Correlation Matrix

Panel A: Realized Volatility							
	CAC 40	DAX	FTSE 100	NIKKEI 225	SMI	S&P 500	S&P/TSX
CAC 40	1.0000	-	-	-	-	-	-
DAX	0.9544	1.0000	-	-	-	-	-
FTSE 100	0.9377	0.9169	1.0000	-	-	-	-
NIKKEI 225	0.5762	0.5806	0.6172	1.0000	-	-	-
SMI	0.8813	0.8807	0.9043	0.6360	1.0000	-	-
S&P 500	0.8605	0.8317	0.8785	0.6294	0.8121	1.0000	-
S&P/TSX	0.8404	0.8302	0.8520	0.5368	0.7847	0.8754	1.0000
Panel B: Realized Skewness							
	CAC 40	DAX	FTSE 100	NIKKEI 225	SMI	S&P 500	S&P/TSX
CAC 40	1.0000	-	-	-	-	-	-
DAX	0.8444	1.0000	-	-	-	-	-
FTSE 100	0.7902	0.8012	1.0000	-	-	-	-
NIKKEI 225	0.4079	0.4655	0.4225	1.0000	-	-	-
SMI	0.7077	0.7230	0.7276	0.4347	1.0000	-	-
S&P 500	0.4723	0.5476	0.4889	0.4054	0.4129	1.0000	-
S&P/TSX	0.4104	0.4707	0.4402	0.3962	0.3773	0.7102	1.0000
Panel C: Realized Kurtosis							
	CAC 40	DAX	FTSE 100	NIKKEI 225	SMI	S&P 500	S&P/TSX
CAC 40	1.0000	-	-	-	-	-	-
DAX	0.8517	1.0000	-	-	-	-	-
FTSE 100	0.7695	0.7950	1.0000	-	-	-	-
NIKKEI 225	0.2975	0.3412	0.3774	1.0000	-	-	-
SMI	0.6961	0.7230	0.6908	0.3538	1.0000	-	-
S&P 500	0.3880	0.3819	0.4073	0.3729	0.3680	1.0000	-
S&P/TSX	0.4057	0.4235	0.4364	0.3999	0.3935	0.6882	1.0000

4. METHODOLOGY

This section describes how VAR methodology and its relevant procedures are applied to our research. In accordance with the purpose of the dissertation, I apply Vector Autoregressive (VAR) framework by employing weekly realized volatility, skewness and kurtosis. Since this study involves two sections, I construct two VAR models to evaluate stock and FX market relations within and between markets. Furthermore, I extend VAR framework to three procedures. Dynamic behaviour of financial markets is attempted to explain by Impulse Response Functions, Granger Causality tests to understand the relationship between financial markets.

4.1 Estimating VAR Models

It is a common situation in econometric time-series models that all variables are simultaneously affected by each other. In other words, dependant variable and explanatory variables might have joint explanatory powers at the same time. Sims (1980) criticize the lack of clear identification on choosing dependent and independent variable. If the model variables are simultaneous, then every variable should be treated as endogenous variable. Therefore, VAR framework are developed based on Sim's critique.

Simple bivariate VAR specification with *ith* lagged of variables consists of two joint OLS regressions as shown below (Asteriou and Hall, 2016):

$$y_t = c_1 + \beta_{11}^{i} y_{t-i} + \alpha_{11}^{i} x_{t-i} + u_{yt} \qquad (5)$$

$$x_t = c_2 + \beta_{21}^{i} x_{t-i} + \alpha_{21}^{i} y_{t-i} + u_{xt} \qquad (6)$$

y_t and x_t refers distinct time-series data with their corresponding error terms, u_{yt} and u_{xt}.

Alternatively, a generalized bivariate VAR (2) process with p lagged periods can be written using matrix system as follows:

$$\begin{bmatrix} y_t \\ x_t \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \begin{bmatrix} \beta_{11}^{1} & \beta_{12}^{1} \\ \beta_{21}^{1} & \beta_{22}^{1} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ x_{t-1} \end{bmatrix} + \cdots + \begin{bmatrix} \beta_{11}^{p} & \beta_{12}^{p} \\ \beta_{21}^{p} & \beta_{22}^{p} \end{bmatrix} \begin{bmatrix} y_{t-p} \\ x_{t-p} \end{bmatrix} + \begin{bmatrix} u_{yt} \\ u_{xt} \end{bmatrix} \qquad (7)$$

or:

$$Z_t = \Gamma_0 + \Gamma_1 Z_{t-1} + \cdots + \Gamma_p Z_{t-p} + u_t \qquad (8)$$

where Z_t is a vector of time series (t=1,…,p) and Γ_i (i=1,…,p) is 2×2 parametric matrix.

As seen above, both series are treated as endogenous variable in corresponding models. The model can be easily extended to the cases where it has more lags or variables. This research constructs bivariate VAR models with p lags.

VAR approach has many advantageous thanks to its simplicity. Researchers do not have to determine which variables should be endogenous or exogenous. Similarly, VAR methodology simply applies the OLS approach quickly (Asteriou and Hall, 2016). On the other hand, VAR models have some drawbacks and heavily criticized due to its *atheoretic* structure, optimum lag lengths and stationarity condition. First, the model does not provide any theoretical background about the specification of the model. Threating every variables as both explanatory and dependent might increase the possibility of spurious regressions. Second, determination of appropriate lag lengths is not clear. A number of information criteria might point out different lags for the same model. Moreover, multivariate VAR models with high lag lengths substantially reduce degrees of freedom. Final concern about VAR models is stationarity. The model requires variables in which they are stationary. However, many financial time-series data can embody different orders of integration (Brooks, 2014). Having several variables with different order of integration will not be suitable for VAR models.

4.2 The Models

Since this dissertation involves two main research questions, VAR models are built in two sections as shown below. Both section uses bivariate VAR models for selected countries.

In this research, optimum lag lengths are chosen based on the Akaike information criterion (AIC) based on the work of Akaike (1974). There exist several other information criterion which estimate the best model towards its degrees of freedom and corresponding R-square value. One reason to choose AIC is to reduce the existence of autocorrelation. That is to say, AIC points out VAR models which have higher number of lag lengths compare to the other information criterion. Therefore, high number of lags reduce to possibility of autocorrelation.

4.2.1. Model 1: Stock Market – FX Rate Relationship within One Country

I construct four VAR models for Germany, the UK, Canada and Japan using weekly realized volatility. Stock indices and FX rates of each country are the components of bivariate VAR. Since USD is the benchmark currency throughout the world, FX rates represents the national currency against to USD. Model 1 represents the bivariate VAR:

Model 1:

$$Z_t = \Gamma_0 + \sum_{j=1}^{p} \Gamma_j Z_{t-j} + u_t \tag{9}$$

where $Z_t = \begin{bmatrix} STOCK\ INDEX_{t,i} \\ FX\ RATE_{t,i} \end{bmatrix}$ which is a vector element at time *t* for country *i*. Γ_j (j=1,…,p) denotes the parametric matrix of corresponding explanatory variable up to lag p.

Following the same method in Model 1, stock market and FX relations are examined via realized skewness and realized kurtosis for selected countries.

4.2.2. Model 2: Stock Market Relations across Countries

As emphasized on Chapter 2, the USA is the main transmitter in terms of stock and FX volatilities. Following the same notion, I construct six bivariate VAR models using realized volatility of S&P 500 and one other index. In other words, each bivariate VAR model involves two variables: (1) one major index mentioned above and (2) S&P 500. In this way, mutual volatility associations between S&P 500 and the other selected index are examined as shown below:

Model 2:

$$Z_t = \Gamma_0 + \sum_{j=1}^{p} \Gamma_j Z_{t-j} + u_t \tag{10}$$

where $Z_t = \begin{bmatrix} STOCK\ INDEX_{t,USA} \\ STOCK\ INDEX_{t,i} \end{bmatrix}$ is the vector element at time *t* for USA and country *i*. Γ_j (j=1,…p) denotes the parametric matrix of corresponding explanatory variable up to lag p. In order to avoid confusion, I refer ‘other’ to express one of the countries such as France, Germany, the UK, Japan, Switzerland and Canada.

Along with the same methodology in Model 2, cross market relations via realized skewness and realized kurtosis are estimated by bivariate VAR models for the same countries.

4.3 Augmented Dickey-Fuller (ADF) Test

It is worth noting that stationarity assumption need to be reconsidered in detail. VAR approach requires that all of the variables used in model should be stationary. Therefore, the variables should be checked whether they have unit root or not.

Among a wide variety of unit root tests, the ADF is the most common and widely accepted test. Dickey and Fuller (1979) propose a testing procedure:

$$\Delta y_t = \mu + \beta_1 t + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t \tag{11}$$

where the first differenced series (Δy_t) can be regressed over a drift (μ), time trend (t) and its past values (Δy_{t-i}). Lag length (p) can be chosen based on the information criteria. Also, ADF model can be tailored for corresponding of data with or without drift and time trend.

ADF constructs the null hypothesis of unit root (non-stationary). The alternative hypothesis represent that the series is stationary.

$$H_0: \delta_i = 0$$

$$H_1: \delta_i < 0$$

Before constructing VAR models, it is required to satisfy stationary conditions for each series. ADF test results will be given in Chapter 5.

4.4 Granger Causality

One of the advantages of VAR models is that they allow us to predict causality. Granger causality test gauges the ability of one variable to predict another. Granger (1969) developed a causality test based on the lagged variables of the variables. It can be conducted via VAR process by following these steps (Asteriou and Hall, 2016):

y_t is regressed on both its lagged '*y*' terms and lagged '*y*' plus '*x*' terms as specified in Equation 12 and 13, respectively.

$$y_t = a_1 + \sum_{j=1}^{m} \gamma_j y_{t-j} + \varepsilon_{1t} \qquad (12)$$

$$y_t = a_1 + \sum_{i=1}^{n} \beta_i x_{t-i} + \sum_{j=1}^{m} \gamma_j y_{t-j} + \varepsilon_{2t} \qquad (13)$$

where ε_{1t} and ε_{2t} are uncorrelated white- noise terms.

F-statistic is calculated based on residual sum of squares (RSS) for Equation (12) (RSS_R) and for Equation (13) (RSS_U). If calculated F-statistic exceeds F-critical value, we reject the null hypothesis which indicates that x_t does not cause y_t. Alternative hypothesis is, on the other hand, shows x_t does cause y_t.

$$H_0: \sum_{i=1}^{n} \beta_i = 0$$

$$H_1: \sum_{i=1}^{n} \beta_i \neq 0$$

Based on F-test results, Granger causality reveal four different outcomes. y_t and x_t might exhibit unidirectional causality from one way to another or, exhibit bidirectional causality relationship in which both variables are Granger cause of each other. Alternatively, both variables may not reveal any causal relation.

In this research, Granger causality test is applied within the VAR framework.

4.5 Impulse Response Analysis

One popular analysis to understand the dynamic relationships between variables is ‘generalized’ impulse response analysis as suggested by Peseran and Shin (1998). They evaluate the response of an external shock to dynamic system.

Generalized response of system after m days $\{\varphi_j(m)\}$ later to an exogenous shock (innovation) to *jth* variable:

$$\varphi_j(m) = \sigma_{jj}^{-0.5} \pi_m \textstyle\sum_\varepsilon e_j \quad \text{(m=0, 1, 2, …)} \qquad (14)$$

where $\sum_\varepsilon$ variance-covariance matrix of error is term and e_j is K×1 selection vector. π_m can be computed as follows:

$$\pi_m = \begin{cases} \sum_{j=1}^{i} \pi_{i-j} \Gamma_j \; if \; i = 1,2, \dots, p \\ \sum_{j=1}^{p} \pi_{i-j} \Gamma_j \;\; if \; i > p \end{cases} \quad (15)$$

Γ_j denotes the matrix of corresponding explanatory variable in Equation 9 and 10.

In this dissertation, spillover effects are defined based on impulse response analysis. Subsequent sections refer volatility, skewness and kurtosis spillover effects by relying on their impulse response functions.

5. EMPIRICAL RESULTS

In this chapter, empirical results are discussed in detailed way. Since the study involves many countries via their high order moments, I divide the chapter into two major section. Each section consists of Unit Root tests, Impulse Response Analyses and Granger Causality results.

5.1 Model 1: Stock – FX Markets

This section attempts to explain the relationship between stock market and FX rate within the same economy. As introduced in Chapter 4, I construct bivariate VAR models using the country's major stock index and the FX rate against USD. Further VAR procedures such as Impulse Response Analysis and VAR Granger Causality tests are applied. The relationship is examined in the moments of realized volatility, skewness and kurtosis.

5.1.1 Unit Root Tests

Stationary process describes a series in which the distributions of its value are constant over time. In practise, it is needed to obtain the variables should require stability in terms of mean, variance and covariance as time progress (Wooldridge, 2009). In order to understand the relationship between variables, stationarity condition should be satisfied before conducting the analysis. VAR methodology requires the stationarity condition for each variables used in the model.

Table 6 exhibits Augmented Dickey-Fuller (ADF) test results through utilizing intercept and trend and intercept. Since all variables have a constant, simple version of ADF test without trend and intercept did not applied. Results are statistically significant at 1% and reject the null hypothesis of 'unit root' except two variables. EUR/USD and USD/JPY on volatility level are significant at 5%.

Table 6. ADF Test Results (1)

Panel A: Realized Volatility	**Test Statistics**	
Index	Intercept	Trend and Intercept
DAX	-6.2861(***)	-6.2770(***)
FTSE 100	-6.4937(***)	-6.5150(***)
NIKKEI 225	-9.3104(***)	-9.5341(***)
S&P/TSX	-4.0379(***)	-4.0658(***)
S&P 500	-9.3682(***)	-9.4966(***)
EUR/USD	-3.7841(***)	-3.8182(**)
GBP/USD	-3.7510(***)	-4.4193(***)
USD/CAD	-3.7736(***)	-4.3426(***)
USD/JPY	-3.6961(***)	-3.8419(**)
Panel B: Realized Skewness		
DAX	-19.6771(***)	-19.6812(***)
FTSE 100	-18.9077(***)	-18.9255(***)
NIKKEI 225	-16.1214(***)	-16.1295(***)
S&P/TSX	-18.6073(***)	-18.5714(***)
S&P 500	-19.4892(***)	-19.4522(***)
EUR/USD	-16.2613(***)	-16.2403(***)
GBP/USD	-16.7207(***)	-16.6880(***)
USD/CAD	-17.0438(***)	-17.0783(***)
USD/JPY	-17.4175(***)	-17.5138(***)
Panel C: Realized Kurtosis		
DAX	-6.2861(***)	-6.2770(***)
FTSE 100	-14.4865(***)	-14.5691(***)
NIKKEI 225	-15.8119(***)	-15.7820(***)
S&P/TSX	-14.5535(***)	-14.5694(***)
S&P 500	-16.3187(***)	-16.3155(***)
EUR/USD	-15.4048(***)	-15.3917(***)
GBP/USD	-15.6676(***)	-15.6579(***)
USD/CAD	-15.1177(***)	-15.0981(***)
USD/JPY	-15.9166(***)	-15.9042(***)

*Note: Lag lengths are based in Schwarz information criterion. * denotes significance in 10%, ** in 5%, *** in 1%.*

5.1.2 Impulse Response Functions

Impulse responses in VAR models shows how a particular shock to explanatory variable will affect dependent variable. Following the 'Cholesky Decomposition' method, I examine VAR impulse responses between stock market and FX rate via each higher moment. Following sections show impulse responses in realized volatility, skewness and kurtosis. In this research, market relations via higher moments are defined as spillover effects based on impulse response analysis.

i) Impulse Responses for Realized Volatility

Figure 1 provides empirical evidence for realized volatility impulse responses between stock indices and FX rates. In the VAR model, I integrate a specific shock which equals to one standard deviation into the stock index and FX rate, respectively. A shock in the FX rate volatility negatively effects the stock index volatility for Germany, the UK and Japan. For Canada, the reaction is around zero. Figure 1 clearly shows that the size of the response of stock indices to FX volatility is substantially low in all cases. On the other hand, one standard deviation shock in stock indices induces a strong increase in the FX volatility. All countries follow similar response patterns. A high response within the first two periods is followed by gradually decreasing reactions.

In general, impulse response functions can be seen as an indicator of realized volatility spillover effects. In figure 1, there are positive and unidirectional volatility spillovers from stock markets to FX markets. The spillover effects from FX rates to stock indices are not consistent and the magnitude of this spillover effect is smaller. Interestingly, the results support the 'stock-oriented' approach. Stronger return spillover effects advocate the existing literature for developed countries (e.g. Smith, 1992; Ajayi and Mougoue, 1996; Yang and Doong, 2004).

ii) Impulse Responses for Realized Skewness

Realized skewness represent the degree of asymmetry on return distributions. Del Brio *et al.* (2017) highlight the importance of high order moments in terms of international portfolio management. It is implied that investors try to find assets which have positive skewness and relatively low kurtosis. Therefore, it is important to understand realized skewness relations between stock and FX markets.

Figure 2 shows realized skewness spillover effects via impulse response functions. DAX, FTSE 100, NIKKEI 225 and S&P/TSX are influenced very slightly in period 2 after a shock given into FX rates. Meanwhile, response of FX rates to stock market shocks are nearly zero and die out in the third period, except NIKKEI 225.

It is observed that there is no significant evidence of realized skewness spillovers for the Germany, the UK and Canada. Japan is the only country that has positive unidirectional skewness spillovers when a positive response induced by a shock to stock market. However, all other responses are extremely small and die out quickly.

Empirical results are in line with the previous studies. Do *et al.* (2015, 2016) found that realized skewness spillovers in developed countries are considerably smaller than the spillovers in emerging countries. Moreover, Hung *et al.* (2014) emphasized the importance of co-skewness during the crisis period. It becomes a significant explanatory variable during the crisis period rather than market beta. In our case, it can be clearly said that the results show no evidence of realized spillovers. As previous studies pointed out, skewness spillovers may not exist in among developed financial markets especially during non-crisis period.

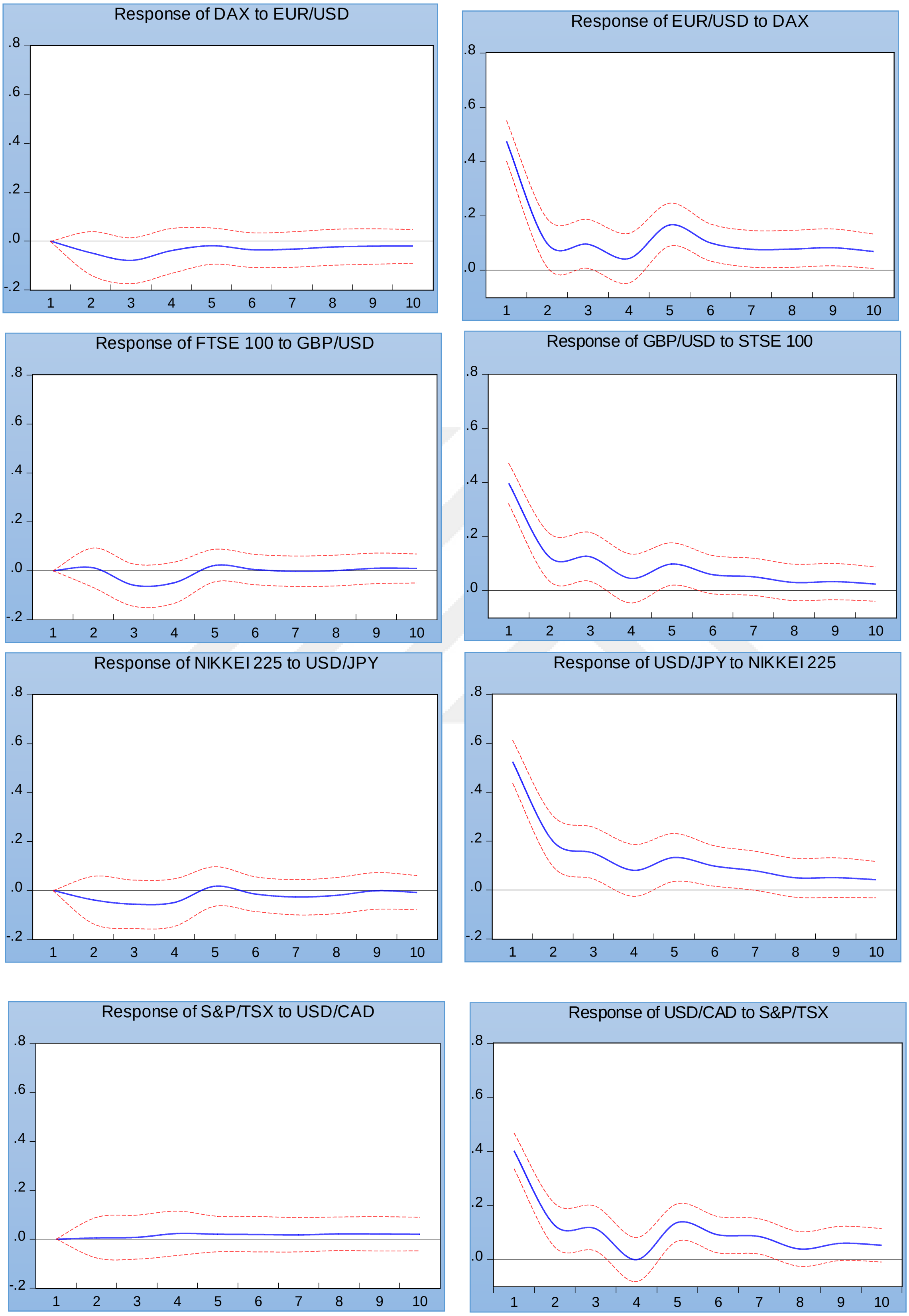
iii) Impulse Responses for Realized Kurtosis

Realized kurtosis roughly describes the shape of distribution through the magnitude of tails and peak. In other words, it gives significant insights about the frequency of extreme cases. From investor's perspective, kurtosis plays an important role especially during the periods of financial turbulences.

In our case, realized kurtosis spillovers via impulse response functions is shown in Figure 3. It is observed that there are unidirectional kurtosis spillovers from stock indices to FX rates. When a shock integrated to stock markets, FX rates simultaneously respond to the shock. Spillover effects disappear in the third period. On the other hand, results do not indicate any evidence for realized kurtosis spillovers from FX rates to stock markets.

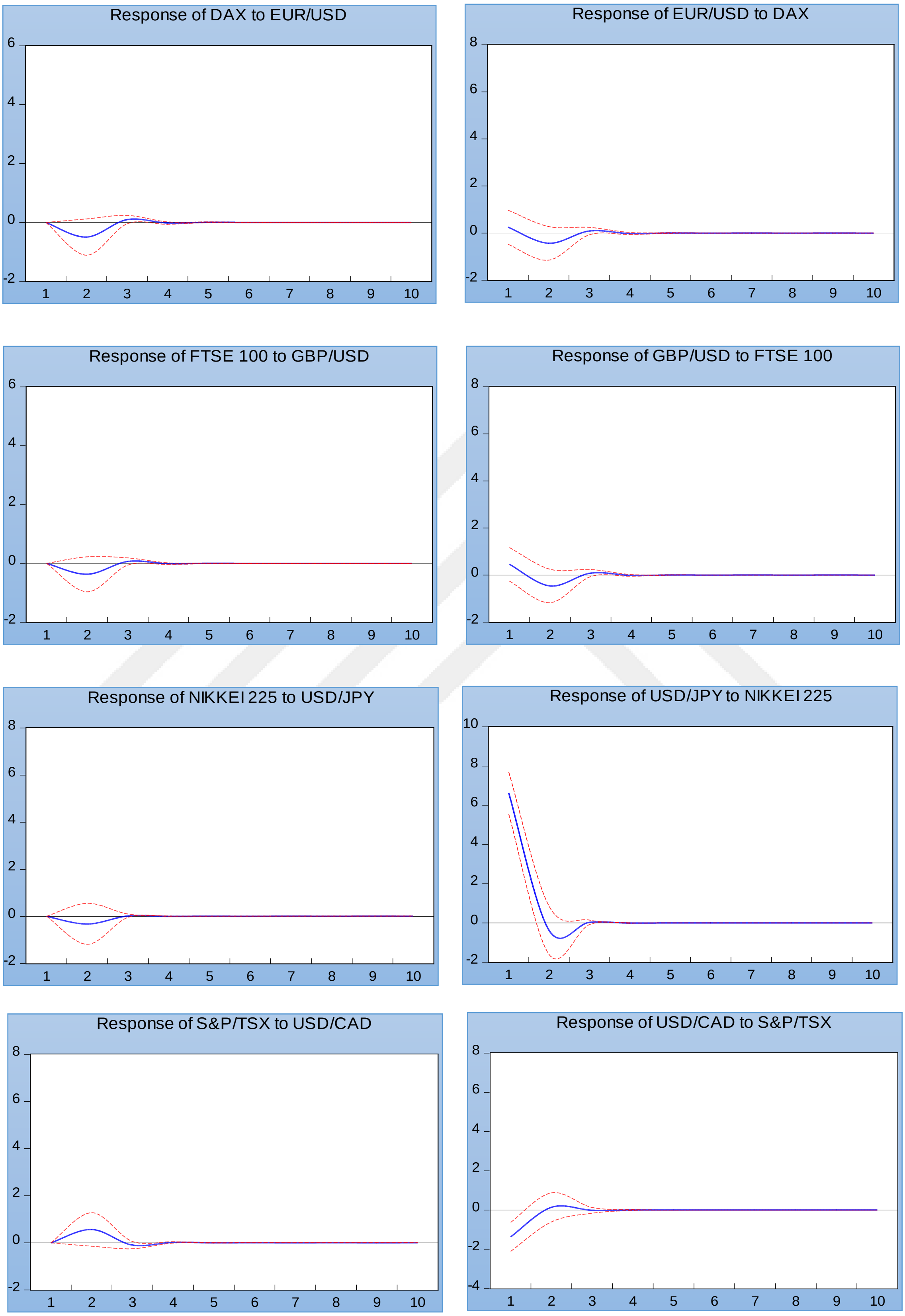
Previous papers reveal mixed results on realized kurtosis spillovers. Do *et al.* (2015) do not found kurtosis spillovers between stock and FX markets in regional analysis framework. On the other hand, there is evidence of kurtosis spillovers in European developed countries (Do *et al.*, 2016). Although previous papers contain significant differences in terms of methodology and time periods, our results support the existence of kurtosis spillovers in developed countries.

Figure 1 Realized Volatility - Generalized Impulse Response Functions



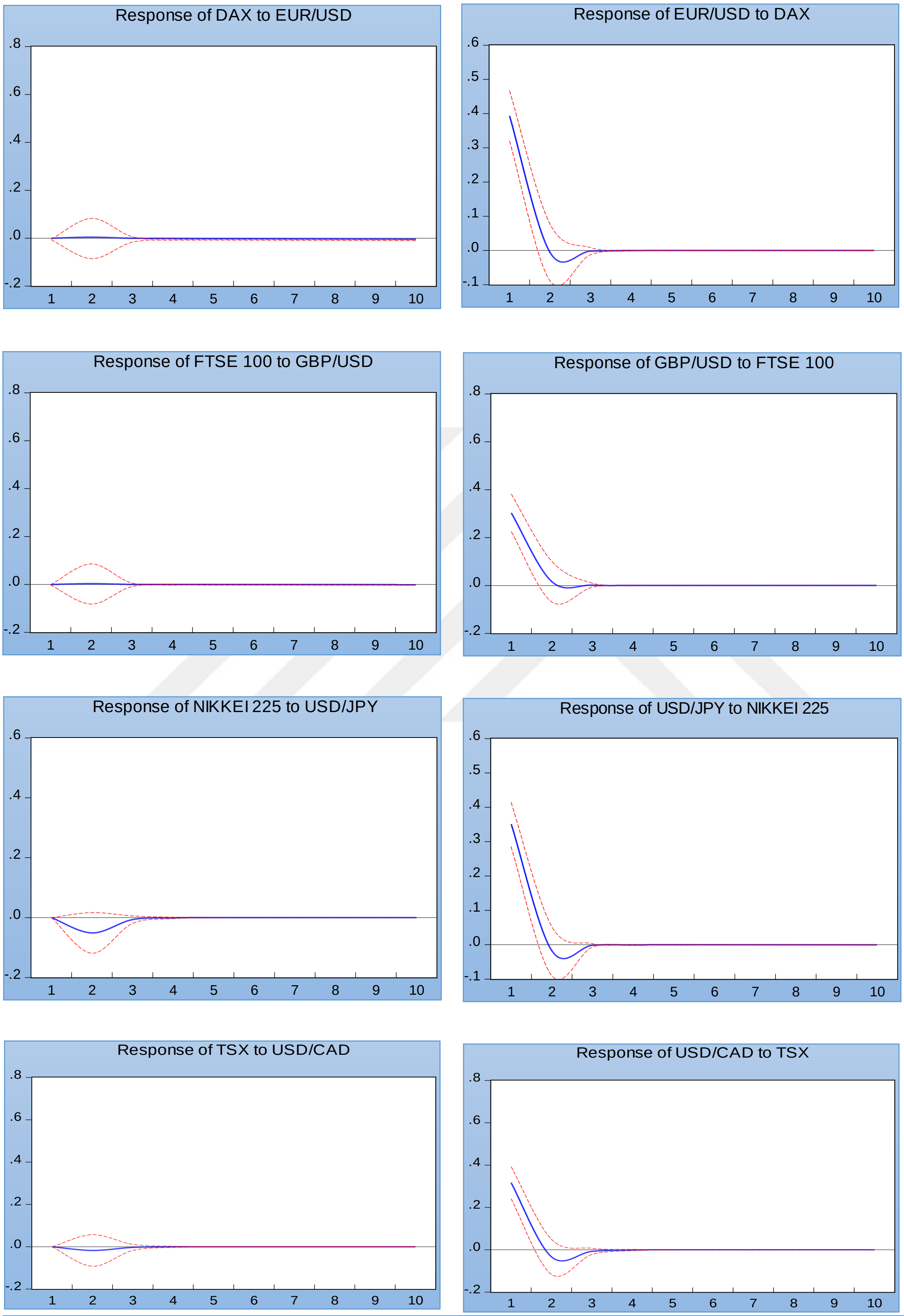
Note: Blue line represents the Impulse Response Function. Red lines 95% denotes Confidence Interval Bounds.

Figure 2. Realized Skewness - Generalized Impulse Response Functions



Note: Blue line represents the Impulse Response Function. Red lines 95% denotes Confidence Interval Bounds.

Figure 3. Realized Kurtosis - Generalized Impulse Response Functions



Note: Blue line represents the Impulse Response Function. Red lines 95% denotes Confidence Interval Bounds.

5.1.3 Granger Causality Tests

This section represents Granger causality test results between stock and FX market. Following tables illustrates volatility, skewness and kurtosis level Granger causality test result within the VAR framework.

Table 7 shows the volatility level causality results with corresponding Chi-sq values and p-values. There are unidirectional causalities from stock markets to FX markets in Germany and Canada. Also, Japan has bidirectional causal relationship between these markets while the UK does not show any Granger causality.

Although volatility level causality tests reveal mixed results, it can be said that stock market markets cause FX markets in most cases. The results are parallel to the findings in impulse response functions. Strong volatility spillover effects that are founded in impulse response analyses support the Granger causality tests. Theoretically, the results advocate the stock-oriented approach as introduced by Gavin (1989) and Branson (1993).

Table 7. Granger Causality Test Results – Realized Volatility

Null Hypothesis	Causality	Chi-sq	p-value
DAX does not cause EUR/USD	DAX → EUR/USD	8.5236	0.0141(**)
EUR/USD does not cause DAX	EUR/USD → DAX	2.4980	0.2868
FTSE 100 does not cause GBP/USD	FTSE 100 → GBP/USD	0.1371	0.9337
GBP/USD does not cause FTSE 100	GBP/USD → FTSE 100	3.8981	0.1424
NIKKEI 225 does not cause USD/JPY	NIKKEI 225 → USD/JPY	8.0205	0.0181(**)
USD/JPY does not cause NIKKEI 225	USD/JPY → NIKKEI 225	10.7924	0.0045(***)
S&P/TSX does not cause USD/CAD	S&P/TSX → USD/CAD	8.0737	0.0177(**)
USD/CAD does not cause S&P/TSX	USD/CAD → S&P/TSX	0.3722	0.8302

*Note: * denotes significance level in 10%, ** in 5%, *** in 1%.*

Table 8 exhibits causal relationships between realized skewness of stock and FX markets. As it clearly seen in the table, there is no evidence of causality in all cases. Our results are parallel to the findings in impulse response analyses. Both procedures do not support the existence of skewness spillover effects and causal relationship between stock and FX markets.

As mentioned in previous studies (see e.g. Hung *et al.,* 2014; Do *et al.,* 2015, 2016), skewness spillovers between markets within the same economy do not exist during non-crisis periods. Similarly, Hashmi and Tay (2007) find no conditional skewness spillovers in six Asian stock markets. Hence, our results are analogous with the existing literature.

Table 8. Granger Causality Test Results – Realized Skewness

Null Hypothesis	Causality	Chi-sq	p-value
DAX does not cause EUR/USD	DAX → EUR/USD	1.6413	0.4402
EUR/USD does not cause DAX	EUR/USD → DAX	4.0751	0.1303
FTSE 100 does not cause GBP/USD	FTSE 100 → GBP/USD	1.9383	0.3794
GBP/USD does not cause FTSE 100	GBP/USD → FTSE 100	2.9261	0.2315
NIKKEI 225 does not cause USD/JPY	NIKKEI 225 → USD/JPY	0.1127	0.9452
USD/JPY does not cause NIKKEI 225	USD/JPY → NIKKEI 225	0.8360	0.6584
S&P/TSX does not cause USD/CAD	S&P/TSX → USD/CAD	0.1105	0.9463
USD/CAD does not cause S&P/TSX	USD/CAD → S&P/TSX	2.8744	0.2376

*Note: * denotes significance level in 10%, ** in 5%, *** in 1%.*

Table 9 shows kurtosis level Granger causality test results and corresponding Chi-square and p-values. Fourth moment causality relationships exhibit similar results with realized skewness. There is no significant evidence of causal relationships between markets. Canada is the only exception that exhibits a causality from stock market to FX market. Overall, causality results are not parallel to the kurtosis spillover effects found via impulse responses.

Table 9. Granger Causality Test Results – Realized Kurtosis

Null Hypothesis	Causality	Chi-sq	p-value
DAX does not cause EUR/USD	DAX → EUR/USD	1.0068	0.6045
EUR/USD does not cause DAX	EUR/USD → DAX	1.5008	0.4722
FTSE 100 does not cause GBP/USD	FTSE 100 → GBP/USD	0.4685	0.4937
GBP/USD does not cause FTSE 100	GBP/USD → FTSE 100	0.0077	0.9303
NIKKEI 225 does not cause USD/JPY	NIKKEI 225 → USD/JPY	1.6684	0.4342
USD/JPY does not cause NIKKEI 225	USD/JPY → NIKKEI 225	1.7236	0.4224
S&P/TSX does not cause USD/CAD	S&P/TSX → USD/CAD	4.2076	0.0402(**)
USD/CAD does not cause S&P/TSX	USD/CAD → S&P/TSX	0.0915	0.7623

*Note: * denotes significance level in 10%, ** in 5%, *** in 1%.*

5.2 Model 2: Stock - Stock Markets

This section attempts to evaluate the stock market relations between developed countries. I analyse the stock market relations in the moments of realized volatility, skewness and kurtosis by following a specific methodology. In this section, bivariate VAR models constructed by employing major stock market indices in developed economies with S/P 500 index. VAR models seek to describe aggregate effect of US financial markets on the other major stock markets. Impulse response analyses and Granger Causality are applied to detect spillovers and causalities.

US stock markets need a special attention due to its large market capitalizations. Table 10 shows individual proportions of stock markets used in section 2. As it seen in Table 10, US stock markets possess 40.71% of the world stock markets in terms of market capitalization in 2016. Thus, the US stock markets can be seen as a leading financial market around the world.

Besides the magnitude of the US stock markets, the selected other stock markets hold 22% of the world's total market capitalization. Total share of all stock markets cover 62.35% of world's total market cap. Therefore, it can be clearly said that the majority of world equity market are taken into account in this study.

Table 10. Percentage of Stock Markets (market cap)

Stock Markets	World Share
NYSE Group	29.13%
Nasdaq - US	11.58%
TMX Group	2.97%
Japan Exchange Group	7.37%
Euronext/Paris	1.80%
London Stock Exchange	4.87%
Deutsche Börse AG	2.55%
SIX Swiss Exchange	2.09%
Total	62.35%

Note: Author's own calculations based on the WFE Annual Statistics 2016 Report.

5.2.1 Unit Root Tests

Before constructing VAR models, stationarity premise of VAR specification should be satisfied. To do so, ADF unit root test is applied through utilizing intercept and trend and intercept.

Test statistics with constant, constant and trend factors are given in Table 11. According to the results, all of the variables are statistically significant at 1 % which means they satisfy the stationarity condition. It is noteworthy to say that realized volatility and kurtosis are in their natural logarithmic form while realized skewness is not.

Table 11. ADF Test Results (2)

Panel A: Realized Volatility	**Test Statistics**	
Index	Intercept	Intercept and Level
CAC 40	-5.8345(***)	-7.4220(***)
DAX	-5.6320(***)	-5.7442(***)
FTSE 100	-5.7212(***)	-5.9935(***)
NIKKEI 225	-5.7027(***)	-5.7632(***)
SMI	-9.2940(***)	-9.3708(***)
S&P 500	-6.0598(***)	-10.5152(***)
S&P/TSX	-5.7069(***)	-5.9260(***)
Panel B: Realized Skewness		
CAC 40	-21.9566(***)	-21.9692(***)
DAX	-22.1310(***)	-22.1264(***)
FTSE 100	-21.2747(***)	-21.2602(***)
NIKKEI 225	-19.9476(***)	-19.9337(***)
SMI	-20.6564(***)	-20.6308(***)
S&P 500	-22.4248(***)	-22.4057(***)
S&P/TSX	-20.7843(***)	-20.7647(***)
Panel C: Realized Kurtosis		
CAC 40	-17.1723(***)	-17.2312(***)
DAX	-17.7483(***)	-17.8432(***)
FTSE 100	-17.7231(***)	-17.7572(***)
NIKKEI 225	-17.8888(***)	-17.9443(***)
SMI	-18.8906(***)	-18.8889(***)
S&P 500	-17.9005(***)	-17.9044(***)
S&P/TSX	-16.9575(***)	-17.1001(***)

*Note: Lag lengths are based in Schwarz information criterion. * denotes significance in 10%, ** in 5%, *** in 1%.*

5.2.2 Impulse Response Functions

The relationship between the US stock markets and other advanced financial markets are examined by conducting impulse response functions within the framework of VAR model. Following sections exhibit impulse response results in high order moments of stock returns. As it emphasized before, market linkages are indicated as spillover effects based on their corresponding impulse response results.

i) Impulse Responses for Realized Volatility

Figure 4 shows realized volatility spillovers between the USA and selected other country. A shock in the S&P 500 substantially influence the other markets. Response to this shock continue to exist along the weeks. It is observed that all countries follow a similar pattern. Conversely, volatility spillover effects from other stock markets to the US is close to zero which shows tiny evidence of spillovers. Realized volatilities in CAC 40, DAX, FTSE 100 and SMI lead to a slight, positive affect while NIKKEI 225 effect negatively the US. In general, there is a strong evidence of unidirectional spillover effects from the US to the other developed economies. The results show that S&P 500 is the major transmitter of world's aggregate stock market volatility.

The findings are show some similarities with previous studies in some aspects. Based on the Engle *et al.* (1990)'s terminology, there is a strong evidence of *meteor showers* which induce volatility spillovers from the US to other countries. However, the relevant literature examines volatility spillovers with quiet different methods. Thus, it can be said that our results show similarities with meteor shower patterns. Similarly, Dimpfl and Jung (2012) indicates the USA is major transmitter in terms of volatility spillovers. Despite different methodologies, our results advocate previous findings.

ii) Impulse Responses for Realized Skewness

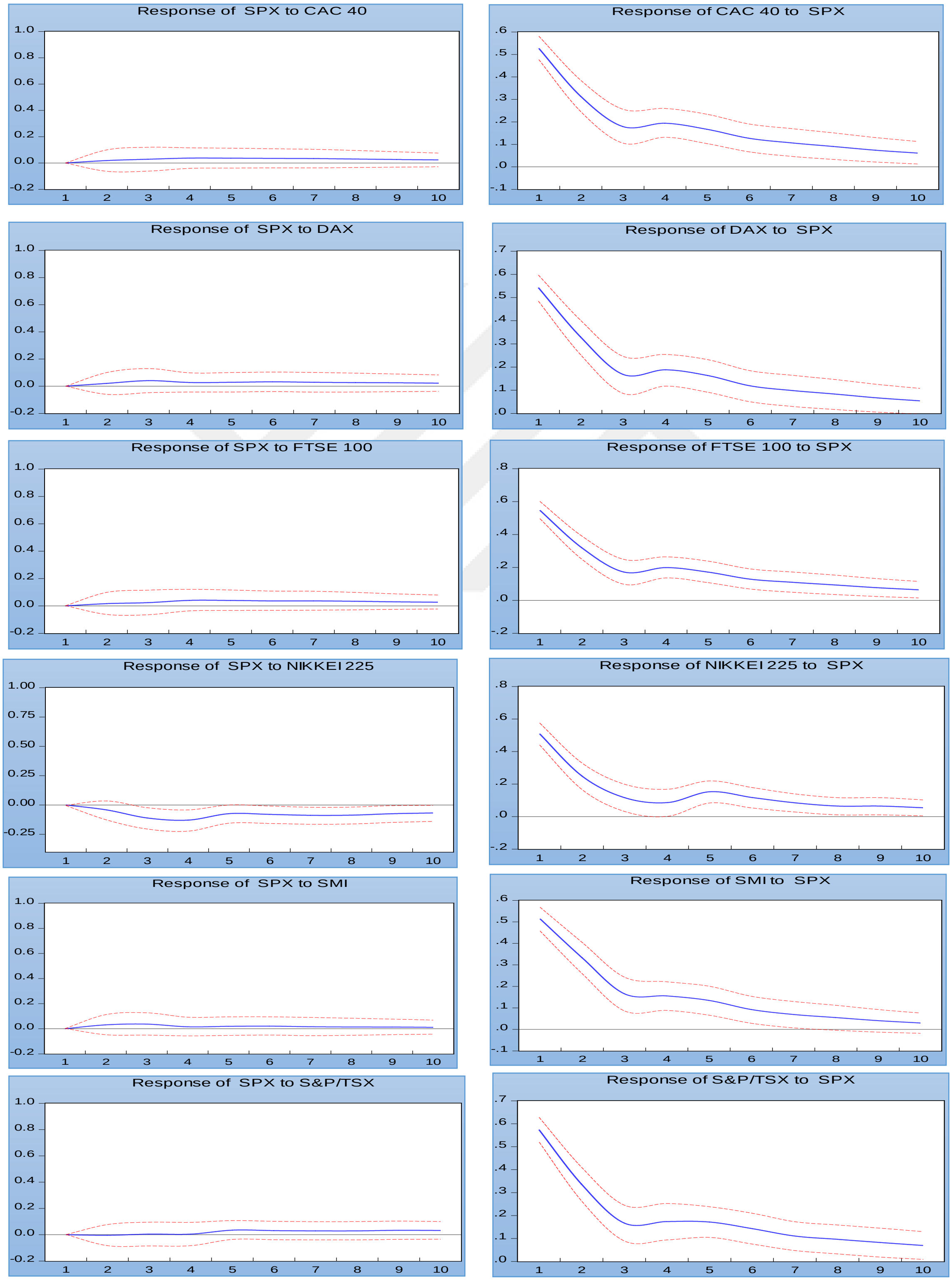
Figure 5 illustrates the empirical evidence of realized skewness spillovers between the US and other stock markets. Financial dependence of selected financial markets to US stock markets are shown in third order moment. A shock in S&P 500 simultaneously induce the other stock markets whereas the response disappear in the third period. In addition, response of S&P 500 to the shocks in other stock markets reveal a small effect and die out instantly. Although there is enough evidence unidirectional skewness spillovers from the US to other countries, one should notice that skewness spillovers die out quickly in all cases. Results are similar to the empirical findings of Do *et al.* (2016) in which they find evidence of skewness spillovers between stock markets in advanced financial markets.

iii) Impulse Responses for Realized Skewness

Figure 6 exhibits kurtosis spillovers between the US and other stock markets. A shock in the US stock markets positively affects France, Germany, the UK and Switzerland. However, the responses disappear after the second period. For Japan and Canada, results continue to exist until period 9. On the other hand, an impulse that comes from selected countries does not significantly influence S&P 500 index. For Japan and Canada, spillover effects fluctuate around zero until period 7.

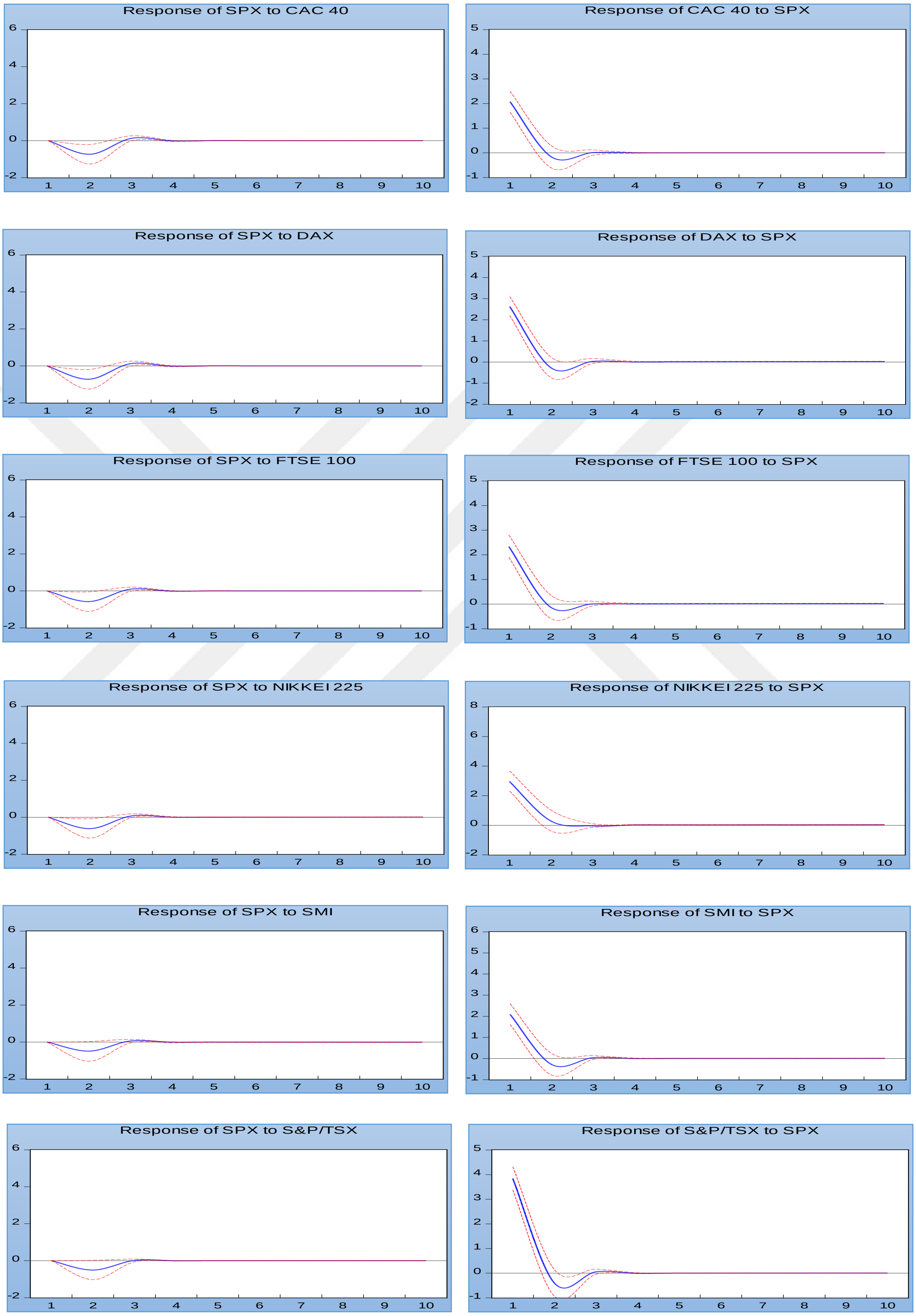
Analogous to the results for realized volatility and skewness spillovers, there are unidirectional kurtosis spillovers exist from the US to other markets. However, they die out quickly. Empirical findings are in line with the Do *et al.* (2016).

Figure 4. Realized Volatility - Generalized Impulse Response Functions



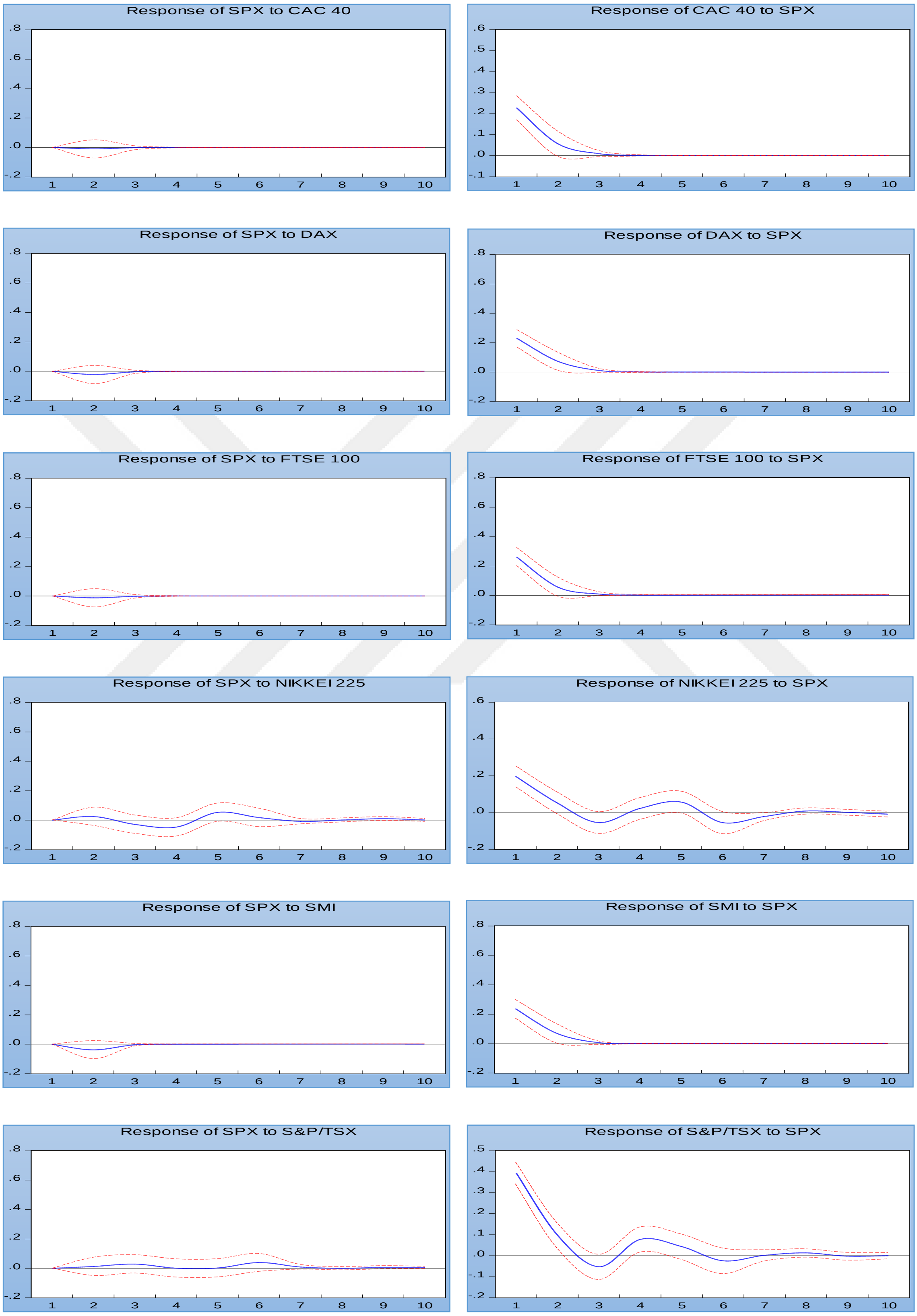
Note: Blue line represents the Impulse Response Function. Red lines 95% denotes Confidence Interval Bounds.

Figure 5. Realized Skewness - Generalized Impulse Response Functions



Note: Blue line represents the Impulse Response Function. Red lines 95% denotes Confidence Interval Bounds.

Figure 6. Realized Kurtosis - Generalized Impulse Response Functions



Note: Blue line represents the Impulse Response Function. Red lines 95% denotes Confidence Interval Bounds.

5.2.3 Granger Causality Tests

Granger causality test simply determine the way of causality between variables. Specifically, it can be defined as a correlation between the current value of one variable and past values of the other variable. In our case, realized volatility of S&P 500 and the other stock market index are examined in terms of causality. Following tables demonstrates causal relationship between stock markets via volatility, skewness and kurtosis levels.

Table 12 shows the casual relationship between realized volatility of stock indices. There are unidirectional causality from France, Switzerland to the US stock markets. Also, bidirectional causalities occur in the UK and Canada towards the US. On the other hand, Germany and Japan do not have any causality relationship with the US. In general, empirical findings are mixed. However, as it seen in Table 12, Granger causality relations are mostly from other countries to the US. The results are nearly in line with the realized volatility spillover effects indicated by impulse responses.

Table 12. Granger Causality Test Results – Realized Volatility

Null hypothesis	Causality	Chi-sq	p-value
CAC 40 does not cause SPX	CAC 40 → SPX	8.5401	0.0147(**)
SPX does not cause CAC 40	SPX → CAC 40	2.5610	0.2791
DAX does not cause SPX	DAX → SPX	4.4916	0.1072
SPX does not cause DAX	SPX → DAX	4.2992	0.1179
FTSE 100 does not cause SPX	FTSE 100 → SPX	4.8146	0.0914(*)
SPX does not cause FTSE 100	SPX → FTSE 100	6.2083	0.0460(**)
NIKKEI does not cause SPX	NIKKEI 225 → SPX	4.6074	0.1013
SPX does not cause NIKKEI 225	SPX → NIKKEI 225	0.9124	0.6340
SMI does not cause SPX	SMI → SPX	10.0881	0.0069(**)
SPX does not cause SMI	SPX → SMI	0.3965	0.8203
S&P/TSX does not cause SPX	S&P/TSX → SPX	15.0351	0.0006(**)
SPX does not cause S&P/TSX	SPX → S&P/TSX	9.3550	0.0098(**)

*Note: * denotes significance level in 10%, ** in 5%, *** in 1%.*

Granger causality results are surprising because S&P 500 index is influenced by the changes in CAC 40, FTSE 100 SMI and S&P/TSX. A great number of studies found volatility spillovers from the US markets to other markets (see, e.g. Hamao *et al.,* 1990; Susmel and Engle, 1990; Lee *et al.,* 2004) whereas some paper indicate that the US can be Granger-caused by other in some cases. For instance, Dornau (1999), Peiro *et al.* (1998), Baur and Jung (2006) find evidence about contemporaneous effects towards US stock markets. Therefore, the results in Table 12 shows that volatility causalities occur not only from US to other markets but also vice versa in some cases.

In Table 13, realized skewness causality results are striking. Granger causality runs from all of the stock markets to the US. Although significance levels vary within 1% to 10%, the results clearly indicate that S&P 500 index is directly affected by other stock markets in terms of skewness.

Causality results contradicts with the skewness spillovers. Impulse response analysis shows small-magnitude spillovers from the US stock markets to the others whereas causality runs from other financial markets to the USA. On the other hand, skewness spillover effects are particularly weak in all cases.

Table 13. Granger Causality Test Results – Realized Skewness

Null hypothesis	**Causality**	**Chi-sq**	**p-value**
CAC 40 does not cause SPX	CAC 40 → SPX	7.8599	0.0051(***)
SPX does not cause CAC 40	SPX → CAC 40	0.0708	0.7901
DAX does not cause SPX	DAX → SPX	7.5113	0.0061(***)
SPX does not cause DAX	SPX → DAX	0.0124	0.9112
FTSE 100 does not cause SPX	FTSE 100 → SPX	4.8507	0.0276(**)
SPX does not cause FTSE 100	SPX → FTSE 100	0.0742	0.7854
NIKKEI does not cause SPX	NIKKEI 225 → SPX	5.5700	0.0183(**)
SPX does not cause NIKKEI 225	SPX → NIKKEI 225	0.8935	0.3445
SMI does not cause SPX	SMI → SPX	3.5167	0.0608(*)
SPX does not cause SMI	SPX → SMI	0.6056	0.4364
S&P/TSX does not cause SPX	S&P/TSX → SPX	3.7814	0.0518(*)
SPX does not cause S&P/TSX	SPX → S&P/TSX	1.2561	0.2624

*Note: * denotes significance level in 10%, ** in 5%, *** in 1%.*

To the best of my knowledge, there is no study that investigates realized skewness co-movements among stock markets via Granger causality tests. Therefore, the results in Table 13 firstly indicate that the realized skewness of other countries can help to predict realized skewness of S&P 500.

Kurtosis level Granger causalities are shown in Table 14. S&P 500 index is Granger cause of DAX and SMI with 10% and 5% significance level, respectively. However, kurtosis level test causality results provide little evidence of causal relations between financial markets. In addition, these results reveal some differences to the kurtosis spillover effects. However, similarly to the skewness spillovers, kurtosis spillovers are substantially small in magnitude and die out quickly.

Table 14. Granger Causality Test Results – Realized Kurtosis

Null hypothesis	Causality	Chi-sq	p-value
CAC 40 does not cause SPX	CAC 40 → SPX	0.1047	0.7463
SPX does not cause CAC 40	SPX → CAC 40	0.9174	0.3381
DAX does not cause SPX	DAX → SPX	0.5016	0.4788
SPX does not cause DAX	SPX → DAX	3.1077	0.0779(*)
FTSE 100 does not cause SPX	FTSE 100 → SPX	0.1741	0.6765
SPX does not cause FTSE 100	SPX → FTSE 100	0.9072	0.3409
NIKKEI does not cause SPX	NIKKEI 225 → SPX	0.0334	0.8550
SPX does not cause NIKKEI 225	SPX → NIKKEI 225	1.4730	0.2249
SMI does not cause SPX	SMI → SPX	1.5386	0.2148
SPX does not cause SMI	SPX → SMI	3.8900	0.0486(**)
S&P/TSX does not cause SPX	S&P/TSX → SPX	0.0084	0.9269
SPX does not cause S&P/TSX	SPX → S&P/TSX	1.9339	0.1643

*Note: * denotes significance level in 10%, ** in 5%, *** in 1%.*

6. CONCLUSION

The availability of high frequency data allows researchers to estimate the volatility of assets more precisely. Andersen (2001a) *et al.* suggest a new method to measure volatility. Using intradaily data, realized volatility is calculated by summing up 5-minute squared returns within a day. This framework enables us to measure the volatility in non-parametric fashion. A vast number of studies employ realized volatility with a model-free fashion. Meanwhile, higher realized measures such as skewness and kurtosis are calculated with the same notion as suggested by Amaya *et al.* (2011). In this dissertation, realized measures play a major role in order to understand financial market linkages. I calculate realized volatility, skewness and kurtosis using 5-minute returns of major stock indices and FX rates. Then, I examine the relationship between stock and FX markets via higher moments within VAR framework. Furthermore, stock market co-movements between the US and other developed countries are investigated within the same framework. Impulse Response Functions and Granger Causality tests are applied to detect spillovers and causalities between financial markets.

Realized volatility plays a significant role to gauge financial market linkages. Volatility is the most common measure of financial risk. Volatility co-movements between financial markets show how financial markets are connected with each other in terms of risk. In this research, there exist strong evidence of volatility co-movements between financial markets. Impulse response functions indicate unidirectional volatility spillovers from stock markets to FX rate within one country. Also, Granger causality tests mostly shows that stock markets are Granger-cause FX markets. Results are in line with the stock-oriented approach in which stock markets effects the FX rates. Similarly, I find unidirectional volatility spillovers from S&P 500 to the other major stock indices. Volatility spillover results are in line with previous studies. However, Granger causality tests reveal mixed results. There exist unidirectional and bidirectional causalities between the US and the others. It can be said that US stock markets are both transmitter and receiver of realized volatility. It should be noted that volatility spillovers represent how S&P 500 index influence the other stock indices in short-term while Granger test results show general causal relationship between markets.

One common misunderstanding is threating volatility as the risk itself. In other words, volatility is a measure of risk and it may not completely capture all risk components. Further realized moments are able to predict financial market linkages as well as volatility models.

Skewness can be defined as a measure of asymmetry in the probability distributions. Assets with positive skewness are desirable for investors. In the context of financial markets, realized skewness can help to understand market linkages. Hashmi and Tay (2007) asserts that conditional skewness can improve the efficiency of volatility spillover models. In a similar way, I construct bivariate VAR models using realized skewness. Empirical results reveal positive realized skewness spillovers from S&P 500 to other stock indices. However, the spillover effects die out in the third week. Interestingly, there are unidirectional Granger causalities from all of the selected stock indices to S&P 500. To the best of my knowledge, this dissertation is the first study that found Granger causality from developed countries to the USA. On the other hand, there is no evidence of skewness spillovers and Granger causality between stock and FX markets.

In addition to realized volatility and skewness, realized kurtosis can explain market linkages. It describes the magnitude of tails and peak in the mean in probability distribution. In practice, investors reasonably prefer the assets with low kurtosis. In terms of market linkages, positive kurtosis relationship between markets indicates that the risk components of financial assets are integrated. When extreme movements occur in one of the financial markets, then it will trigger the movements in integrated countries. Hence, kurtosis can help to explain co-movements of financial markets besides realized volatility and skewness. In this research, Bivariate VAR models provide evidence of kurtosis level integration of financial markets. Empirical findings exhibit kurtosis spillovers from stock markets to FX rates. Meanwhile, there exist positive kurtosis spillovers from S&P 500 to other major stock indices. In both sections, the spillover effects disappear quickly. Unlike impulse response analysis, there is no strong causal relationship both within / between stock and FX markets.

Finally, this research reveal following remarks in the application of high order moments. First, realized skewness and kurtosis are able to explain financial market linkages. Secondly, stock and FX market linkages support stock-oriented approach on the contrary of mainstream literature. Furthermore, US financial markets provide striking results in Granger causality test. Skewness level causalities are running from other developed markets to the USA in all cases.

This research has some limitations due to data constraints. High frequency data for emerging countries do not exist and contain errors. For this reason, emerging countries cannot be considered in this research. Also, the sample data do not cover the global crisis period. It reduces the scope of research significantly. Further studies may extend the time interval and apply for emerging countries. Other financial markets such as bond, oil and gold markets may be used for further research.

Word count: 12869

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