Essays on International Financial Markets Interdependence

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Declaration of Authorship

I, WALID ABASS MOHAMMED

certify that the thesis I have presented for examination for the PhD degree of Salford Business School, University of Salford is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

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Finally, I certify that chapter 4 of this thesis "Challenges of Stock Prediction" is published at IGI Global as a book chapter.

I, Walid A. Mohammed, contributed in excess of 100 percent of the work on this chapter, including the empirical analysis and writing of the text.

Walid A. Mohammed

30 September 2020

Abstract

This thesis consists of five chapters. Chapter one showcases the analysis of the three empirical studies presented in this thesis. Chapter two provides broad literature review. Chapter three investigates the transmission of information between developed and developing countries. In particular, foreign exchange market's return and volatility spillovers channel. A fundamental question is whether the magnitude of return and volatility spillovers is bidirectional between developed and developing countries. In this chapter, I investigate the "static and dynamic" return and volatility spillovers transmission across developed and developing countries. Quoted against the U.S. dollar, I study twenty-three global currencies over 2005 – 2016. Focusing on the spillover index methodology, the generalised VAR framework is employed. The findings indicate no evidence of bidirectional return and volatility spillovers between developed and developing countries. However, a unidirectional volatility spillover from developed to developing countries is highlighted. Furthermore, the findings also document significant bidirectional volatility spillover within the European region (Eurozone and non-Eurozone currencies) with the British Pound (GBP) and the Euro (EUR) as the most significant transmitters of volatility. The findings reiterate the prominence of volatility spillover to financial regulators.

Chapter four contributes to the out-of-sample's stock returns forecasting problem and investigates both its econometric underpinnings and predictability. According to Welch and Goyal (2008) there is little or zero evidence of the effectiveness of both (in-sample and out-of-sample) models in predicting equity returns. Thus, using daily data, this chapter examines whether the U.S. S&P stock exchange follow a random walk process, which required by market efficiency. We use a model-comparison approach, which compares an ex-post forecasts from a naïve model against those

obtained from numerous alternative models such as ARIMA models, random walk without *drift* and Simple exponential smoothing.

Chapter five assesses the dynamic behaviour of credit and house prices in advanced modern economies over the last three decades. The analysis is based on the GMM panel VAR, and Fixed-effects estimated using annual data for the G7 countries over the period 1980-2017. Thus, the empirical analysis of this chapter attempts to offer some contribution to the contemporaneous issues affecting the macroeconomic performance by investigating the dynamic behaviour of credit, house prices, GDP, consumption, and loans to the private sector. The main finding here is the strong link between the dynamic behaviour of the aforementioned variables in advanced modern economies. Finally, chapter six concludes and discusses the research implications and future study.

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Definitions and Abbreviations

GBP	British Pound Sterling
EUR	Euro
AUD	Australian Dollar
CHF	Swiss Franc
JPY	Japanese Yen
ISK	Islandic Krona
CZK	Czech Republic Koruna
HKD	Hong Kong Dollar
SGD	Singaporean Dollar
KRW	South Korean Won
TRY	Turkish Lira
INR	Indian Rupiah
ARS	Argentine Peso
MYR	Malaysian Ringgit
THB	Thai Baht
MXN	Mexican Peso
SAR	Saudi Arabian Riyal
AED	United Arab Emirates dirham

ZAR	South African rand
NGN	Nigerian naira
VAR	Vector Autoregressive
OSW	Centre for Eastern Studies
BREIST	British Exist
BIS	Bank for International Settlements
ARIMA	Autoregressive Intergraded Moving Average
ANN	Artificial Neural Network
BNN	Back Propagation Neural Network
SARIMA	Seasonal Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
SRM	Structural Vector Machine
SMA	Simple Moving Average
MACD	Moving Average Convergence Divergence
MLP	Multi-layer Perception
EMA	Exponential Moving Average
ACF	Autocorrelation Function
PACF	Partial Autocorrelation Function
MA	Moving Average
BIC	Bayesian Criterion
AIC	Akaike Information Criterion

SER	Standard Error of Regression
MSE	Mean Square Error
PVAR	Panel Vector Autoregression
G7	The Group of Seven countries
LTV	Loan to Value
OIRFs	Orthogonalised Impulse Response Functions
GDP	Growth Domestic Product
OLS	Ordinary Least Square
GMM	Generalised Method of Moment
MMSC	Model and Moment Selection Criteria
IRF	Impulse Response Function
VMA	Vector Moving Average
FEVD	Forecast-Error Variance Decomposition
OECD	Organisation for Economic Cooperation and Development
FE	Fixed-effect
CD	Coefficient of Determination

1 Research Project Overview

Introduction

Understanding the interdependent nature of the financial markets and the potential risk encompassed in such phenomenon is crucial for guiding stability and growth in the global financial system and the real economy. Indeed, there is a tremendous power incapacitated within the financial markets; if it unleashed without prior control, it poses financial devastations and maybe years of nuclear fall-out. Recent studies in this area, including cyber risks (Bouveret, 2018; Bascand, 2018) attempted to understand the type and magnitude of financial risks threaten the financial system and the real economy as a consequence of the global financial markets' interconnectedness. After the recent financial crisis of (2007-09), the financial markets are now centre stage in the markets' efficiency debates. This is because the development of systemic risks engulfed different financial systems, including capital market, interbank market, sovereign risk and credit risk heightening.

Analytically, this derives the aim of this thesis from three significant perspectives. (a) is the magnitudes of the global foreign exchange's spillover channel in the macroeconomic activity. In particularly, return and volatility spillover channel between developed and the developing countries. (b) is the time series modelling and forecasting, especially the out-of-sample forecasting of stock market returns. And (c) is the dynamic behaviour of credit, house prices, GDP, loans to the private sector, consumption and the macroeconomy. Thus, this introduction provides a detailed overview of these issues, which explored in the following three empirical chapters, including resemblance and contrast in their approaches and motivation. However, Chapter 2, which is before the three empirical studies provides a broad literature review to highlight the research gaps that this thesis is investigating.

Chapter 3, *Measuring Intra-Foreign Exchange Market Return and Volatility Spillover across Developed and Developing Countries*, investigates whether the effect of returns and volatility spillover is bidirectional between developed and developing countries. According to McMillan and Speight (2010), investigating the financial market interdependence and the detection of the presence of return and volatility spillover is important issue that affect the financial decisions of numerous market participants. In addition, Moshirian (2011) suggests that the recent financial turmoil has mostly swayed the global financial markets in both developed and the developing countries. Thus, there is extensive literature concerning the "return and volatility spillover" in stock, securities and bond markets in a regional and cross-country context. In particular, the literature is rich regarding the spillovers between two financial markets such as the stock and foreign exchange markets in developed countries (e.g., Apergis and Rezitis 2001; Francis et al., 2006; Beer and Hebein 2011; Grobys 2015). Also, ample literature study returns and spillover transmission between the stock and foreign exchange markets in emerging and developing countries (e.g., O'Donnell and Morales 2009; Fedorova and Saleem 2009; Choi et al., 2010; Walid et al., 2011; Okpara and Odionye 2012; Kang and Yoon 2013; Oberholzer and Boetticher 2015).

That being said, the foreign exchange market channel has not received equal attention; in particular, return and volatility spillover channel among developed and the developing countries. In that fashion, the contribution of chapter 3 addresses this gap in the literature.

According to Diebold and Yilmaz (2009), the negative consequences of the volatility spillovers due to the interconnected nature of the global financial markets primarily documented during the recent financial crisis, which may relate to the current financial markets' innovation. From a normative perspective, we find significant bidirectional volatility spillover within the European region (Eurozone and non-Eurozone currencies) due to innovation and the increased financial interlinkages.

Chapter 4, *Time Series Modelling and Forecasting: Challenges of Stock forecasting* investigates the out-of-sample forecasting of the stock market returns. However, the global stock markets (which trade around-the-clock) primarily affected during the crisis of 2008, causing Dow Jones to plunge 777.68 points (Schwert, 2011). Such recurring phenomenon triggered extensive academic studies (pre-and-post the recent crisis) to investigate the correlation between stock returns and investment portfolios (Samuelson 1966; Morck et al., 1990; Lal 2010; Barro and Ursúa 2017). This is because, the stock returns prediction involves high risk and high profits; thus, it is a source of attraction to many businesses, investors and economists. That being said, stock markets are significantly influencing investments and capital growth. Morck et al., (1990) identified three theoretical explanations to the correlation between the stock returns and investments: (1) Stock markets are passive predictors of future activities; thus, managers may not depend on them to make investment decisions. (2) Managers may rely on the stock markets as a source of information to make investment decisions, which may or may not be accurate regarding future fundamentals. Finally, the third theoretical point may offer the best explanation about the correlation between stock markets and investments. It suggests that stock markets affect investments by influencing the cost of funds and external financing. Therefore, successful and accurate predictions of the stock market returns mitigate losses and ultimately results in profit maximisation. However, traditionally, firms and businesses use discounted cash flow methods to forecast earnings (Steiger, 2010). This traditional forecasting method requires a long history of performance, firms with positive earnings and comparable firms. Therefore, the literature on the stock returns forecast is extensively rich with a special focus on the in-sample (IS) forecast (King, Snyder, and Koehler 2006; Clark and McCracken 2006; Narayan et al., 2014; and Sousa et al., 2016). On the other hand, the literature on the out-of-sample (OOS) stock returns forecast is limited at best with inconsistent results. Rapach et al., (2010) argue that the forecasting literature still unable to deliver consistently superior out-of-sample forecast of the U.S. equity premium.

The contribution of this thesis attempts to fill this gap in the literature by offering up-to-date forecasting techniques to assist financial managers and businesses in making successful business decisions. In particular, chapter 4 presents empirical analysis and accurate results of the U.S. S&P stock market returns predictability. In this chapter, we use the random walk with *drift* as a naïve model, then we compare the forecasts from the naïve model with those of the alternative[1] models. The findings show that the random walk with *drift* outperformed the alternative models and that the U.S. S&P stock market follows a random walk hypothesis.

Chapter 5 studies *the dynamic behaviour of credit availability, house prices, GDP, loans from central banks to the private sector, consumption in the G7 economies*. This is because shocks to these important variables may trigger severe repercussions on economic activity and collective price changes (Goodhart and Hofmann 2008). However, over the last couple of years, many economies experienced rapid credit growth, especially during the time running up to the recent crisis. This triggered an unsustainable house prices' boom which later materialised into busts; causing severe balance sheet vulnerabilities for financial and nonfinancial sectors (Bakker et al. 2012). As a result, the dynamic behaviour of rapid credit growth and house prices boom does not only

[1] The alternative models under investigation include the random walk without *drift*; moving average and exponential smoothing models; and ARIMA models 1,0,0; 0,1,0; 2,0,0; 0,1,1).

affect asset prices; instead, it is also associated with financial crises (Reinhart and Rogoff, 2009). Moreover, the relationship between consumption and house prices are also considered in the literature, for example (Quigley and Shiller 2003; Ludwig and Slock 2004) argue that the variations in housing wealth have significant effects on consumption. Also, Attanasio et al., (2009) suggest that the relationship between consumption and house prices is stronger for younger households, which is inconsistent with the wealth channel. Kisman (2017) finds that the lagged GDP per capita and credit expansion through banks are some of the factors may affect economic growth.

As of today, several studies (Goodhart and Hofmann 2008; Burnside et al., 2016) are addressing this issue. Although, none of the studies investigates the dynamic behaviour of credit availability, house prices, GDP, consumption, and loans from central banks to the private sector in advanced modern economies. We believe chapter 5 provides an interesting and important addition to the relevant literature regarding the dynamic behaviour of the important economic variables mentioned above in the G7 Economies. Using panel VAR modelling with quarterly data over the last three decades, chapter 5 attempts to address the following unanswered questions: What is the interrelated nature between the dynamic behaviour of credit availability, house prices, GDP, consumption and the loans from central banks to the private sector? If any, does it play a significant role in advanced modern economies, concerning money lending qualities, credit creation, investment decisions, consumption and real output? The empirical findings show robust evidence that the collective behaviour of house prices, credit, consumption, GDP, and loans to the private sector have significant repercussions on modern developed economies, in this case, G7 economies.

The empirical approach applied in this thesis, concerning similarities, both chapter 3 and 4 are financial risk-oriented, regarding risk in financial markets and financial system as a whole, respectively. Thus, the ultimate objective of chapter 3 and 4 is to mitigate the spillover risk in financial markets and to advance the stock market returns predictability. Chapter 5 is a more policy-oriented which provides exciting results to academic discussions, policymakers and regulators. On the other hand, the final chapter summarises the outcome and initial results of the thesis, including a future work recommendation. However, each chapter has its "own" introduction, literature discussion, as well as a conclusion that contains the summary of the main findings.

2

Literature Review

This chapter provides broad review of the literature concerning the three empirical chapters conducted in this thesis; however, each chapter has it is own detailed literature review. The purpose is to provide general idea about the objectives of the three empirical chapters while showcases the overarching aim of the thesis.

As we have already stated the introduction, this thesis examines the global foreign exchange's spillover channel; time series forecasting, especially stock returns forecast; and the dynamic behaviour of credit, house prices, GDP, loans to the private sector, consumption and the macroeconomy. Thus, the motivation of this thesis is related to different strands of the literature. For example, chapter three, is related to the classic literature that studies the global foreign exchange spillover channel, in particular, between developed and developing countries. Chapter four relates to the vast literature of time series forecasting, particularity, stock market returns. And finally, chapter five relates to the classic literature of the multidirectional link between credit availability, house prices, GDP, loans to the private sector, consumption and the macroeconomy.

However, there is extensive studies dealing with the spillover channel of foreign exchange market. This is attributed to the rise of global financial interconnectedness associated not only with the increasing cross-border gross but also currency exposures (Georgiadis and Zhu 2019). For example, Nicolaos (2012) investigates the volatility spillover and return co-movements of the British pound, Swiss franc, Japanese yen and the euro against the U.S. dollar pre and post the introduction of the euro. The author applied the generalised VAR analysis, dynamic correlations, variance decomposition, and the spillover index methodology. He found significant volatility spillovers and co-movements among the four exchange returns. Most importantly, Nicolaos's result suggests that the euro (Deutsche mark) is the main transmitter across other markets with net volatility spillovers of 8% and 15%; while the British pound is the dominant receiver of volatility spillover with a net of -11% and -13% before and after the euro period. Using the generalised vector autoregressive methodology, Diebold and Yilmaz (2012) propose important measures of the total and directional volatility spillovers. They characterise the daily volatility spillover among four key U.S. asset classes[2] from January 1999 to January 2010. The authors suggest that despite significant fluctuations among the four asset classes, the cross-market volatility spillovers were insignificant before the crisis of 2007. Nonetheless, they show evidence of considerable volatility spillovers from the stock market to the bonds, commodities, and the foreign exchange markets during financial crisis, in particular, after Lehman Brothers' collapse in September 2008.

Huynh et al., (2020) study the directional spillover effects (return and volatility spillover) across nine U.S. dollar exchange rates involving the most traded currencies[3] under the influence of the trade policy's uncertainty. The authors argue, there is asymmetric spillovers and connectedness among the currencies under investigation between December 1993 to July 2019; when there is trade policy uncertainty. Further, they find strong volatility spillover than return connectedness between the trade policy uncertainty and exchange rates.

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[2] The four U.S. asset classes include stocks, bonds, commodities, and foreign exchange.

[3] Currencies under investigation include, Canadian dollar (CAD), Swiss franc (CHF), Euro (EUR), Japanese yen (JPY), British pound (GBP), Australian dollar (AUD), New Zealand dollar (NZD), Swedish krona (SEK) and the Norwegian krone (NOK).

Some of the above studies tried to identify the magnitude of return and volatility spillover from the foreign exchange market to another asset class markets. Others, studied the effect of return and volatility spillovers among the most important currencies globally i.e., currencies from developed countries. That being said, the return and volatility spillover between developed and developing countries are under-researched. In particular, the effect of return and volatility spillover between developed and developing countries pre and post the recent financial crisis of 2008. This is because the recent financial crisis, which triggered in the U.S housing market has also engulfed most of the developed countries. As a consequence, chapter three investigates the extent to which developing countries are also affected due to the return and volatility spillover channel. Thus, the aim of chapter three is to fill this gap in the literature.

This thesis is also related to the time series forecasting literature, especially the stock return's forecasting problem. This is because the stock return forecast is a critical modelling process for investors and firms to predict future revenues and any possible earning fluctuations. The essence of the stock market investments is the trade-off between risk and return. Thus, forecasting is a widely used tool to evaluate investment portfolios, and foresee potential distressed markets, and allocate resources ((DeMiguel et al., 2009; Rapach and Zhou, 2013). Also, it is considered as a fundamental method for investment decision making for individuals as well as institutional investors alike.

Despite the growing interest in the stock returns forecast, the in-sample and out-of-sample return predictability remain controversial (Rapach et al., 2010). Welch and Goyal (2008) comprehensively re-examine numerous variables[4] that predict the equity premium over 30 years period from 1975 to 2005.

[4] The variables include dividend yields, dividend price ratios, dividend pay-out ratios, earning-price ratios, dividend yields, beta premia, book-market ratios, interest rates and consumption-based ratios.

Using multiple regression models, their findings suggest that (a) the majority of the in-sample prediction models did not perform well for almost 30 years (1975 – 2004). And (b) the out-of- sample prediction models performed extremely poor; and the authors conclude that the equity prediction models are not robust. On the other hand, Cochrane (2008) argues that the findings of (Welch and Goyal 2008) should not be interpreted as evidence against returns predictability; rather, their findings explore the difficulty of returns predictability concerning trade strategies. Cochrane (2008) also argues that if returns are not predictable, then dividend growth MUST be forecastable to enable the generation of the observed variation in the dividend-price ratios. Ferreira and Santa-Clara (2011) propose the sum-of-the-part (SOP) method to forecast different components[5] of the stock market returns separately, over 1927-2007. The authors argue that the SOP method provides better out-of-sample forecast than the historical mean and predictive regression. They also suggest that due to the absence of estimation error, the SOP method outperformed the predictive regression model. Brown et al., (2016) extended the (Modigliani and Cohn 1979) money illusion hypothesis to a cross sectional asset pricing in order to measure the inflation-illusion related to mispricing at the stock level. They argue that both overpricing and under-pricing contribute to the anomalous returns.

During the last few years, forecasting stock returns has also attracted distinguished numbers of the artificial neural networks (ANNs) models, (see, Preminger and Franck 2007; Kumar and Ravi 2007; Egrioglu et al., 2009; Khashei and Bijari 2010; Ticknor 2013). For example, Guresen et al., (2011) examines the effectiveness of different ANN models in forecasting the stock market returns. In particular, the authors compared the multi-layer perception (MLP), dynamic artificial neural network (DAN2), and the hybrid neural networks. Their results show that the classical ANN model MLP outperforms the DAN2 and the hybrid neural networks.

[5] The components include earnings growth, price–earnings growth, and the dividend–price ratio.

However, chapter four of this thesis contributes to the out-of-sample's stock returns forecasting problem. Our approach is relatively different from the above studies in terms of methodology. We use the random walk with *drift* as a naïve model, then we compare the ex post forecast from the naïve model with those generated from the alternative[6] models. The random walk with and without *drift* is widely used in the literature (see, Engel and Hamilton 1990; Diebold et al., 1994; Engel 1994; Faust et al., 2003; Moosa and Burns 2013a). for example, using both in-sample and out-of-sample tests, Sousa et al., (2016) provide evidence of stock return predictability for the BRICS[7] countries. They also argue that the standard forecasting metrics such as mean squared forecasting error provides more favourable results than a simple regression.

And finally, this thesis is also related to the classic literature of credit availability, house prices, GDP, loans to the private sector, consumption and the macroeconomy. For example, Greiber et al., (2007) investigate the relationship between money and housing variables in both the euro area and the U.S. They argue that for both the euro area and the U.S. there is significant bidirectional links between money supply and housing. Attanasio et al., (2009) argue that for younger households, the relationships between house prices and consumption tends to be stronger than that of older households. Using panel vector autoregressive (PVAR) methodology, Love and Ariss (2014) investigate the interaction between different macroeconomic aggregates and the loan quality in Egypt. Applying a panel of banks over 1993 – 2010, they find that a positive shock to (capital inflows & growth) in gross domestic product (GDP) improves banks' loan portfolio quality. The authors also suggest that higher lending rates may lead to contrary selection problems and consequently to a drop in the portfolio quality.

[6] The alternative models include ARIMA models, random walk without *drift* and the Simple exponential smoothing.
[7] The BRICS countries include Brazil, Russia, India, China and South Africa.

Also, using quarterly data over the period 1990 – 2012, Cesa-Bianchi et al., (2015) compare house prices cycles in emerging and advanced economies. They find that compared with advanced economies, house prices in emerging economies grow faster, more volatile, and less synchronised. The authors also argue that unlike advanced economies, the global liquidity shock has stronger impact on house prices and consumption in emerging economies. Applying panel data for 20 OECD countries, Anundsenet al., (2016) evaluate house prices and credit in affecting the likelihood of a financial crisis over the period of 1975 – 2014. They find that credit booms effect to both households and non-financial enterprises should be considered when evaluating the stability of the financial system. Moreover, the authors find evidence that the global housing market developments have predictive power for domestic financial stability.

Using the workhorse models of consumption, Berger et al., (2018) show evidence that consumption responses to permanent house price shocks. The authors suggest number of factors that trigger consumption responses such as the level of debt, the level of credit supply, and the size and history of house price shocks. Aikman et al., (2020) incorporate financial condition index (FCI) to combine information from asset prices and nonprice terms including lending standards for both business and household credit. They find that when credit-to-GDP gap is low, it creates positive shocks, which stimulates economic activity and a sustained expansion. The authors also argue that if credit-to-GDP gap or growth is high, positive shocks to the financial conditions stimulate economic activity in the short-run leading to excess borrowing and economic contractions.

The literature discussed above provides different results regarding the effect of important macroeconomic variables in the stability of the financial system nationally, regionally and globally. However, the literature about the casual relationship between credit availability, house prices, loans from central banks to private sector, GDP, and consumption still under-researched. Chapter five fills this gap in the literature where we examine the causal relationship between credit availability, house prices, GDP, loans from central banks to the private sector, and consumption in the G7 economies.

3

Measuring intra-foreign exchange market return and volatility spillover across developed and developing countries

3.1. Introduction

The current era of the global economic events and financial turbulence increased the attentiveness of market participants and academic research. Prompted by the recent financial crisis (2007-09), a large number of studies scrutinised the magnitude of return and volatility spillovers' transmission across the globe. Nonetheless, the foreign exchange market received scant attention. A few studies investigate the exchange rate co-movements and volatility spillover across developed countries,[8] whereas others produced insignificant results on regional spillover's transmission. Given the trillions of dollars of exchange rate trading in international financial markets; it is important to fully understand and investigate in greater depth the potential spillovers of international currencies. This is an important aspect that is taken into serious account from the investors for the formation of their position and portfolios.

Before the recent financial turmoil, the foreign exchange market's connectedness to the global macroeconomic instability, for some, appeared to be less worrisome, whereas, in fact, the behaviour of the stock prices (which extensively studied) mainly explained by volatilities in the foreign exchange market (Kim, 2003).

[8] See, for example (Andersen et al., 2001; Pérez-Rodrìguez 2006; Boero et al., 2011; and Rajhans and Jain (2015).

The purpose of this chapter is to contribute to the incomplete investigation of the intra-foreign exchange market's spillover channel. It aims at broadening the significance of the financial markets' return and volatility spillover between developed and developing countries. A key question is whether the effect of return and volatility spillovers is bidirectional between developed and developing countries. This is because the recent financial crisis which originated in major financial hubs in developed countries, primarily in the U.S., that developing countries are not responsible for, nevertheless they seriously affected by it.

To address the return and volatility spillover transmission (across developed and developing countries), we model the daily spot exchange rates for 23 global currencies, including the seven most-traded globally.[9] In particular, we adopt the generalised vector autoregressive (VAR) approach focusing on the variance decomposition of Diebold and Yilmaz (2009). The innovative feature of this approach besides being rigorous it allows the aggregation of valuable information across-markets into a single spillover index. The unique structure of the spillover index is designed to unleash an in-depth analysis of the negative pullovers' transmission across-markets, i.e., how a shock in a particular market is due to exogenous/endogenous shocks to other markets.

We also examine the time-varying net volatility spillover between developed and the developing countries using the autoregressive conditional heteroskedasticity (ARCH) model. The time-varying volatility identifies the specific point of significant shifts in the volatility spillover between developed and developing countries during the years of our sample (2005 – 2016).

The ARCH model, which is first introduced by (Engle 1982) is widely used in the literature (Bollerslev et al., 1994; Kaur 2004; Basher et al., 2007) for it is ability to

[9] According to the BIS (2013), the USD, EUR, GBP, AUD, CAD, JPY and the CHF are the most traded globally, account for almost 90 per cent of the global foreign exchange turnover.

capture persistence in time-varying volatility based on squared returns. And most importantly, to investigate the nature of the net volatility and net pairwise spillover effects between developed and developing countries, we implement (Diebold and Yilmaz, 2012) methodology. By doing so, we are able to show the difference between the amount of the gross volatility shocks within our sample that transmitted to and received from developed and the developing countries.

To enhance the reliability of the findings, we provide evidence in different dimensions (using a sample of twenty-three global currencies over 2005-2016). The first is the static analysis dimension, which provides results in the form of spillover Tables. The second is the dynamic analysis, which yields the spillover plots; both analyses are provided in section (3.5) of this chapter. Third, is the time-varying net volatility results, which we provide in the form of figures in section (3.6). Finally, the net volatility and net pairwise spillover effects provided in a from of figures in section (3.7) as well as in Appendix (A).

Overall, this chapter is the first (to our knowledge) to document the transmission of returns and volatility spillover between developed and the developing countries. The analysis is based on large daily spot exchange rates' dataset covers a long period pre and post the most recent events in the global economy. In particular, the chapter provides results based on extensive empirical analyses such as the spillover index (both static and dynamic analyses), time-varying net volatility, net volatility and net pairwise volatility effects.

Guided by the empirical approach described above, the main findings indicate that no evidence of bidirectional volatility spillovers between developed and developing countries. Although, unsurprisingly, the results highlight evidence of unidirectional volatility spillovers pouring from developed to developing countries. In particular, the volatility spillovers from developed to the developing countries seem to be specifically strong following the collapse of Lehman Brothers' in 2008. Another curious outcome of the findings is that developed countries are the most receiver and transmitter of volatility spillover, dominated by the British pound, Australian dollar, and the euro, whereas developing countries are a net receiver of volatility spillover. The findings, therefore, indicate that the currency crisis tends to be regional (Glick and Rose 1998; Yarovaya and others 2016).

Meanwhile, in light of the recent financial crisis, the analytical results demonstrate that the cross-country spillovers activities between developed and developing countries are insignificant, while the financial risk propagated during the recent financial crisis engulfed the global economy. That being said, because of the recent financial markets' development, for instance, financial engineering, (collateral debt obligation, credit default swap and derivative securities) financial risks triggered different means of spreading across the global economy, which still needs to be discovered, understood and spoken appropriately.

The rest of this chapter is organised as follows: Section 3.2 discusses some critical arguments of related literature. Section 3.3 then introduces the data used in the analysis and the empirical methodology applied in section (3.4). In section 3.5, we provide empirical results, including the robustness and some descriptive statistics. Section 2.6 discusses the time-varying volatility. Section 2.7 introduces the net spillovers and net pairwise volatility spillovers. Section 3.8 concludes.

3.2. Related Literature

To date, the foreign exchange market's (which trades around-the-clock) spillover channel is one of the most intensely debated issues in recent literature. As early as (1989), Diebold and Nerlove provide some evidence of correlation in the foreign exchange rates' volatility spillover. By contrast, Engle et al., (1990) established the first thread-tying efforts of the intra-day exchange rate's volatility spillover within one country (heat waves) and across-borders (meteor shower). The "heat waves" is a hypothesis indicates that the volatility in one market will continue in the same market next day. However, the “meteor shower” is a phenomenon implies that a volatility in one market can spillover to another market. In this paper, the authors provide evidence of transmitted volatility spillover from one market to another. This opening up, particularly after the recent financial crisis, highlights the importance of the stock market’s (which also trades around-the-clock) spillover and the foreign exchange market. Also, there is some growing evidence in the literature supports the association of return and volatility spillovers with global economic events and financial crises. (See, Diebold and Yilamz 2009; Beirne et al., 2009; Yilamz 2009; Gebka 2012; Jung and Maderitsch 2014; Ghosh 2014; Choudhry and Jayasekera 2014; Antonakakis et al., 2015; and Mozumder et al., 2015, for reviews).

The prominence of empirically measuring the effect of return and volatility spillover has increasingly deepened after the recent financial crisis (2007/09). This is due to the repercussions of the shocking types of financial risks stemming from the interconnected nature of the financial markets. Diebold and Yilmaz (2012) produced a substantial contribution to the field where they emphasised that the threats of cross-market volatility spillover principally increased after the recent global financial crisis. Further, they also show that the positive correlation, particularly, volatility spillover, can primarily affect other markets through the stock market channel. The authors’ findings came as a greater acknowledgement to the previous arguments as well as triggered extensive studies in the potential financial risk of cross market’s volatility spillover (see Fedorova and Saleem 2009; Mohanty et al., 2011; Maghyereh and Awartani 2012; Jouini 2013; Shinagawa 2014; Do et al., 2015 for reviews).

Moreover, an essential strand of the literature argues that the effect of return and volatility spillovers may act differently during, before and after the financial crisis’s episodes. Based on Vector Autoregressive (VAR) models, Diebold and Yilamz (2009) provided measures of volatility spillover and return spillover. In this paper, the authors' approach is different from the work of Engle et al., (1990) because they applied variance decomposition to critically aggregate the spillover effects from across-markets into a single spillover index (measure). They examined nineteen[10] global equity markets (from the 1990s to 2009) and found striking evidence that return spillover displays slightly increasing trend but no bursts, while, volatility spillover display no trend but strong bursts concomitant with crises events. *Why this should be so is a contentious matter the literature has yet little say about*. However, the Diebold-Yilmaz approach (variance decomposition) is a powerful tool, which provides striking evidence that spillover has a time-varying intensity and the nature of the time-variation is interestingly different concerning returns vs volatilities.

Along the same line, the effect of return and volatility spillovers on global economic trend and business cycle did not go unnoticed. Some studies argue that volatility spillover inflicts business cycle synchronisation amid countries through four channels including; the exchange rate channel; confidence channel[11]; trade channel; and the financial integration channel (*see*, Imbs 2004; Eickmeier 2007; Imbs 2010; and Claessens et al., 2011 for reviews). A broader effect of volatility spillover in the global economy is suggested by (Yılmaz 2009; and Antonakakis et al., 2015), who argue that the spillover effect could also be transmitted through business cycle shocks across economies.

The interconnectedness of the volatility spillover indices with economic events and financial crises is also recognised in the literature (see, Diebold and Yilamz 2009; Beirne et al., 2009; Yilamz 2009; Gebka 2012; Jung and Maderitsch 2014; Ghosh 2014; Choudhry and Jayasekera 2014; Antonakakis et al., 2015; Mozumder et al., 2015; for reviews). These authors opine that the intensity of volatility spillover effect

[10] Seven developed stock markets (in the US, UK, France, Germany, Hong Kong, Japan and Australia) and twelve emerging markets (Indonesia, South Korea, Malaysia, Philippines, Singapore, Taiwan, Thailand, Argentina, Brazil, Chile, Mexico and Turkey).

[11] The confidence channel represents the domestic agents' responses to the potential spillover coming from foreign shocks to the local economy (Eickmeier 2007).

materialises before, during and after economic events and financial crises episodes. Their findings imply that this phenomenon is due to the interconnected nature of the financial markets and the business cycle channels. As a result, the recent global financial turmoil has divided the literature in the area of return and volatility spillovers into two main phases. The first phase concerns the cross-border financial linkages (i.e., international spillover of asset prices' shocks) across different asset classes (Diebold and Yilmaz 2009; Arouri et al., 2011; Ehrmann et al., 2011; Krause and Tse 2013; Ezzati 2013**;** Lyócsa et al., 2014 and Balli et al., 2015). The second phase studied the domestic spillover of asset prices' shocks across different financial markets, (Fedorova and Saleem 2010**;** Diebold and Yilmaz 2010; Jung and Maderitsch 2014; Yen-Hsien Lee 2014; and Mozumder et al., 2015). These studies denote that there is a correlation between asset returns and volatility spillover deemed positively with economic events and financial crisis episodes, and the level of the correlation high/low depends on the size of the shocks.

In addition, several studies examined the national and international return co-movements and volatility spillover of equity and bond markets (*see*, Engle and Susmel 1993; King et al., 1994; Kearney and Daly 1998; Edwards and Susmel 2001; Ehrmann et al., 2005; Yang 2013; Andrikopoulos et al., 2014; Jawadi et al., 2015; and Chiang et al., 2016, *for reviews*). On similar grounds, other literature studied the relationship between stock and foreign exchange markets regarding return and spillover effect. For example, using EGARCH model, Mozumder et al., (2015) examined the volatility spillover between stock prices and exchange rates (in three emerging and three developed countries) during the recent pre-financial crisis, crisis, and post-crisis episodes. They found evidence of asymmetric volatility spillover between exchange rates and stock prices, in particular during the financial crisis period. Some of the literature identified unidirectional and bidirectional volatility spillover between stock and foreign exchange markets (see Mishra et al., 2007;

Morales 2008; Fedorova and Saleem 2010; Agrawal et al., 2010; Krause and Tse 2013; Ezzati 2013; Louzis 2013; Do et al., 2015; Jawadi et al., 2015; Grobys 2015 and Ngo 2020 for reviews). Other studies found evidence of co-movement between stock markets and oil prices; and argue that the stock markets have significant positive exposure to oil prices shocks (e.g., Edwards and Susmel, 2001; Filis et al., 2011; Masih et al., 2011; Arouri et al., 2011; Jouini, 2013; and Kang et al., 2014).

A significant breakthrough in the area of foreign exchange market volatility spillover is the work of Diebold and Nerlove (1989). In this paper, the authors show evidence of correlation in the volatility of the foreign exchange's returns. Their findings triggered extensive studies investigating the behaviour of return and volatility spillover through the foreign exchange's market channel. This opening up, particularly after the recent financial crisis, highlights the importance of return and volatility spillovers and their indices nature, which at best, associated with economic events and financial crises. For example, Baillie and Bollerslev (1990) studied four foreign exchange spot rate series on an hourly basis using the GARCH model. The authors did not find evidence of volatility spillover either between the currencies or across the border. A different perspective by Anderson and Bollerslev (1998) sees substantial volatility spillover in foreign exchange markets with particular emphasis on ARCH and stochastic volatility models as good predictors of volatility forecasts. A similar argument by Hong (2001), examined the volatility spillover between the Japanese yen and the Deutsche mark. He found substantial evidence of simultaneous interaction between the two currencies and that a change in the Deutsche Marks volatility Granger-causes a change in the Japanese yen, but not vice-versa. Dungey and Martin (2004) applied a multifactor model to examine the contagion contribution of foreign exchange market volatility during the East Asia currency crisis; they found evidence of significant contagion.

Building on the backgrounds above, some literature studied the exchange rate co-movements and volatility spillover across developed countries. In particular, the financial transmission between the euro (EUR), British pound (GBP), Australian dollar (AUD), Swiss franc (CHF), and the Japanese yen vis-á-vis the U.S. dollar, (e.g., Andersen et al., 2001; Pérez-Rodrìguez 2006; Boero et al., 2011; and Rajhans and Jain 2015). They found a high correlation between the euro and British pound against the U.S. dollar and that the British pound is a net receiver. Nikkinen et al., (2006) studied the future expected volatility linkages among major European currencies (the euro, British pound and the Swiss franc) against the U.S. dollar. They found future volatility linkages between the major currencies and that the British pound and the Swiss franc are significantly affected by the implied volatility of the euro. Using a residual cross-correlation approach, Inagaki (2007) examined the volatility spillover between the British pound and the euro against the U.S. dollar. He found unidirectional volatility spillover from the euro to the British pound. Jayasinghe and Tsui (2008) applied GARCH models to examine the foreign exchange rates' exposure of sectorial indexes in the Japanese industries. They found significant evidence of asymmetric conditional volatility of exchange rate exposure in different Japanese industrial sectors. Applying the non-causality approach, Bekirkos and Diks (2008) examined the linearity and non-linearity linkages across six major currencies.[12] They found a significant bidirectional and unidirectional causal non-linear relationship, and that return spillover displays asymmetries of substantial higher-order moments. Using Diebold and Yilmaz's spillover index methodology, McMillan and Speight (2010) examined the nature of interdependence, return and volatility spillover of the British pound, U.S. dollar and the Japanese yen against the euro. They found evidence of substantial unidirectional volatility spillover from the U.S. dollar to the British pound and the Japanese yen. Boero et al., (2011) found an increase in co-

[12] The British Pound (GBP), euro (EUR), Japanese yen (JPY), Australian dollar (AUD), Swiss franc (CHF) and Canadian dollar (CAD) vis-á-vis the U.S. dollar.

movements between the euro and the British pound after the introduction of the euro compared to the pre-euro era. A different perspective is offered by Antonakakis (2012), using VAR model, the author found significant return co-movements and volatility spillover between major exchange rates before the introduction of euro and lower during the post-euro periods.

The main conclusion drawn from these studies is the evidence of return co-movements and volatility spillover across developed countries' exchange rates or (major currencies). However, little attention is given to examining the behaviour of asset return and volatility spillovers' transmission between foreign exchange markets across developed and developing countries. Only a few of the literature (which focused mainly on central European foreign exchange markets) have produced limited results due to the lack of considering large sample size dominating different countries across both categories. For instance, applying high-frequency data in a global trading context, Cai et al., (2008) examine the effect of the euro-dollar and the dollar-yen exchange rates' transmissions across five regions (the Asia Pacific, Asia-Europe overlap, Europe, the Europe-America overlap, and America). They advocate significant informational linkages at both; own-region and inter-region levels. They also argue that the Europe-America overlap trading region is the largest source of spillovers to the other trading areas.

Further, using a GARCH-BECK model developed by Engle and Kroner (1995), Fedorova and Saleem (2010), explored the currency markets relationship between the Czech Republic, Hungary, Poland, and Russia. They found indications of return and volatility spillover interconnectedness. Employing a multivariate GARCH model, Lee (2010) studies volatility transmission across ten[13] emerging foreign exchange markets. He advocates that there is evidence of regional spillovers and

[13]Five in Latin America (Chile, Brazil, Colombia, Peru, and Mexico) and five in Asia (South-Korea, Indonesia, Philippines, Thailand, and China)

transmission of external shocks across the countries, with particular emphasis on the Japanese yen and the U.S. S&P 500 are the primary external influence. Bubák et al., (2011) examine the volatility transmission across three central European's emerging markets, in particular, among Czech, Hungarian and Polish currencies. The authors' main finding is a significant intra-regional volatility spillover across central European's foreign exchange markets. Kim et al., (2015) study the spillover effects of the recent U.S. financial crisis across five emerging Asian's countries (Indonesia, Taiwan, Thailand, Korea and the Philippines). According to their findings, the collapse of Lehman Brothers in September 2008 is per se evidence of financial contagion.

Notwithstanding, some literature studied the foreign exchange rates' return and volatility spillovers between developed and developing countries; they have either considered specific regions "Europe, Asia, America and Latin America" or used data from limited samples. For example, Kotzé and Kavli (2014) employed the Diebold and Yilmaz methodology to data from 1997 to 2011 across fourteen [14] global currencies. Their result suggests that returns spillover has increased steadily over the years with a mild reaction to economic events; in contrast, volatility spillover has increased significantly since the recent global financial crisis and has a strong response to economic events. Nonetheless, their data sample ignored some of the Asian's key player economies such as oil producers (Saudi Arabia) among other vital economies.

In comparison to the above studies, this chapter provides a thorough investigation of the transmitted information between developed and developing countries through the intra-foreign exchange market channel, particularly, the return and volatility

[14] Currencies are the U.S. dollar, euro, Japanese yen, British pound, Australian dollar, Swiss franc, Canadian dollar, Korean won, Mexican pesos, Indian rupee, South African rand, Brazilian real, Nigerian naira, Egyptian pound and Kenyan shilling.

spillover transmission. We examine broad data samples from twenty-three [15] developed and developing countries (which have received somewhat limited attention) before, during and after the recent financial crisis. As a result, this chapter provides more insights into the financial transmissions between developed and developing countries. The extended data sample from 2005 to 2016 emphatically help in a way, to unfold the effect of return and volatility spillovers across global foreign exchange markets, which currently dominate the focus of policymakers as well as financial managers.

On top of that, while volatility spillover strongly relates to crises events, (Diebold and Yilmaz, 2009), this chapter proclaims impressive results that return spillover likewise incurs high correlation, especially among the most traded currencies, i.e., currencies from developed countries. According to Fratzscher (2003), return co-movement may constitute a high correlation due to similarities in fundamentals or exposure to common external shocks. In this regard, Diebold and Yilmaz (2009) attributed return spillover to the recent financial markets' innovations. The highlighted results in this chapter, speak to both arguments mentioned expeditiously concerning return co-movement and volatility spillover. This means financial managers may take into consideration the interconnected behaviour of return and volatility spillover to oversee potential risk exposures and prevent financial instability.

[15] Currencies from nine developed countries, the British pound (GBP), euro (EUR), Australian dollar (AUD), Canadian dollar (CAD), Swiss franc (CHF), Japanese yen (JPY), Icelandic krona (ISK), Czech Republic koruna (CZK), Hong Kong dollar (HKD) Singapore dollar (SGD), and South Korean won (KRW) and currencies from eleven developing countries including the Russian roble (RUB), Turkish lira (TRY), Indian rupee (INR), Indonesian rupiah (IDR), Argentine peso (ARS), Malaysian ringgit (MYR), Thai baht (THB), Mexican peso (MXN), Saudi Arabian riyal (SAR), United Arab Emirates dirham (AED), South African rand (ZAR) and Nigerian naira (NGN).

3.3. Database and Methodology

3.3.1. Database

The underlying data employed in this study consists of daily spot exchange rates of currencies comprises a total of twenty-three developed and developing countries across the globe vis-á-vis the U.S. dollar. Taken from DataStream Thomson Reuters through the WM/Reuters channel the sample period starts in 31 May 2005 and ends in 01 June 2016. Since we investigate the spillovers effect between developed and developing countries, our study period facilitates the production of comprehensive and precise measures of return spillover and volatility spillover pre-and-post the recent financial crisis of 2007-09.

The series include currencies from ten developed countries, the British pound (GBP), euro (EUR), Australian dollar (AUD), Canadian dollar (CAD), Swiss franc (CHF), Japanese yen (JPY), Icelandic krona (ISK), Czech Republic koruna (CZK), Hong Kong dollar (HKD) Singapore dollar (SGD), and South Korean won (KRW), and currencies from eleven developing countries, including Russian ruble (RUB), Turkish lira (TRY), Indian rupee (INR), Indonesian rupiah (IDR), Argentine peso (ARS), Malaysian ringgit (MYR), Thai baht (THB), Mexican peso (MXN), Saudi Arabian riyal (SAR), United Arab Emirates dirham (AED), South African rand (ZAR) and Nigerian naira (NGN). According to the Bank for International Settlement (BIS) report (2013), the underlying chosen currencies in this chapter include the most actively traded currencies across-financial markets globally. Moreover, it is also including currencies from oil rich countries such as Saudi Arabia.

3.3.2. Obtaining Daily Returns

To obtain the daily returns series, we calculate the daily change in log price of close data, when price data is not available for a given day due to a holiday or in the case of omitted value; we use the previous day value. As spot rates are non-stationary, we calculate the daily exchange rate returns as:

$r_t = ln(y_t) - ln(y_{t-1})$, where y_t is the spot exchange rate at time t, with t = 1, 2……, T, and the natural logarithm ln. Table 1 provides a variety of descriptive statistics for returns.

3.3.3 Obtaining Daily Return Volatilities

A different approach could be employed to achieve the global foreign exchange market historical volatility, but in this study, we have followed the improved estimators of security price fluctuations of Garman and Klass (1980) and Alizadeh et al. (2002). The instinct of this methodology is that the underlying volatility estimators based on historical opening, closing, high and low prices and transaction volume. The underlying model assumption is that diffusion process governs security prices:

$$P(t) = \emptyset\big(B(t)\big) \tag{3.1}$$

Where P represents the security price, t is time, $\emptyset$ is a monotonic time-independent[16] transformation, and $B\ \langle t\rangle$ is a diffusion process with differential representation:

$$dB = \sigma\ dz \tag{3.2}$$

Where dz is the standard Gauss-Wiener process and σ is an unknown constant to be estimated. Implicitly the phenomenon is dealing with the transformed "price" series, and the geometrical price would mean logarithm of the original price, and volatility would mean "variance" of the original logarithmic prices. The original root of Garman and Klass methodology is the Brownian motion, where they added three different estimation methods. They based their methodology estimation on the

[16] Monotonicity and time-independence both employed to assure that the same set of sample paths generates the sample maximum & minimum values of B and P Garman and Klass (1980).

notion of historical opening, closing, high and low prices and the transaction volume; through which they provided the following best analytic scale-invariant estimator:

$$\sigma_t = \sqrt{\frac{N}{n} . \sum_{i=1}^{N} \frac{1}{2} . (\log\left(\frac{H_i}{L_i}\right))^2 - (2.\log(2) - 1). \log(\frac{C_i}{O_i})^2} \quad (3.3)$$

Where σ_t is an unknown constant to be estimated, N is the number of trading days in the year and n is the chosen sample. H is today's high, L is today's low, O and C are today's opening and closing respectively. Explaining the coefficients of the above formulae is beyond the scope of this study for now. However, to obtain the foreign exchange market volatilities, we have used an intra-day high, low, opening and closing data. When price data is not available for a given day due to a holiday or in the case of omitted value, we use the previous day value. Table 2 shows descriptive statistics for global foreign exchange volatilities.

3.4. Methodology

To examine return and volatility spillovers across the broad cross-section of twenty-three global foreign exchange currencies, we have employed generalised vector autoregressive (VAR) methodology, focusing mainly on variance decompositions proposed by Diebold and Yilmaz (2009). The concept of variance decomposition is very rigorous and helpful as it allows the aggregation of valuable information across-markets into a single spillover index. In other words, how shocks in market A is due to exogenous shocks to other markets. Which best expressed by employing the phenomenon of variance decomposition concomitant with an N-variable VAR by adding the shares of the forecast error variance for each asset i coming from shocks to an asset j, for all $j \neq i$ tallying up across all i = 1,………, N. Then considering the example of simple covariance stationary first-order two-variable VAR,

$$x_t = \Phi x_{t-1} + \varepsilon_t \tag{3.4}$$

Where $x_t = (x_{1t,} x_{2t})$ and Φ is a parameter matrix. In the following empirical work, x will be either a vector of foreign exchange returns or a vector of foreign exchange return volatilities. The moving average representation of the VAR is given by:

$$x_t = \Theta(L)\varepsilon_t \tag{3.5}$$

Where Θ (L) = $(1 - \Phi L)^{-1}$ which for simplicity could be rewritten as:

$$x_t = A(L)\, u_t \tag{3.6}$$

Where, $A(L) = \Theta(L)Q^{-1}$, $u_t = Q_t\, \varepsilon_t$, $E(u_t\, u') = 1$, and Q^{-1} is the unique Cholesky factorisation of the covariance matrix of ε_t. Then considering the 1-step-ahead forecast, the precise approach would be the Wiener-Kolmogorov linear least-squares forecast as:

$$x_t + 1, t = \Phi x_t \tag{3.7}$$

With corresponding 1-step-ahead error vector:

$$e_t + 1, t = x_{t+1} - x_{t+1,t} = A_0\, u_{t+1} = \begin{bmatrix} a_{0,11} & a_{0,12} \\ a_{o,21} & a_{0,22} \end{bmatrix} \begin{bmatrix} u_{1,t+1} \\ u_{2,t+1} \end{bmatrix} \tag{3.8}$$

And comprises the following covariance matrix;

$$E(e_{t,+1,t}\, e'_{t+1,t}) = A_0 A'_0. \tag{3.9}$$

To clarify, the variance of the 1-step-ahead error in forecasting x_{1t} is $a_{0,11}^2 + a_{0,12}^2$, and the variance of the 1-step-ahead error in forecasting x_{2t} is $a_{0,21}^2 + a_{0,22}^2$. Diebold and Yilmaz (2009) utilised the mechanism of variance decompositions to split the forecast error variances of each variable into parts attributable to a broader system shock. That facilitate answering the question of what fraction of the 1-step-ahead error variance in forecasting x_1 is due to shocks to x_1? And shocks to x_2?. And likewise, what portion of the 1-step-ahead error variance in forecasting x_2 is due to shocks to x_1? And shocks to x_2?

3.4.1. The spillover Index

Having understood the notion of variance decompositions described above, the spillover index of Diebold and Yilmaz (2009) then proposed representing the fractions of the 1-step-ahead error variances in forecasting x_i due to shocks to x_j, for $i, j = 1,2, i \neq j$. These two-variables construct the spillover index with two possible spillovers outcomes. First, x_{1t} which represents shocks that affect the forecast error variance of x_{2t} with the contribution ($a_{0,21}^2$). Second, x_{2t} similarly represents shocks that affect the forecast error variance of x_{1t} with a contribution ($a_{0,12}^2$) totalling the spillover to $a_{0,12}^2 + a_{0,21}^2$ which best expressed relative to the total forecast error variation as a ratio percentage projecting the spillover index as:

$$s = \frac{a_{0,12}^2 + a_{0,21}^2}{trace(A_0 A'_0)} \times 100 \tag{3.10}$$

Interestingly, the spillover index can be sufficiently generalised to wider dynamic environments particularly for the general case of a p^{th}-order N-variable VAR, using H-step-ahead forecast as:

$$s = \frac{\sum_{h-0}^{H-1} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} a_{h,ij}^2}{\sum_{h=o}^{H-1} trace(A_h A'_h)} \times 100 \tag{3.11}$$

To examine the data, the spillover index described above allows the aggregation degree of cross-market spillovers across the large data, which consists of 2872 sample into a single spillover measure. We use second-order 23 variable with 10-step-ahead forecasts.

3.4.2. Net Spillovers

To generate the net volatility spillovers, we follow (Diebold and Yilmaz 2012) by first calculating the directional spillovers. It can be done through normalising the elements of the generalised variance decomposition matrix. This way, we can measure the directional volatility spillovers received by (developing) countries from the developed countries or vice versa as follow:

$$S_{i.}^{\dot{g}} = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}_{ij}^{\dot{g}}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{\dot{g}}(H)} .100 = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}_{ij}^{\dot{g}}(H)}{N} .100. \qquad (3.12)$$

Thus, from the above equation, the net volatility spillovers can be obtained from market i to all other markets j as follow:

$$S_{i}^{\dot{g}}(H) = S_{.i}^{\dot{g}} - S_{.i}^{\dot{g}}(H). \qquad (3.13)$$

3.4.3. Net pairwise spillovers

Given the net volatility spillover described in equation (3.12), which provides the net volatility of each market contribution to others, then it is relatively easy to examine the net pairwise volatility as follow:

$$S_{ij}^{\dot{g}}(H) = \left(\frac{\tilde{\theta}_{ji}^{\dot{g}}(H)}{\sum_{i,k=1}^{N} \tilde{\theta}_{ik}^{\dot{g}}(H)} - \frac{\tilde{\theta}_{ij}^{\dot{g}}(H)}{\sum_{j,k=1}^{N} \tilde{\theta}_{jk}^{\dot{g}}(H)} \right) .100 \qquad (3.14)$$

$$= \left(\frac{\tilde{\theta}_{ji}^{\dot{g}}(H) - \tilde{\theta}_{ij}^{\dot{g}}(H)}{N} \right) .100 \qquad (3.15)$$

Similarly, the net pairwise volatility spillover between market i and j represented by the difference between the gross volatility shocks communicated from market i to market j included those communicated from j to i.

3.4.4. ARCH Model

A basic autoregressive conditional heteroscedasticity (ARCH) model construct from two equations (a mean equation and a variance equation). The mean equation, which defines the behviour of the time series data mean. So, the mean equation is the linear regression function, which contains constant and other explanatory variables. in the following equation, the mean function only contains an intercept:

$$y_t \ = \beta + e_t \tag{3.16}$$

Considering the eq.3.15, the time series is expected vary about its mean (β) randomly. In this case, the error of the regression is distributed normally and heteroskedastic too. The variance of the current error period depends on the information, which revealed in the proceeding period (Poon 2005). However, the variance equation defines the error variance behaviour where the variance e_t is given the symbol h_t as follow:

$$h_t = a + a_1 e_{t-1}^2 \tag{3.17}$$

It is clear from eq.3.17 that h_t depends on the squared error in the proceeding time period (Bollerslev et al., 1994). Also, in this equation, the parameters have to be positive to ensure the variance h_t, is positive. In addition, the large multiplier (LM) test can also be used to examine the presence of ARCH effects in the data, (i.e., whether α>0). However, to carry out this test, we estimate the mean equation, then saved and squared the estimated residuals, $\hat{e}_t^2$. Then, for the first order ARCH model, we regressed $\hat{e}_t^2$ on the lagged residuals $\hat{e}_{t-1}^2$ and the following constant:

$$\hat{e}_t^2 = y_0 + y_1 \hat{e}_{t-1}^2 + v_t \tag{3.18}$$

Where, v_t represents the random term; and the null and alternative hypothesis are:

$$H_0: y_1 = 0$$

$$H_1: y_1 \neq 0$$

Table 7 shows the result of the large multiplier (LM) test which confirms the presence of ARCH in the data. So, the forecasted error variance is an in-sample prediction model essentially based on estimated variance function as follow:

$$\hat{h}_{t+1} = \hat{a}_0 + \left(r_t - \hat{\beta}_0\right)^2 \tag{3.19}$$

Figure 11 demonstrates the forecast error variance ($\left(r_t - \hat{\beta}_0\right)^2$ in a form of htarch, which reflects the years of my sample (2005 – 2016).

3.5. Empirical Results

3.5.1. Descriptive Statistics

Table 1 and 2 provide descriptive statistics of return and volatility spillovers, respectively. The underlying data consists of twenty-three[17] global currencies vis-á-vis the U.S. dollar and the sample size is 2871. Returns are calculated as a daily change in log price of close data (as described in the data section) and return

[17] Currencies from ten developed countries, the British pound (GBP), euro (EUR), Australian dollar (AUD), Canadian dollar (CAD), Swiss franc (CHF), Japanese yen (JPY), Icelandic krona (ISK), Czech Republic koruna (CZK), Singapore dollar (SGD), Hong Kong dollar (HKD) and South Korean won (KRW) and currencies from eleven developing countries including the Russian ruble (RUB), Turkish lira (TRY), Indian rupee (INR), Indonesian rupiah (IDR), Argentine peso (ARS), Malaysian ringgit (MYR), Thai baht (THB), Mexican peso (MXN), Saudi Arabian riyal (SAR), United Arab Emirates dirham (AED), South African rand (ZAR) and Nigerian naira (NGN).

volatilities as signified in equation (3.3) above. Currencies under research have been selected based on the most actively traded globally for both developed and developing countries. The augmented dicky-fuller (ADF) test results (Table 1 and 2) for each currency is statistically significant, which means currencies under investigation are stationery. For the return's series (Table 1), fourteen[18]currencies recorded little negative means denoting slight appreciation (during the sample period) against the U.S. dollar. Whereas seven currencies recorded small depreciation including the Swiss franc (CHF), Singaporean dollar (SGD), Thai baht (THB), Hong Kong dollar (HKD), Saudi Arabian riyal (SAR), United Arab dirham (AED) and the South African rand (ZAR). Kurtosis coefficients are significantly high for developing countries in both returns and volatility spillovers. These are exciting facts indicate that the data distribution is leptokurtic[19] which means the risk for the currencies of developing countries is coming from outlier events setting the ground for extreme remarks to arise. Moreover, the root means square-deviation[20] of volatility spillover series (Table 2) shows significant dispersion for eight developing countries.[21] For more elaboration on the data, see Table (1 & 2) below.

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[18] The euro, British pound (GBP), Australian dollar (AUD), Islandic krona (ISK), Czech Republic koruna (CZK), Turkey lira (TRY), Indian rupee (INR), Indonesian rupiah (IDR), Argentinian pesos (ARS), Malaysian ringgit (MYR), Mexican peso (MXN), South Korean won (KRW), Japanese yen (JPY) and the Nigerian naira (NGN).

[19] Leptokurtic distribution said to have positive statistical value with higher peaks around the mean compared to normal distribution which in most circumstances leads to thick tails on both sides.

[20] The root mean square-deviation is the other statistical term for the standard deviation.

[21] Countries are India, Indonesia, Argentina, Malaysia, Thailand, Mexico, South Africa and Nigeria.

Table 1: **Descriptive Statistics, Global Foreign Exchange Market Returns, 2005 -2016.**

Country	United Kingdom	European Union	Australia	Canada	Japan
Mean	0.000	0.000	0.000	0.000	0.000
Standard Error	0.005	0.006	0.008	0.006	0.007
Kurtosis	3.230	2.023	11.717	2.861	4.121
Skewness	0.408	-0.048	0.830	-0.036	-0.127
Minimum	-0.029	-0.036	-0.067	0.033	-0.044
Maximum	0.039	0.029	0.095	0.158	0.039
ADF	-51.4786**	-53.4031**	-55.7591**	-54.8177**	-58.9361**

Country	Switzerland	Iceland	Hong Kong	Czech Republic	Singapore
Mean	-0.000	0.000	-0.000	0.000	-0.000
Standard Error	0.007	0.010	0.000	0.008	0.003
Kurtosis	80.611	56.384	265.198	3.729	4.424
Skewness	-2.676	0.238	-9.076	0.222	0.057
Minimum	-0.157	-0.134	-0.032	-0.050	-0.022
Maximum	0.095	0.147	0.030	0.053	0.026
ADF	-53.7565**	-55.5139**	-44.7012**	-54.0658**	-54.7277**

Country	South Korea	Russia	Turkey	India	Indonesia
Mean	0.000	0.000	0.000	0.000	0.042
Standard Error	0.007	0.009	0.008	0.004	0.851
Kurtosis	32.781	45.221	7.001	5.945	2729.823
Skewness	0.408	0.736	0.788	1.172	51.701
Minimum	-0.103	-0.141	-0.053	-0.035	-0.098
Maximum	0.107	0.143	0.070	0.037	97.952
ADF	-50.3963**	-50.9994**	-53.9350**	-52.8286**	-54.2572**

Country	Argentine	Malaysia	Thailand	Mexico	Saudi Arabia
Mean	0.000	0.000	-0.000	0.000	0.000
Standard Error	0.007	0.004	0.005	0.007	0.012
Kurtosis	1657.464	5.182	149.717	13.351	42.832
Skewness	36.964	-0.369	1.659	0.962	0.568
Minimum	-.0.031	-0.035	-0.104	-0.061	-0.133
Maximum	0.355	0.029	0.115	0.081	0.153
ADF	-36.8414**	-53.5359**	-53.5815**	-23.8200**	-53.5792**

Country	United Arab Emirates	South Africa	Nigeria
Mean	-0.000	0.000	0.025
Standard error	0.008	0.011	1.385
Kurtosis	77.821	25.199	2870.718
Skewness	0.769	1.691	53.572
Minimum	-0.108	-0.065	-0.986
Maximum	0.122	0.175	74.250
ADF	-53.5681**	-28.1001**	-37.4842**

Notes: Returns are in real terms and measured by calculating the daily change in the log price of close data and the sample size is 2871. * P < 0.1; ** P < 0.05; *** P < 0.01.

Table 2: Descriptive Statistics, Global Foreign Exchange Market Volatility, 2005 – 2016.

Country	United Kingdom	European Union	Australia	Canada	Switzerland
Mean	0.000	0.000	0.002	0.000	0.000
Standard error	0.000	0.002	0.072	0.000	0.009
Kurtosis	111.561	2866.973	1433.442	107.130	2802.957
Skewness	8.004	53.520	37.873	7.968	52.685
Minimum	0.000	0.000	0.000	0.000	0.000
Maximum	0.002	0.150	2.765	0.002	0.506
ADF	-31.2667**	-53.5757**	-30.9404**	-32.0489**	-53.5742**

Country	Japan	Iceland	Czech Republic	Hong Kong	Singapore
Mean	0.000	0.000	0.000	0.000	0.000
Standard error	0.000	0.001	0.000	0.000	0.000
Kurtosis	259.795	1429.986	65.781	760.508	709.547
Skewness	12.947	35.395	6.512	25.702	20.668
Minimum	0.000	0.000	0.000	0.000	0.000
Maximum	0.003	0.088	0.003	0.000	0.001
ADF	-42.3771**	25.7536**	-30.9438**	-15.8937**	-28.6243**

Country	South Korea	Russia	Turkey	India	Indonesia
Mean	0.001	0.003	0.430	0.003	0.191
Standard error	0.088	0.155	23.055	0.128	2.665
Kurtosis	2871.851	2871.755	2871.999	1214.471	226.509
Skewness	53.588	53.587	53.591	34.377	14.893
Minimum	0.000	0.000	0.000	0.000	0.000
Maximum	4.751	8.310	1235.575	4.7415	42.769
ADF	-53.5699**	-53.5818**	-53.5817**	-53.6088**	-19.8196**

Country	Argentine	Malaysia	Thailand	Mexico	Saudi Arabia
Mean	0.000	-0.000	0.001	0.000	0.000
Standard error	0.000	0.004	0.088	0.000	0.000
Kurtosis	38.627	2843.605	2871.925	658.920	2785.065
Skewness	5.767	53.194	53.589	22.598	52.431
Minimum	0.000	0.000	0.000	0.000	0.000
Maximum	0.002	0.246	0.726	0.014	0.029
ADF	-36.8414**	-53.5359**	-53.5815**	-23.8200**	-53.5792**

Country	United Arab Emirates	South Africa	Nigeria
Mean	0.000	0.000	0.025
Standard error	0.000	0.021	0.541
Kurtosis	2854.287	2868.012	750.063
Skewness	53.347	53.535	25.985
Minimum	0.000	0.000	0.000
Maximum	0.003	1.161	18.821
ADF	-53.5681**	-28.1001**	-37.4842**

Notes: Volatilities are for daily spot closing returns. We employ high-frequency intra-day data (high, low, opening and closing) to obtain the returns volatilities using formulae (3.3) described above. The sample size is 2871, consult text for more elaboration. * $P < 0.1$; ** $P < 0.05$; *** $P < 0.01$.

3.5.2. Return and Volatility Spillovers: Static Analysis (Spillover Tables)

Now, we turn to offer an in-depth analysis of return and volatility spillover transmission across global foreign exchange markets by interpreting the spirit of spillover indexes based on Diebold and Yilmaz (2009). The study comprises two steps. First, we provide full static-sample analysis, and then successively proceed to interpret the dynamic rolling-sample version. By employing the spillover index, we extract return and volatility spillovers throughout the entire sample (2005 – 2016). Thus, we present the spillover indexes for both "returns and volatilities" in Table 3 and 4, respectively. The variables (i, j) placed under each table represent the contribution projected to the variance of the 10-week-ahead[22] real foreign exchange (returns Table 1 and volatility Table 2) forecast error of country i coming from innovations to the foreign exchange (returns Table 1 and volatility Table 2) of country j.

In both tables, the lower corner of the first column from the right sums the "contributions from others" and similarly from the left sums the "contribution to others." Intuitively, the spillover tables designed to delineate the input and output decomposition of the spillover index. Both products "input and output" help to successfully scrutinise the effect of return and volatility spillovers of global foreign exchange markets across developed and developing countries. With regard to return spillover (Table 3), touching on developed countries' "contribution to others", we observe that the GBP and the EUR are responsible for the most significant shares of the error variance in forecasting 10 week-ahead, totalling 102 percent and 100 per cent respectively. However, in contrast to each other's contribution, the innovations to the GBP returns are accountable for 99 percent of the error variance in forecasting 10- week-ahead EUR returns whereas, changes to the EUR returns are responsible

[22] Based on weekly vector auto-regressions of order 2, the results were generated and identified by a Cholesky factorisation.

for just 99.9 per cent of the error variance in forecasting 10-week-ahead GBP returns. In other terms, return spillover from the GBP to the EUR and vice versa are almost the same. In addition, there is insignificant return contribution coming from developed to developing countries; one exception is the Mexican peso (MXN) which received the sums of 11 per cent, 1.2 per cent and 8.3 per cent from the British pound (GBP), euro (EUR) and the Australian dollar (AUD).

Moreover, in contrast with the return contribution coming from developing countries' to developed countries again, the contributions account for almost zero percent. However, return spillover amongst developed countries is sizeable and positive, such that innovations to/from each country's returns effectively raise and fall together. This means there are tremendous cross-market interconnectedness and financial interdependence amid developed countries. In contrast, return spillover among developing countries again is trivial at best or virtually none existence. A point worth noting, the results show that all countries (developed and developing) during the years of the sample (2005 – 2016) their "own" return contribution is significantly high.

For example, in Table 3, return, the 99% estimated contribution to the forecast error variance of the GBP returns (in 10-week-ahead forecasting) is entirely due to innovations to its "own" returns, and similarly for the EUR is 99.9 per cent, ISL and CZE are 43 per cent and 78 per cent, respectively. This is per se reflects on the proportion of "contribution from others." It is also clear from Table 3, return; that developed countries receive the highest "contribution from others" led by the Czech Republic 38 per cent, Canada 31 per cent, Japan and South Korea 24 per cent equally. Interestingly, the GBP "contribution from others" account for only 1 per cent.

Table 3

Spillover Table. Global Foreign Exchange (FX) Market Return, 31/05/2005 – 01/06/2016

From

	UK	EU	AUS	CAN	CHE	JPN	ISL	CZE	HKG	SGP	KOR	RUS	TUR	IND	IDN	ARG	MYS	THA	MEX	SAU	ARE	ZAF	NGA	From Others
UK	**99.0**	0.0	0.0	0.4	0.0	0.1	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	1
EU	0.0	**99.9**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
AUS	0.0	0.0	**99.3**	0.0	0.0	0.1	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.0	0.0	1
CAN	0.7	0.0	0.0	**69.1**	0.0	11.6	10.3	4.9	0.4	0.5	0.5	0.0	0.0	0.0	0.0	0.4	0.0	0.3	1.2	0.0	0.2	0.0	0.0	31
CHE	0.0	0.0	0.0	0.0	**100**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
JPN	0.4	0.0	0.0	11.4	0.0	**75.8**	0.9	6.0	0.5	0.5	0.9	0.0	0.0	0.0	0.0	0.2	0.0	0.3	3.1	0.0	0.0	0.0	0.0	24
ISL	0.1	0.0	0.0	0.3	0.0	3.8	**88.2**	0.2	0.2	0.1	0.1	0.0	0.0	0.0	0.0	0.2	0.0	0.5	6.3	0.0	0.0	0.0	0.0	12
CZE	0.3	0.0	0.0	22.1	0.1	11.3	1.1	**61.5**	0.3	1.7	0.1	0.0	0.0	0.0	0.0	0.3	0.0	0.5	0.5	0.0	0.0	0.0	0.0	38
HKG	0.1	0.0	0.0	0.8	0.0	0.5	0.1	0.2	**97.8**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.3	0.0	0.0	0.0	0.0	2
SGP	0.3	0.0	0.0	5.8	0.0	3.8	0.4	7.8	0.2	**80.9**	0.1	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.4	0.0	0.0	0.0	0.0	19
KOR	0.0	0.0	0.0	0.1	0.0	0.4	0.2	0.1	22.7	0.0	**76.0**	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.1	0.0	0.0	0.0	0.0	24
RUS	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**99.6**	0.0	0.0	0.0	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
TUR	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	**99.7**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
IND	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**99.9**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
IDN	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	**99.7**	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0
ARG	0.2	0.0	0.0	1.6	0.0	5.4	0.5	2.7	0.3	0.2	0.1	0.0	0.0	0.0	0.0	**85.1**	0.0	1.4	0.8	0.0	0.0	1.6	0.0	15
MYS	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**99.9**	0.0	0.0	0.0	0.0	0.0	0.0	0
THA	0.0	0.0	0.0	0.1	0.0	0.4	0.2	0.1	22.7	0.0	76.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.3**	0.1	0.0	0.0	0.0	0.0	100
MEX	0.1	0.0	0.0	2.5	0.0	5.9	63.8	1.8	0.1	0.3	0.2	0.0	0.0	0.0	0.0	0.2	0.0	0.3	**24.7**	0.0	0.0	0.0	0.0	75
SAU	0.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**99.3**	0.0	0.0	0.0	1
ARE	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	**99.8**	0.0	0.0	0
ZAF	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.4	0.0	0.5	0.0	0.0	0.0	**98.0**	0.0	2
NGA	0.0	0.0	0.0	0.1	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.2	0.0	0.0	0.0	**99.3**	1
Contribution to others	3	0	0	45	0	43	78	24	47	3	78	0	0	0	0	3	0	5	13	0	0	2	0	347
Contribution including own	102	100	99	114	100	119	166	86	145	84	154	100	100	100	100	89	100	5	38	99	100	100	99	15.1%

Note: The fundamental variance decomposition is based on weekly (VAR) of order 2 identified using Cholesky factorisation. The value of (i, j)variables is the estimated contribution to the variance of the 10-day-ahead real foreign exchange (FX) return forecast error of country i coming innovations to real FX returns of country j.

Turning the attention to the global foreign exchange volatility spillover, Table 4, the results show that the total volatility spillover transmission from developed countries (that is a total contribution to others) to developing countries and vice-versa is insignificant. Also developed countries contribute significantly to their "own" total volatility spillover. This result is in line with the argument that the currency crisis tends to be regional (Glick and Rose 1998; Yarovaya et al., 2016). The results also show that intra-regional volatility spillover transmission tends to be significantly higher than the inter-regional volatility spillover. Table 4 highlights the total volatility spillover from the U.K to the Eurozone, Czech Republic, Switzerland, Turkey and Iceland is considerably significant.

Similarly, the total volatility spillover from the Eurozone to the Czech Republic, Switzerland and Iceland is also relatively high and sums to 38.8 percent, 26.8 per cent and 9.6 per cent respectively. This means the British pound (GBP) and the euro (EUR) are the most significant contributors of volatility spillover to others. Another exciting result that the EUR "own" contribution to its total volatility spillover by 65 per cent is considerably high. Again, this result is also in line with the findings presented by Melvin and Melvin, (2003); Cai et al., (2008) and Barunik et al., (2016) that significant volatility spillover transmitted amid currencies within a particular market.

Moreover, this study also documents unidirectional volatility spillover amongst major European currencies. It is clear from Table 4 the total volatility spillover from the EUR to the CZK (that is, EUR contribution to others) is interestingly high. On the other hand, the total volatility spillover of 28 per cent from the GBP to CZK is relatively less compared to the EUR contribution. The EUR is also significantly contributing to the CHF total volatility spillover by 31 per cent, and that is almost double the GBP contribution, which is 18 per cent.

This phenomenon is in line with the findings of Antonakakis (2012) that the EUR-CHF exchange rates move closely together. Also, about the total volatility spillover "contributions from others," the CZK received the largest shares of the total volatility spillover "contribution from others" amount to 67 per cent. The CHF follows it and the EUR which are receiving total volatility of 53 and 35 per cent, respectively.

On the contrary, the GBP receives only 5 per cent of the total "contributions from others," setting its "own" volatility spillover contribution to 95 per cent. The intra-foreign exchange market's cross volatility spillover effect in the European region (Eurozone and non-Eurozone currencies) regarding "contributions to others" is unsurprisingly dominated by the GBP and the EUR. Besides, the EUR also receives a generous amount of the total volatility spillover "from others." Again, the result is in line with the findings presented by Antonakakis (2012); and Barunik et al., (2016) who found the GBP and the EUR to be the dominant net transmitters and receivers of volatility spillover during the period (2000 – 2013).

Shedding more light on volatility spillover transmissions, there is non-negligible unidirectional volatility spillover from the British pound (GBP), euro (EUR) and the Australian dollar (AUD) to East Asian's financial hub, Singapore. Table 4 reports that the total volatility spillover from those currencies to Singaporean dollar (SGD) recorded at 24 per cent, 19.3 per cent, and 10.7 per cent, respectively. This is a clear indication of the insignificant financial interconnectedness between the three regions. Moreover, as a non-developed country, Mexico has also received notable unidirectional volatility spillover from Australian dollar, British pound, Turkish lira, and the euro with the total of 16.4 per cent, 12.3 per cent, 11.8 per cent and 2.2 per cent, respectively. Followed by Indonesia, India, Thailand and South Africa similarly received non-marginal volatility spillover mainly from developed countries.

Table 4

<u>**Spillover Table: Global Foreign Exchange (FX) Market Volatility, 31/05/2005 – 01/06/2016**</u>

	From																							
	UK	EU	AUS	CAN	JPN	CHE	ISL	HKG	CZE	SGP	KOR	RUS	TUR	IND	IDN	ARG	MYS	THA	MEX	SAU	ARE	ZAF	NGA	From Others
UK	**97.4**	0.0	0.2	0.4	0.0	0.1	0.2	0.0	0.6	0.1	0.0	0.2	0.3	0.0	0.0	0.0	0.1	0.0	0.2	0.0	0.1	0.0	0.1	3
EU	39.4	**59.0**	0.3	0.0	0.0	0.2	0.1	0.1	0.2	0.0	0.1	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	41
AUS	24.8	6.2	**62.5**	1.5	0.0	0.3	0.7	0.0	0.2	0.2	0.1	0.1	1.4	0.1	0.0	0.0	0.1	0.0	1.4	0.1	0.1	0.2	0.0	37
CAN	24.6	5.4	15.0	**53.2**	0.0	0.1	0.1	0.0	0.4	0.0	0.0	0.1	0.3	0.1	0.0	0.0	0.2	0.0	0.1	0.1	0.0	0.0	0.0	47
JPN	0.1	0.1	0.1	0.1	**98.1**	0.0	0.4	0.0	0.1	0.2	0.1	0.1	0.1	0.0	0.1	0.0	0.0	0.0	0.1	0.0	0.2	0.0	0.0	2
CHE	17.8	26.8	0.4	0.6	0.0	**53.0**	0.0	0.3	0.3	0.1	0.1	0.0	0.1	0.1	0.0	0.0	0.2	0.0	0.0	0.1	0.0	0.0	0.0	47
ISL	14.4	10.7	1.2	0.3	0.1	0.4	**69.4**	0.4	0.1	0.4	0.3	0.0	0.1	0.0	0.0	0.1	0.1	0.1	1.9	0.0	0.0	0.1	0.0	31
HKG	0.9	1.0	1.5	0.1	0.1	0.0	0.3	**94.5**	0.1	0.0	0.2	0.1	0.1	0.0	0.0	0.0	0.2	0.2	0.1	0.0	0.0	0.1	0.3	5
CZE	33.7	38.8	0.8	0.4	0.0	0.1	0.1	0.0	**25.3**	0.0	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.2	0.1	0.0	0.1	0.0	75
SGP	26.9	14.2	10.2	1.3	0.1	0.4	0.2	1.9	0.5	**43.1**	0.1	0.1	0.1	0.1	0.1	0.0	0.2	0.0	0.3	0.3	0.0	0.1	0.0	57
KOR	8.1	1.7	9.2	1.3	0.1	0.1	1.0	0.2	0.5	7.1	**64.7**	0.0	2.2	0.4	0.1	0.1	0.4	0.0	1.7	0.1	0.0	1.0	0.1	35
RUS	0.1	0.2	0.1	0.1	0.1	0.1	0.1	0.0	0.1	0.1	0.1	**98.1**	0.0	0.1	0.1	0.	0.1	0.0	0.4	0.0	0.0	0.0	0.0	2
TUR	13.2	4.3	10.2	3.5	0.1	1.2	0.6	0.0	1.8	1.1	0.4	0.1	**61.9**	0.0	0.0	0.0	0.0	0.0	0.9	0.1	0.0	0.5	0.0	38
IND	6.8	1.6	4.8	0.9	0.3	0.1	0.3	0.2	0.1	2.9	1.7	0.2	2.0	**76.1**	0.2	0.0	0.3	0.0	1.1	0.1	0.0	0.3	0.0	24
IDN	0.0	0.1	0.0	0.1	0.3	0.1	0.0	0.3	0.0	0.1	0.0	0.2	0.1	0.0	**98.2**	0.0	0.0	0.0	0.3	0.0	0.0	0.0	0.0	2
ARG	0.1	0.0	0.4	0.1	0.1	0.0	0.0	0.0	0.0	0.2	0.1	0.1	0.0	0.0	0.2	**98.3**	0.1	0.0	0.1	0.0	0.0	0.0	0.0	2
MYS	7.2	3.8	5.3	2.1	0.1	0.2	0.1	0.8	0.2	13.0	2.1	0.1	1.2	2.5	0.2	0.1	**59.6**	0.0	1.2	0.1	0.0	0.2	0.0	40
THA	1.8	1.3	1.0	0.1	0.1	0.2	0.1	0.3	0.1	3.3	0.2	0.0	0.4	0.8	0.1	0.0	0.6	**89.4**	0.0	0.0	0.0	0.0	0.0	11
MEX	14.4	2.7	8.7	8.4	0.0	1.1	0.2	0.2	2.0	3.6	0.4	0.1	4.7	0.3	0.3	0.0	0.2	0.0	**52.7**	0.1	0.0	0.0	0.0	47
SAU	0.1	0.1	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.1	0.0	0.2	0.1	0.0	0.1	0.1	0.0	0.0	**98.5**	0.6	0.0	0.0	2
ARE	0.0	0.0	0.1	0.1	0.3	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.6	**98.6**	0.0	0.0	1
ZAF	18.5	5.1	10.7	4.	0.1	0.3	0.7	0.1	2.1	2.6	0.2	0.1	9.4	0.0	0.0	0.0	0.0	0.0	5.7	0.0	0.0	**39.5**	0.0	60
NGA	0.1	0.2	0.0	0.0	0.1	0.2	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.0	0.1	0.0	0.0	0.0	**98.8**	1
Contribution to others	253	124	80	26	2	5	5	5	9	35	6	2	23	5	2	1	3	1	16	2	1	3	1	610
Contribution including own	351	183	143	79	100	58	75	99	35	78	71	100	85	81	100	99	63	90	68	100	100	42	99	26.5%

Note: The fundamental variance decomposition is based on daily (VAR) of order 2 identified using Cholesky factorisation. The value of (i, j) variables is the estimated contribution to the variance of the 10-day-ahead foreign exchange volatility forecast error of country i coming from innovation to the foreign exchange volatility of country j.

Following the discussion of the static version of volatility spillover transmission across global foreign exchange markets during the years of the sample, (2005 – 2016); a key finding is that developed countries contribute substantially to the total volatility transmitted (that is, contributions to others) and received (that is, contributions from others).

On the other hand, developing countries are receiving a non-negligible amount of volatility spillover "from others," and their shares of "contribution to others," are trivial at best. Put more formally. We find that developed countries act as receiver and transmitter of volatility, dominated by the British pound (GBP), Australian dollar (AUD), and the euro (EUR), whereas developing countries are a net receiver of volatility, dominated by Mexico, Indonesia, and India.

So far, we have shown evidence of return and volatility spillovers based on the static version analysis of the spillover indexes presented in table 3 (return) and table 4 (volatility). The indexes of 15.1 percent (for return) and 26.5 percent (volatility) represent the extracted cross-country spillover for the full sample (January 2005 – July 2016), which means virtually 26.1 percent of the forecast error variance comes from the spillover. Aside from scrutinising the broader static effect of return and volatility spillover across the global foreign exchange markets (between developed and developing countries), we now turn to provide a different fashion of the dynamic movement of return and volatility spillover effect.

3.5.3. Return and Volatility Spillovers: Dynamic Analysis (Spillover Plots)

To address the extent of the spillover effect between developed and developing countries we use 200-day rolling samples, which is about six months. The 200-day rolling sample used to demonstrate the spillover variations over time between developed and developing countries since the data we use spans over 2005-2016. The dynamic movement of return and volatility spillovers is designed to capture the effect of the potential recurring movement of spillover by using returns and volatility indexes shown in Table 3 and 4, respectively. The indexes are the sums of all variance decompositions represented in the form of "contribution to others." Employing the indexes, we estimate the model using 200-day rolling samples to scrutinise the evolution of global foreign exchange markets during the years of the sample (2005 – 2016).

Hence, we capture the magnitude and disparities of the spillover for return and volatility, which we present graphically in the form of spillover plots. The era of the 2000s, which began with a recession mainly in developed countries across the European Union and the U.S. undisputedly, documented painful economic events in our history, in particular, the 2007/08 global financial turmoil. Thus, figure 1 for (return's spillover) captured some of the critical events, whereas figure 2, (volatility spillover) appears to be most eventful.

Interestingly, the 200-week rolling samples epitomised in figure 1 and 2 highlighted some of the significant economic events that occurred during the years of the sample (2005 – 2016). As the estimation window moves towards the year 2016, we have captured the following critical economic events;

1. The U.S housing bubble worries, according to Liebowitz (2008) foreclosure rates increased by 43 per cent during the 2nd and the 4th quarter of the year 2006. Subsequently, the mortgage default rates increased significantly.

2. The increasing of foreclosures and mortgage default rates reached about 55 per cent for (prime), and 80 per cent (subprime) hugely devalued mortgage-back-securities at the end of 2007, causing a severe credit crunch.

3. During the same year, the British bank Northern Rock collapsed.

4. Followed by Lehman Brothers, the biggest U.S. investment bank then, filed for bankruptcy on September 15, 2008.

5. Following the above events, among others, comes the worst financial turmoil (2007-2009) since the great depression of (1929 – 1939).

6. The Greece debt crisis, December 2009.

7. The series of European sovereign debt crisis (2009 – 2013),

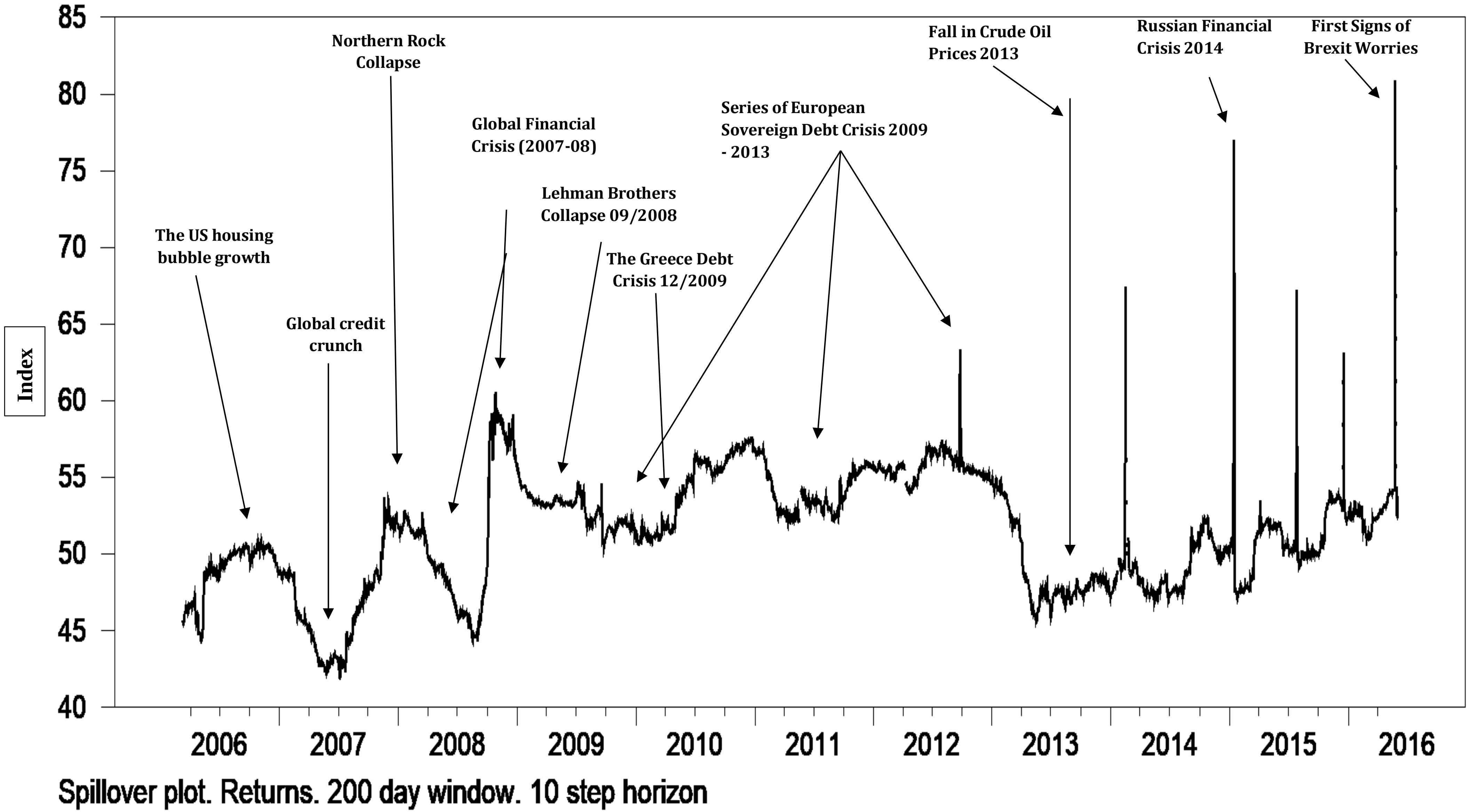
8. The fall in Crude oil prices in 2014.

9. Russia financial crisis (2014 – 2017) according to the Centre for Eastern Studies (OSW), the leading causes of the Russian crisis are the tensions between Russia and the west which led to sanction war, and the dramatic fall in oil prices.

11. First signs of Brexit[23] worries on June 23, 2016, whereby the British pound plunged to its lowest level since 1985.

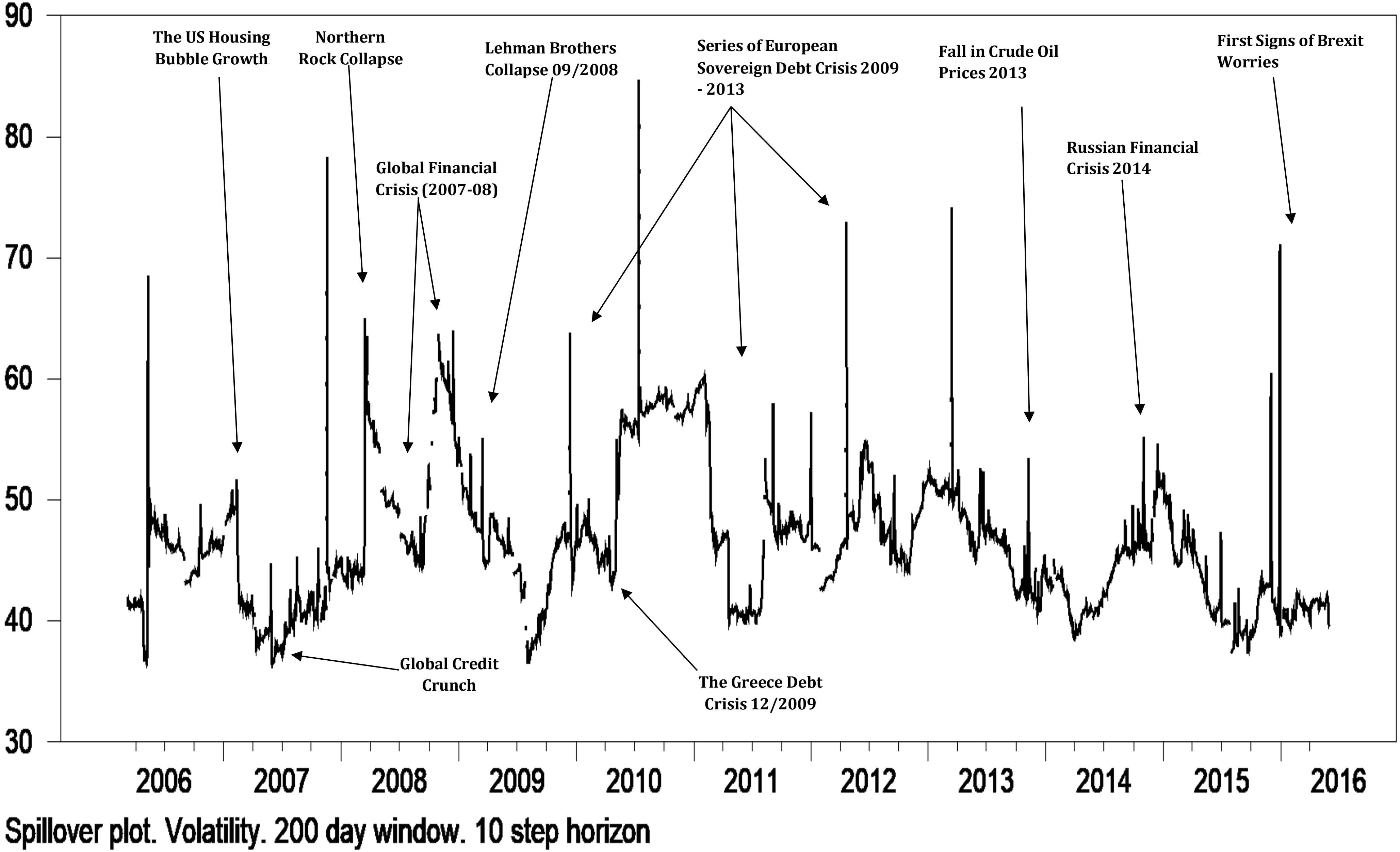
[23] Brexit is the abbreviation for British exist which refers to the "in" or "out" referendum whereby the British citizens have voted to exit the European Union on June 23, 2016.

Figure 1.



Ending Date of Window

Figure 2.



Ending Date of Window

The graphical illustrations above (Fig1 and Fig2) highlight important economic events during the years of the sample (2005 – 2016). The analysis orchestrated here, visually signalise the effect of spillover across intra-foreign exchange markets. The magnitude and extent of the spillover effect of both returns (figure 1) and volatility (figure 2) significantly marked by the crisis episodes of (2007 – 09) financial turmoil. In particular, the series of European sovereign debt crisis (2009 – 2014) and China stock market crash (2015), among others. This means, interestingly, besides volatility spillover, the contribution of return spillover is unexpectedly significant enough to show some commonality with volatility spillover in terms of responding to economic events. Further, we also observe bursts in total return and volatility spillovers which materialised twice in figure 1 and four times in figure 2, respectively. The total return's spillover began to decrease slightly after its strong response to the (2007 – 09) financial turmoil as well as the European sovereign debt crisis in 2009 until China stock market crash in (2015), whereby it shows a dramatic increase.

On the contrary, volatility spillover fluctuated with explicit outbursts virtually with every single economic event highlighted during the years of the full sample (2005 – 2016). Put it differently, the volatility spillover plot (figure 2), depicted the phenomenon of the globally systemically important financial institutions from a series of historical defaults involved too big to fail nature. To check the robustness of the result regarding rolling window width, forecast horizon, and VAR ordering, we perform spillover plots (figure 3) using a 75-week rolling window width. We also used two different variance decomposition forecast horizons; 10-weeks forecast horizon in figure 3 (a) and 2-weeks in figure 3 (b). The results are robust even when employing maximum and minimum volatility spillover across a diversity of alternative VAR ordering using 200-week rolling windows, see (figure 3 and 4).

Figure 3.

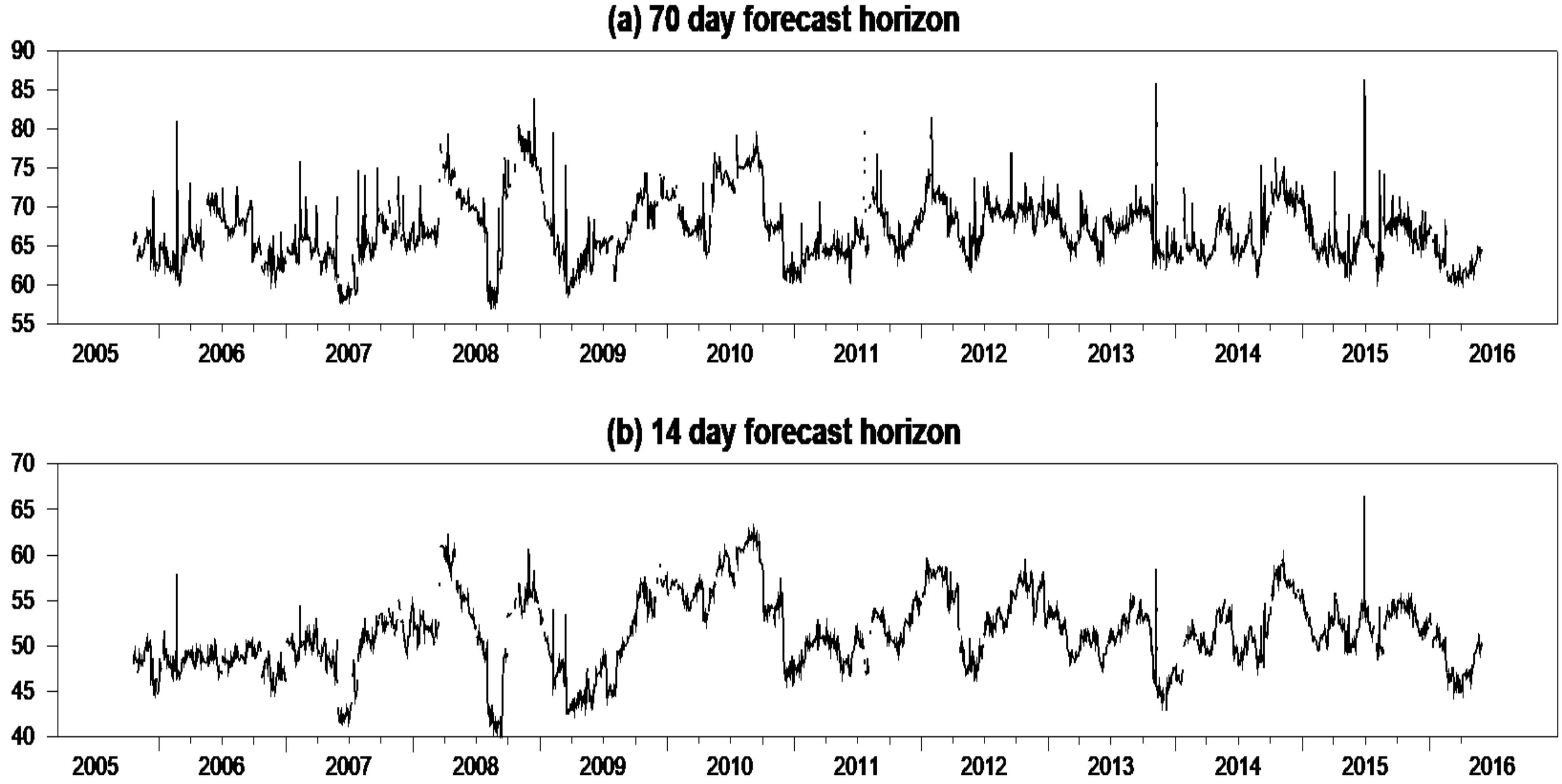


Figure 3 Spillover plot, Global FX Market Volatility
100 day Rolling Window

Figure 4.

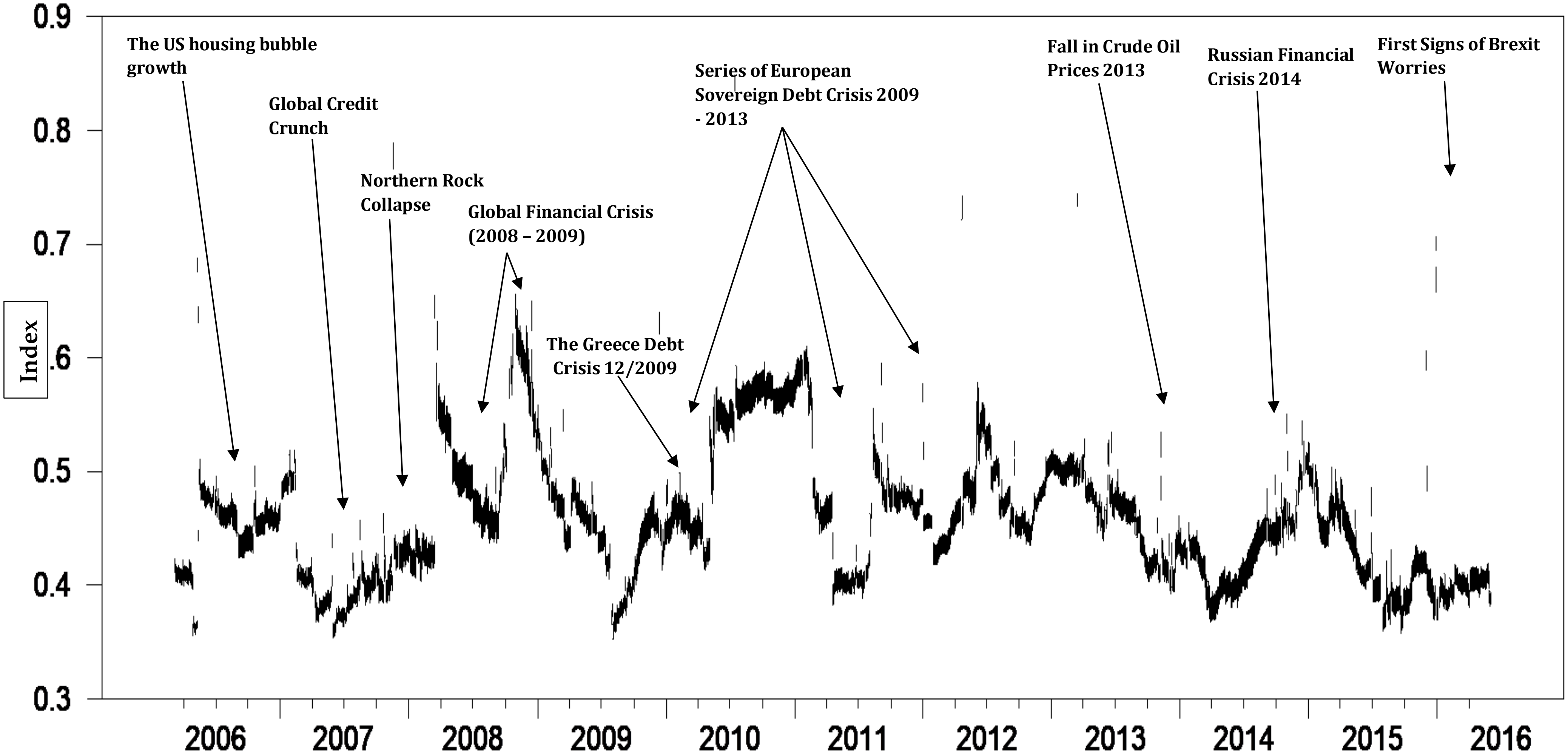


Figure 4. Maximum and minimum spillovers
Randomly Chosen Orderings

Ending Date of Window

3.5.4. Robustness Analysis

Based on the extent of the above results, the maximum and minimum spillover figure 4, shows the variability of the volatility spillovers' magnitude in global foreign exchange markets, which appears to be relatively higher than return spillover. Notwithstanding, we find the behaviour of return spillover in the global currency markets (figure 1) substantially responding to major economic events during the years of the full sample (2005 – 2016). In contrast with the global stock market, Diebold and Yilmaz (2009) found the behaviour of return spillover insignificant and do not bear much resemblance with the behaviour of volatility spillover. In thinking about the magnitude and extent of return and volatility spillovers effect across global foreign exchange markets, it is useful to reflect on the indexes used to perform the spillover analyses, which are "contribution to others" indexes.

Since we find "contribution to others" mainly dominated by developed countries, in particular, the British pound (GBP), euro (EUR), and the Australian dollar (AUD), that make developing countries act as net receivers to return and volatility spillovers. Further, according to the Bank for International Settlements' (BIS) report (2013), the USD, EUR, GBP, AUD, CAD, JPY and the CHF are the most traded globally, account for almost 90 per cent of the global foreign exchange turnover. This means, a substantial amount of return and volatility spillovers transmitted across countries during the years of the full sample (2005 – 2016) which certainly reflected in the above results, (Figs 1, 2, 3 and 4). The findings are robust even when employing maximum and minimum volatility spillover across a diversity of alternative VAR ordering using 200-week rolling windows.

Interestingly, the results highlight the significance of the global foreign exchange markets' spillover channels during crisis periods in several dimensions. One is the cyclical bursts in spillover occurs as a consequence of the significant economic events. Including, the credit crunch of July 2007, Lehman Brothers collapsed in September 2008, the financial turmoil which created havoc during 2007 – 09, the European sovereign debt crisis 2009 – 14 and the fall in Crude oil prices in 2013.

Two, it highlights the potential magnitudes of the spillover effect, particularly from the default of systemically important financial institutions across the global financial system, which spread jitters from the outset of the U.S. subprime mortgage crisis. Three, the size of the shocks which led to bursts in spillover (see, figs. 1, 2, 3 and 4) suggest strong cross-market interconnectedness which reflects the definition of "contagion" presented by Forbes and Rigobon (2002).[24] Four, the results also provide significant insights, particularly to the financial regulators from the perspectives of understanding the effect of spillover from the default of systemically important financial institutions. Finally, they also introduce for investors the issue of cross-market linkages and economic interdependence during crises periods whereby volatility spillover increases substantially.

[24] Forbes and Rigobon (200) defined contagion as "a significant increase in cross-market linkages after a shock to one country or group of countries."

3.6.Time-varying volatility spillovers

In this section, we present the results of the time-varying volatility spillover among developed and developing countries; using autoregressive conditional heteroskedasticity (ARCH). Time varying volatility helps investigate sources of significant shifts in the volatility during the years of our sample (2005 – 2016). This is because ARCH models designed to capture persistence in time varying volatility based on squared returns (Poon, 2005). we begin by illustrating graphically the spillover indices of the developed and developing currencies. The results (Figs. 1 to 6) show that all the currencies in the sample from both (developed and developing) countries are characterised by clustering volatility. Also, the volatility seems to be changing rapidly over time. This indicates that the global foreign exchange market (apart from the Australian dollar, Hong Kong dollar, Indonesian rupiah, and the Argentine peso) experiences somewhat relatively sedate volatility spillovers from 2005 to 2007.

Then, the foreign exchange market's volatility spillovers become much more volatile in 2008, 2013 and 2015. These results are consistent with the dynamic analysis of the spillover indices (Fig 2) which captured the 2008/09 financial crisis, the European sovereign debt crisis 2009/13, and the Russian crisis 2014/15. Figures 1-6 show significant increases of volatility spillovers reflected in the CAD, CHF, JPY, ISK, CZK, HKD, SGD, KRW, TRY, and the Argentine peso (ARS) during the 2008/09 financial crisis. Moreover, the same Figures 1-6 show significant increases of volatility spillovers in the GBP, EUR, CZK, INR, IDR, ARS, and the Malaysian ringgit during the 2009/13 European sovereign debt crisis. These results are also in line with the finding of (Barunik et al., 2017) that the euro and the pound sterling are ''net giver and receiver of volatility spillover.'' This argument also supports the results from the static analysis of volatility spillover Table 4; that developing countries such as the INR, IDR, and the Argentine peso (ARS) are net receiver of volatility.

Figure 5.

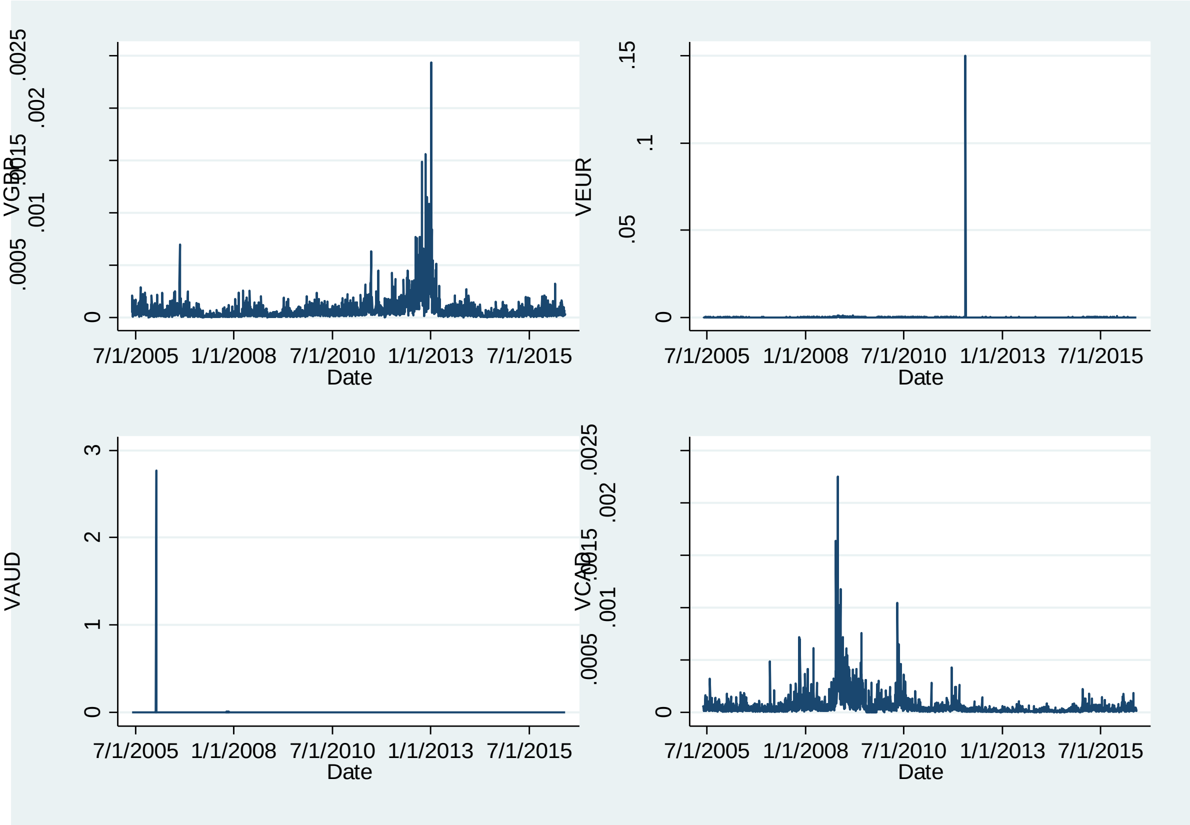


Figure 6.

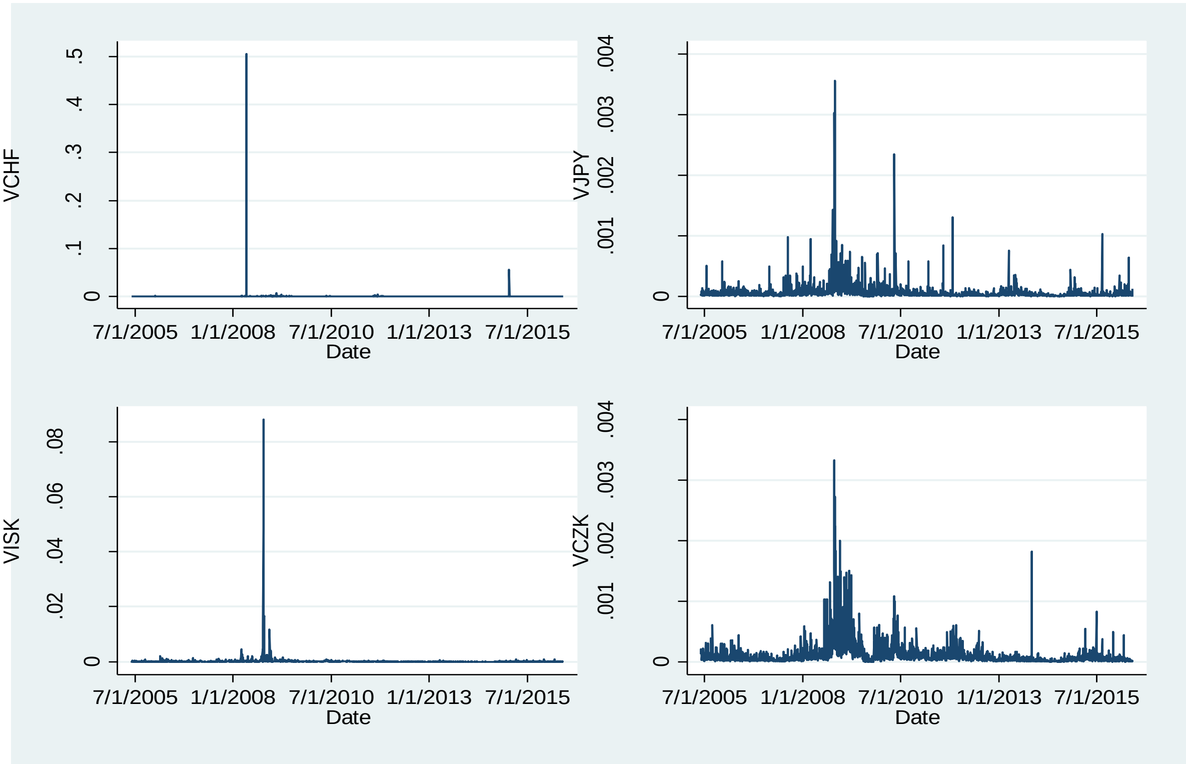


Figure 7.

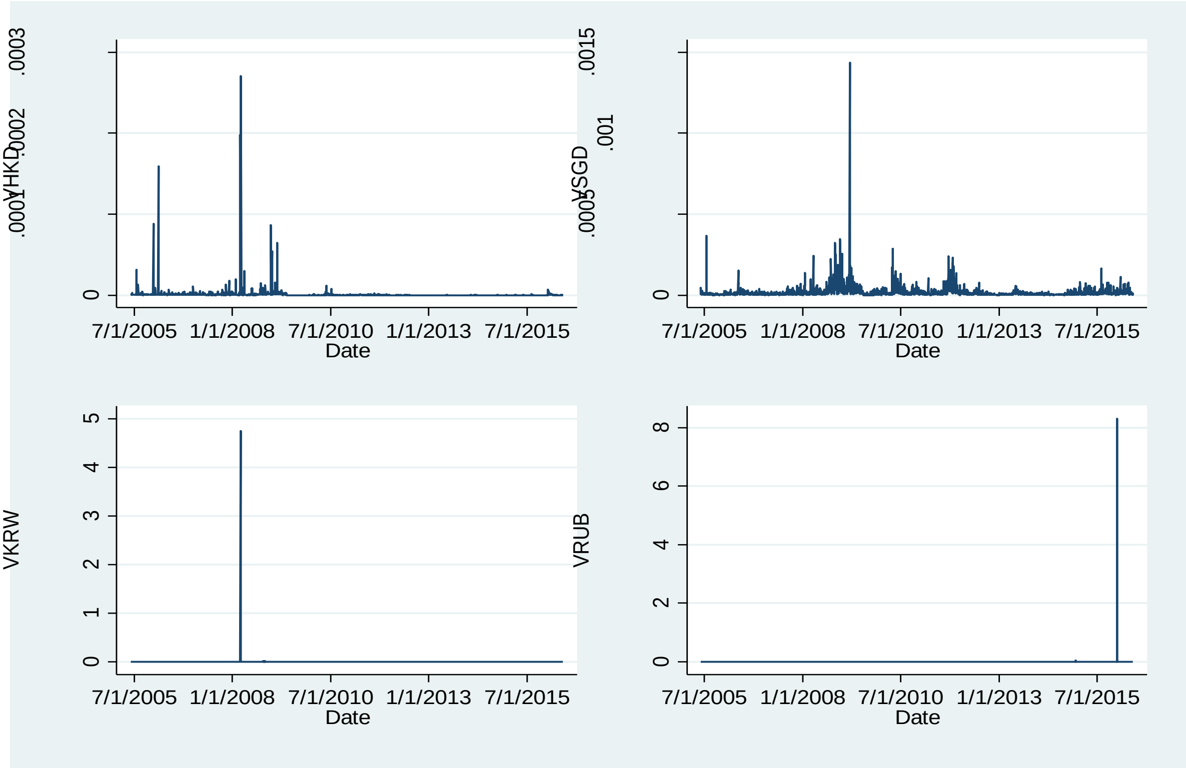


Figure 8.

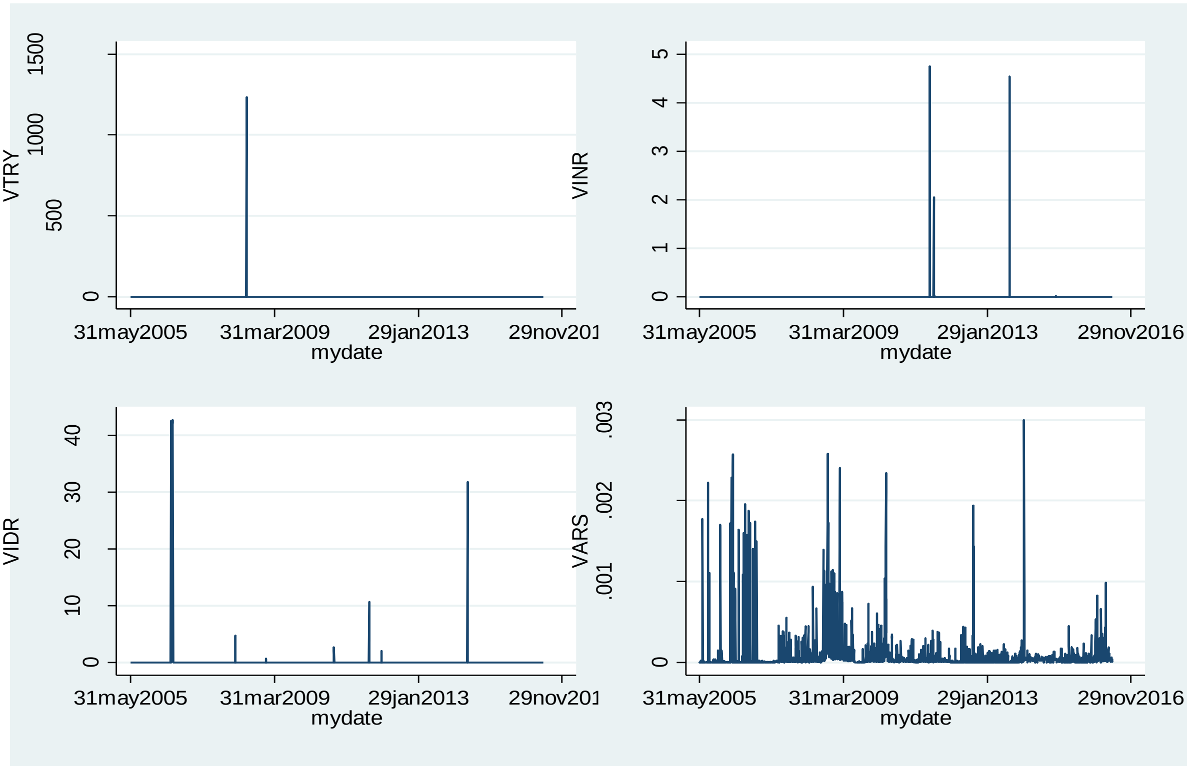


Figure 9.

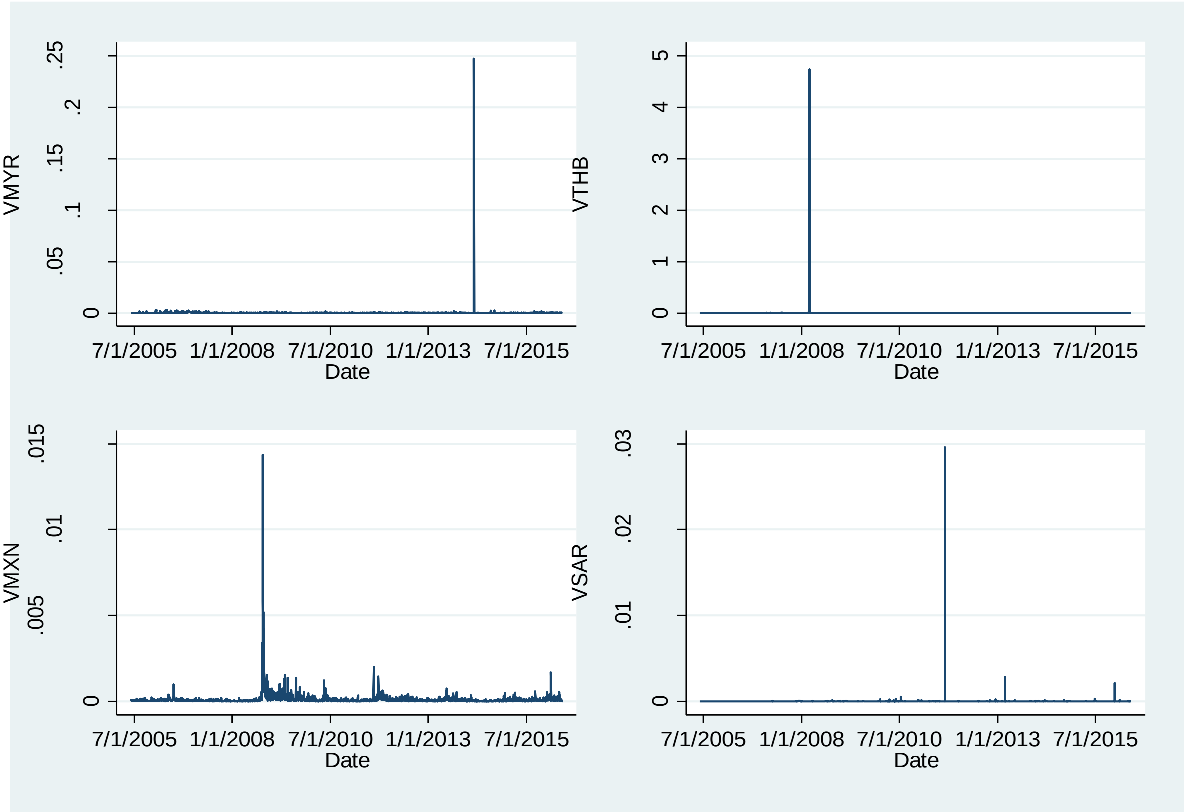
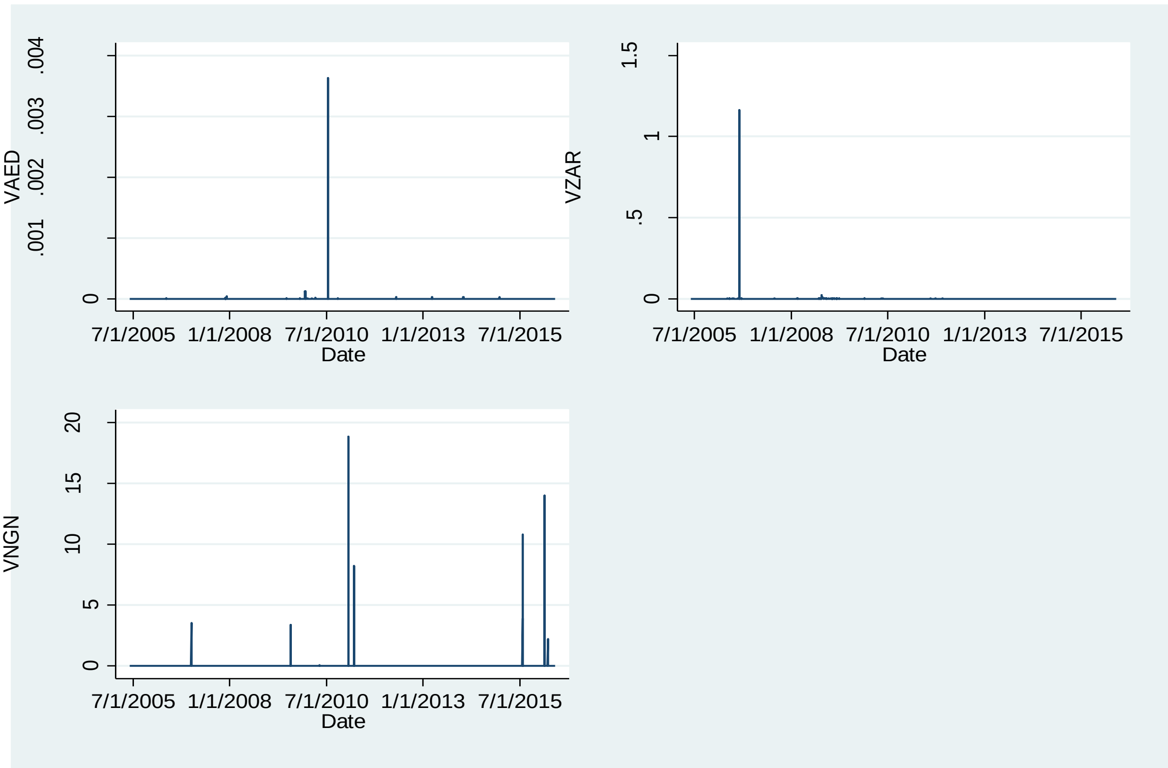


Figure 10.



Moreover, to investigate the time-varying's volatility fluctuations among (developed and developing countries) over different time periods of our sample; we use the Arch model described in section 2.3.4 above. This is due to the nature of the Arch model where 'autoregressive' means high volatility tends to persist, 'conditional' refers to time-varying or specific point on time, and 'heteroskedasticity' refers to non-constant volatility(Poon, 2005). Before applying the Arch (1) model, we first generate the squared residuals using regression, which contains only an intercept.[25] Table 5 shows the regression result of the squared residuals, which called ehat2. This is because the squared residuals ensure that the conditional variance is positive and consequently, the leverage effects can not be captured by the Arch model (Engle, 2001b).

Table 5: Regression (ehat2 L.ehat2)

Variable	Adjusted t^*	p-value
Ehat2	8.12	0.000
No obs: 2.871;	R – squared: 0.022; Adj R-squared: 0.022;	MSE: 1.3e-07

Second, we test the data for the presence of Arch effects using the Box-Pierce large multiplier (LM), which provides the most appropriate results (Alexander, 2001). Table 6 displays the result of the large multiplier (LM) test for the presence of Arch effects in the data.

Table 6: LM test for autoregressive conditional heteroskedasticity (ARCH)

lags(p)	chi2	df	Prob > chi2
1	64.443	1	0.0000

H0: no ARCH effects vs. H1: ARCH(p) disturbance

The LM results show the null and alternative hypotheses, the statistic and its distribution and the p-value, which indicates the presence of Arch (p) model disturbance in the data. Thus, we estimate the Arch (1) model and generate the

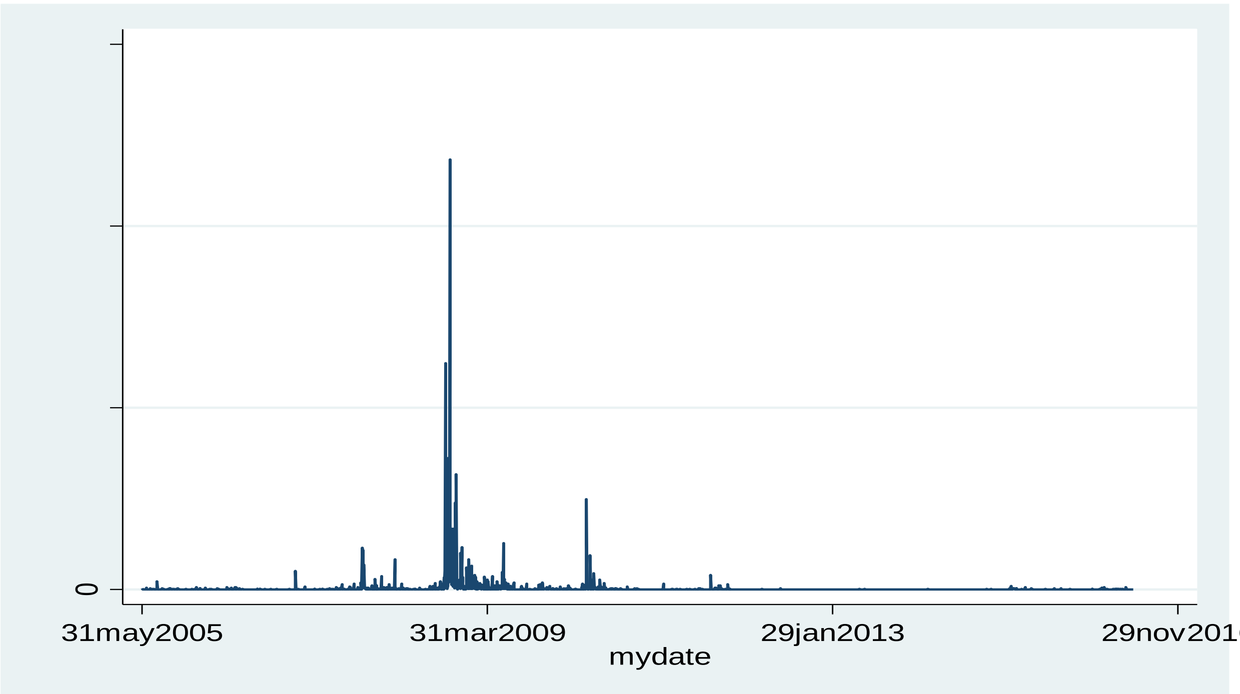
[25] For more elaboration, see the methodology section (2.3.4. above).

forecast error variance, which is essentially an in-sample prediction model based on the estimated variance function, (see equation 3.19 for more details). Table 7 shows the result of the conditional variance of the estimated Arch (1) model, which is saved as a variable called htarch. The conditional variance in the Arch model is allowed to change over time as a function of past error leaving the unconditional variance constant (Bollerslev, 1986). Then we proceeded with plotting the forecast error variance (htarch) against the years of our sample (2005 – 2016). Figure 11 shows the result of Arch (1) model, which implies that the volatility spillovers from developed countries to the developing countries seem to be specifically strong in 2008.

Table 7: htarch ht_1 in 496/500

496.	2.80e-09	2.80e-09
497.	2.24e-09	2.24e-09
498.	2.99e-09	2.99e-09
499.	2.56e-09	2.56e-09
500.	4.02e-09	4.02e-09

Figure 11.



Thus, the result indicates that the foreign exchange market channel between developed and developing countries exhibit time-varying persistence in its conditional volatilities over crisis periods. This result is consistent with the spillover index findings of both static analysis (Table 4) and the dynamic analysis (Figures 2 & 4).

3.6. Net spillovers and net pairwise volatility spillovers

This section presents the results of the net spillover and the net pairwise spillover between developed and developing countries over the years of our sample (2005 – 2016). Above, we discussed the effect of return and volatility spillover between developed and developing countries using the generalised vector autoregressive (VAR) methodology. Thus, we provide results of the spillover index empirically in the form of static analysis 'the spillover tables' as well as a dynamic analysis in the form of 'spillover plots. We also discussed the time-varying volatility spillover among developed and developing countries; using autoregressive conditional heteroskedasticity (ARCH). The key features of the net volatility spillover, it shows the difference between the gross volatility shocks that are transmitted to, and those received from all other markets (Diebold and Yilmaz, 2012). Thus, the net pairwise volatility spillover (Eq.3.14) between country i and j is the difference between the gross volatility shocks transmitted from country i to country j including the transmission from j to i (Diebold and Yilmaz, 2012). As shown in Eq. (3.12), the net volatility spillover offers important information about the amount of volatility in net terms, that each country contributes in other countries. Therefore, the main focus point of this section, is to calculate the net volatility and the net pairwise volatility spillovers between developed and developing countries, which presented in Figs. 12-14, and Figs. 13-15, respectively. Due to the large number of countries (23) in my sample, Figs. 16-65, are provided in Appendix A. After introducing the net spillover and the net pairwise spillover plots; we can now provide detail analysis of the spillovers from developed to the developing countries.

Net Volatility Spillovers, GBP INR EUR IDR

Figure 12.

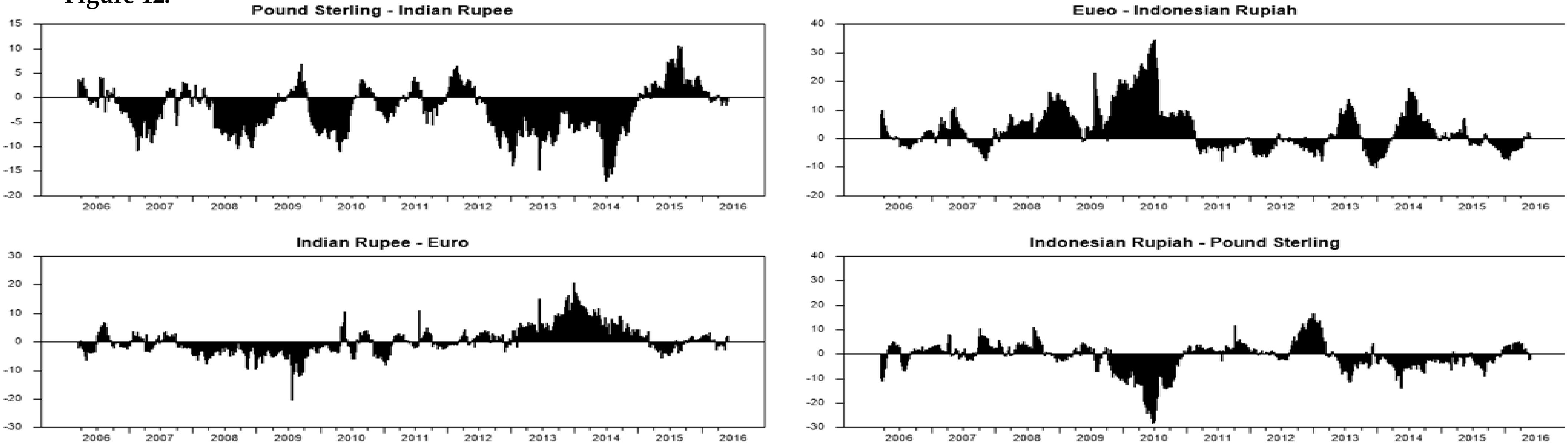


Figure 13.

Net Pairwise Volatility Spillovers,GBP INR EUR IDR

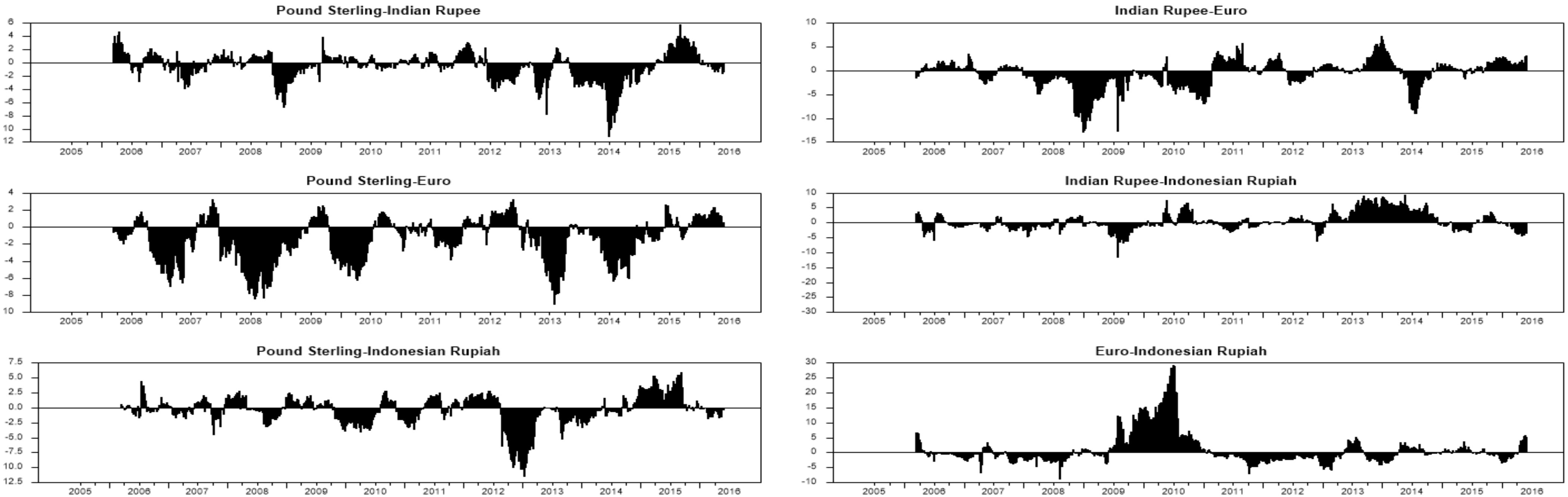


Figure 14.

Net Volatility Spillovers, GBP ARS EUR MYR

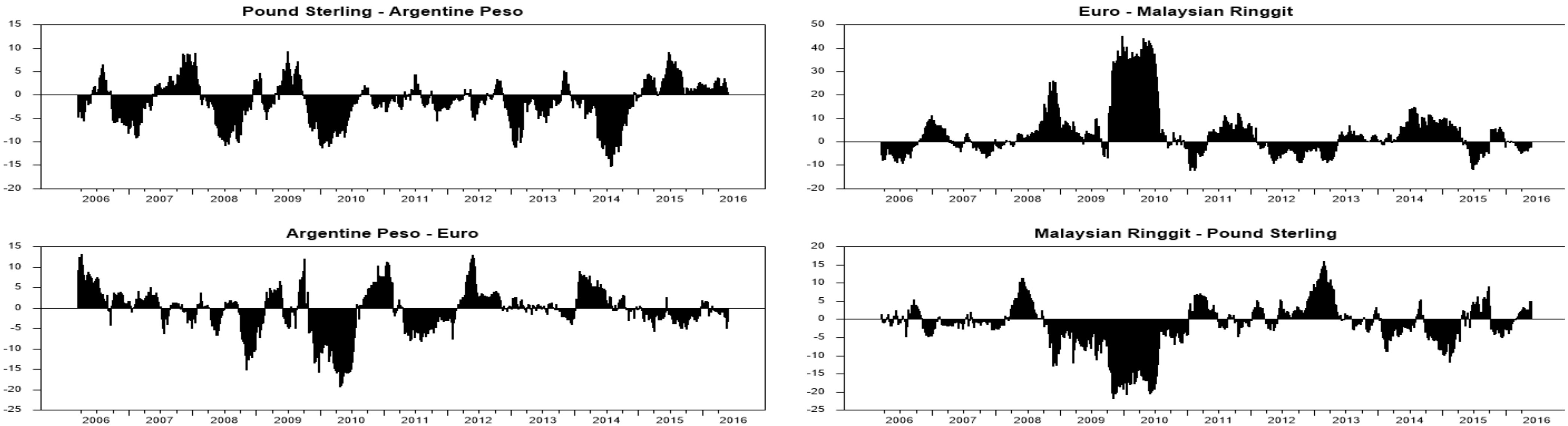
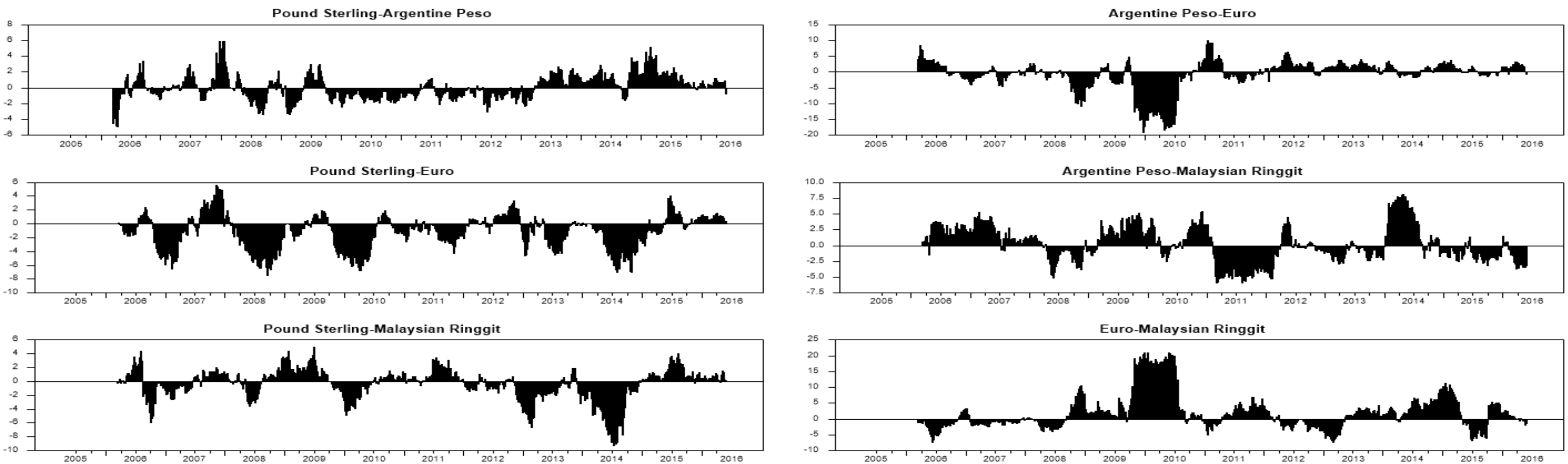


Figure 15.

Net Pairwise Volatility Spillovers,GBP ARS EUR MYR



During the years of our sample (2005 -2016), there were two major events of net volatility spillovers through the global foreign exchange market, in particular during the 2008/09 financial crisis and the European sovereign debt crisis in 2009/13. However, before the recent financial crisis and the European sovereign debt crisis, the net volatility spillovers between developed and developing countries was relatively low. But things changed drastically after 2007 where the net volatility spillover from the EUR to the Malaysian ringgit Fig. 14 jumped to 20% in the third quarters of 2008 and 40% in the third quarters of 2009. These results are consistent with the time-varying volatility results; which implies that the foreign exchange market experiences low volatility from 2005 to 2007. The pound sterling (GBP) and the euro (EUR) Figs. 12-15 both acts as giving and receiving of the net volatility transmissions, with almost similar magnitudes across the global foreign exchange market. This finding supports the static analysis of the spillover index (Table 4) that the pound sterling (GBP) and the euro (EUR) are the main contributors of volatility spillovers. The Indonesian rupiah (IDR) also receives significant amount of volatility spillovers from the euro (EUR) Fig. 13, especially during the recent financial crisis and the European sovereign debt crisis in 2009/13. On the other hand, the euro (EUR) receives a large amount of volatility spillover from the Malaysian ringgit (Fig. 15), which indicates that developed countries act receivers and transmitters of volatility spillovers. The Argentine peso (ARS) contributes as well as receives significant amount of volatility from the Malaysian ringgit (MYR), Fig. 15.

The net volatility spillovers from the pound sterling (GBP) to the euro (EUR) Fig. 15 seems relatively low, while receiving significant amount of volatility spillovers from the euro (EUR). The fact that the pound sterling (GBP) contributes as well as receives large amount of volatility spillovers from the euro (EUR) shows the increased link between developed countries in the global foreign exchange market. For more elaboration about the net volatility spillovers and net pairwise volatility spillovers between developed and developing countries, see figures 16-65 in Appendix A.

3.8. Conclusion

The critical question was whether the effects of return and volatility spillovers are bidirectional between developed and developing countries. Thus, in this study, we examined the impact of return and volatility spillovers on global foreign exchange markets across developed and developing countries. Quoted against the U.S. dollar, the data sample comprises twenty-three global currencies across developed and developing countries. Seven out of which are the most actively traded globally, including the British Pound (GBP), Euro (EUR), Australian Dollar (AUD), Swiss Franc (CHF), Icelandic Krona (ISK), Czech Republic Koruna (CZK), Hong Kong Dollar (HKD). The empirical analysis employed in this study based on daily data, using the generalised VAR framework focusing mainly on the spillover index methodology proposed by Diebold and Yilmaz (2009).

During the years of the sample investigation (2005 – 2016), several exciting economic events reveal the magnitude and extent of the volatility spillover's effect across global foreign exchange markets. In particular, from the perspective of the recent financial markets' interconnectedness. Nevertheless, the findings do not disclose evidence of bidirectional spillover between developed and developing countries. However, we find non-negligible evidence of unidirectional spillovers (table 4) from developed to developing countries. In particular, the Mexican Peso (MXN), Indonesian Ringgit (IDR) and the Indian Rupee (INR) receive unidirectional volatility spillover from the Australian Dollar (AUD), British Pound (GBP), Turkish Lira (TRY), and the Euro (EUR). We also found that developed countries act as receiver and transmitter of volatility, dominated by the British pound (GBP), Australian dollar (AUD), and the euro (EUR), whereas developing countries are a net receiver of volatility, dominated by Mexico, Indonesia, and India. Further, the empirical results conclusively show that the magnitude and extent of the return and volatility spillovers are significantly large within the European region (Eurozone and non-Eurozone currencies). In particular, during the crisis episodes, whereby the volatility spillovers replicate remarkable bursts. This phenomenon is in line with the findings presented by Glick and Rose (1998); and Yarovaya et al., (2015) that the currency crises tend to be regional.

From a policy point of view, this chapter documents significant practical implications. First, the extent of global foreign exchange markets' volatility channel highlights the significance of contagion and systemic risk, particularly from the globally systemically important financial institutions. Second, the substantial return spillovers between developed countries, especially within the European region (Eurozone and non-Eurozone currencies) further quantify the importance of cross-market linkages and the recent financial innovations. Third, it also opens avenues for a better understanding of the potential crisis of a highly interlinked nature mirrored in the historical economic events.

Finally, this chapter contributes to the scarce literature of intra-foreign exchange markets, from the perspective of developed and developing countries. Here, the empirical results show that the spillover channels between developed and developing countries are insignificant. However, this raises the question about how the recent financial turmoil (which affected both developed and developing countries) propagated across the global economies? To conclude, the results presented in this chapter, highlight the need for further research examining the magnitude and extent of the volatility spillover from the default of systemically important financial institutions. From the viewpoint of policymakers, the high-level of financial interconnectedness within the European countries is of extreme concern.

4

Time Series Modelling and Forecasting: Challenges of Stock forecasting

4.1. Introduction

The concept of time series modelling and forecasting developed dramatically over the last few decades due to it is ability to analyse and interpret a vast amount of data based on past observations. Therefore, economic forecasting is the act of scrutinising and analysing past observations to predict future outcomes (Raicharoen et al., 2004). The effort to predict the future attracted much academic research to understand the forecasting performance of time series modelling. Nonetheless, providing accurate and reliable forecasting results depend mainly on accurately and appropriately fitted models. This has led to an increase in the number of efforts to build forecasting models that are capable of providing accurate forecasting results; thus, different time series forecasting models introduced (Melard and Pasteels, 2000; Wall and Stoffer, 2002; Kim, 2003; Adhikari and Agrawal, 2013). As a result, several time series forecasting tools made available in the literature. That being said, forecasting stock returns, for instance, can be a daunting task but also, captivating endeavour.

By any standard, academics and finance practitioners have applied numerous economics variables in the literature to predict the stock returns. The variables expand from book-to-market (Kothari and Shanken 1997; Pontiff and Schall 1998), through valuation and price earnings ratios (Dow 1920; Campbell and Shiller 1998; Fama and French 1989) to inflation rate and stock market volatility (Campbell and

Vuolteenaho 2004; Guo 2006). Most of the stock return forecasting endeavours in the literature focus on the in-sample tests (Clark and McCracken 2006; Narayan et al., 2014; Sousa et al., 2016) showing some evidence of stock return forecastability. On the other hand, the stock returns' out-of-sample tests remain contentious, at the very least, there is inconsistent results in the literature of the stock market forecast. As Rapach et al., (2010) put it, the forecasting literature still unable to deliver consistently superior out-of-sample forecast of the U.S. equity premium. Goyal and Welch (2008) examined whole range of variables[26] to predict equity premium over a 30 years period; and found that both in-sample and out-of-sample models performance unexpectedly, poorly. Also, Darrat and Zhong (2000) applied the standard variance ratio test of (Lo and MacKinlay 1988) to two major Chinese stock exchanges (Shanghai and Shenzhen) and found no evidence of a random walk hypothesis.

This is also due to the stock market data, which is prone to non-economic factors such as natural disasters and political decisions; therefore, it is naturally noisy and highly volatile. The stock data fluctuation is also due to the incomplete information from the past behaviour of the stock market to enable capturing the dependency between future and previous prices (Tay and Cao 2001). The incomplete information concerning the stock market data is often regarded as noisy characteristics, making it a challenge to predict the future prices of the stock returns. In simple terms, this argument falls into the early efficient market hypothesis (EMH) theory that future changes in security prices are difficult to predict (Ang et al., 2011). Due to the rapid increase in trade and investment, the need for the appropriate tools and methods to mitigate risks and maximise gains equally increased.

Thus far, an effort to improve the stock returns forecastability is offered by using vast number of variables in a predictive regression model to reduce the forecasting

[26] Variables include consumption-based macroeconomic ratios (cay), interest rates (in various guises), beta premia, book-market ratios, dividend pay-out ratios, corporate or net issuing ratios, dividend price ratios, dividend yields, and earnings-price ratios.

volatility (Rapach et al., 2010). However, a work to advance the predictive regression model is offered by Westerlund and Narayan (2015a) who added that forecasting regression might face a number of potential setbacks such as predictor endogeneity, persistency and heteroskedasticity (Phan et al., 2015). Moreover, Amanda et al., (2015) used a three-factor model, which arguably explains some large fraction of the stock returns dynamic and improves predictability. Notwithstanding, the lack of consensus in the literature, concerning out-of-sample evidence is a call for improving the forecasting methods to better advance stock returns' predictability (Rapach et al., 2010).

The main focus of this chapter is to contribute to the out-of-sample's stock returns forecasting problem and investigate both its econometric underpinnings and predictability. According to Welch and Goyal (2008) there is little or zero evidence of the effectiveness of both (in-sample and out-of-sample) models in predicting equity returns. Thus, using daily data, this chapter examines whether the U.S. S&P stock exchange follow a random walk process, which required by market efficiency. We use a model-comparison approach, which compares an ex-post forecasts from a naïve model against those obtained from numerous alternative models such as ARIMA models, random walk without *drift* and Simple exponential smoothing. The naïve model used is the random walk with *drift*, and to evaluate the models forecastability we use mean Absolute Percentage error (MAPE), Root Mean Square error (RMSE), Mean Absolute error (MAE), Akaike Information Criterion (AIC), and Mean Percentage error (MPE). The results from the model-comparison approach support the random walk with *drift* hypothesis, which has significant implications for testing market efficiency as well as understanding the stock market forecastability.

The rest of the chapter organised as follows: Section 4.2 discusses the most relevant literature. Section 4.3 provides the methodology applied, and section 4.3.3 discusses the input data. Section 4.4 lays out the empirical results. Section 4.5 concludes.

4.2. Related Literature

Academic and finance practitioners developed strong interest over the years to build time series models that successfully provide real-time forecasts of the stock returns. However, the time series forecasting can either be trend-stationary or contains a component of 'difference stationarity' i.e., random walk (Steland, 2005). The main concern is that shocks to the trend-stationary models is temporary, whereas shocks to the random walk tend to be permanent (Pindyck and Rubinfeld, 1998; Steland, 2005). Using the random walk with *drift* as a naïve model, the purpose of this chapter is to test whether the U.S S&P stock exchange follows a random walk hypothesis. In other words, examining the possibilities of predicting the future values based on past values; a phenomenon discussed over the years (Roll 1986; Fama and French 1988; Lo and MacKinlay 1988; Poterba and Summers 1988; Jegadeesh 1991).

The use of the random walk with *drift* as a benchmark is widely accepted in the literature (Engel and Hamilton; 1990; Diebold et al., 1994; Darrat and Zhong 1994; Halkos and Kevork 2006; Steland 2005; Moosa and Burns 2016). The ultimate results of these studies suggest that the random walk with *drift* provides good comparison standard when the drift-term is different from zero. However, the use of *drift* or no *drift* terms have also produced mixed results in the literature. Some argued, the random walk with or without the *drift* term produce similar results and that the *drift* term does not have a significant effect (Mankiw 1985; Engle 1994). Others suggest the inclusion or exclusion of the *drift* term has a repercussion on the forecasting power, especially for the shorter time predictability (Kilian 1999; Moosa and Burns 2013a). however, numerous studies used the random walk with-and-without *drift* as a naïve model to predict the foreign exchange rates and stock market returns. For example, in the efforts to find a best model to forecast the foreign exchange rates, Rossi (2013) argued, the random walk consistently offers the toughest benchmark, in particular, the random walk without *drift* is hard to beat. Moosa and Burns (2016) did not find empirical evidence to support their findings, which indicate that the random walk without *drift* outperforms the random walk with *drift* in predicting exchange rates. However, they suggest that the random walk with *drift* might perform even better if the *drift* term allowed to change over time by estimating the model in a time-varying parameter. Smith and Ryoo (2003) examined whether the stock price indices follow a random walk in five European's emerging markets (Poland, Portugal, Greece, Hungary and Turkey); they found that only the Turkish stock market follows a random walk hypothesis.

Although we present a brief review about the naïve model in this chapter (random walk with *drift*), I also use ARIMA models, random walk without *drift*, and moving average and exponential smoothing models to test the random walk hypothesis for the U.S S&P stock market. The literature on the field of linear prediction is overwhelmingly rich, which dated back to the pioneering work of (Kolmogorov 1941; and Wiener 1941), where they set the foundation to solve the *signal extraction*[27] problem. The essential functioning of the ARIMA models is deep-rooted in interpreting future information based on observation carried forward from the past, i.e., the previous observations tell us something about the future. That being said, the classical forecasting approach for the ARIMA models based on regression analysis, where the specification of a linear parametric relationship between two variables is essential. Box and Jenkins (1970) provided a solution to the non-stationarity (by, differencing the data) and suggested that ARIMA models can provide accurate forecasting results. Thus, as forecasting tool, ARIMA models acquired the attention in the recent literature mainly, in the field of stock price prediction. The ARIMA models; known as Box-Jenkins methodology, is widely used in the literature as an efficient and accurate tool for forecasting time series data.

[27] Lucas's signal extraction theory based on the claim that firms and investors need to respond to a signal extraction problem in order to make decisions based on prices. In particular, they need to determine which part of the prices changes in their relevant investment portfolios reflected a general change in nominal prices (inflation) and which part reflected a change in real prices for inputs and outputs (Snowdon and Vane 2005).

However, it can only perform well if a stationary time series data is used, otherwise, the data should be made stationary (by differencing) to meet the requirements for accurate forecasting results. Thus, the time series prediction using ARIMA models assumes the case under study generated from linear processes; because it relies on the previous values of the series and the past error-terms for forecasting, (Khashei and Bijari 2010; Wang et al., 2012; Adebiyi and Adewumi 2014). Hansen et al., (1999) used both ARIMA and artificial neural networks (ANNs) to predict different time series data, including IBM stock price, chemical process concentration, chemical process temperature and Wolfer's sunspot numbers. Their findings show that the ANN model provides better forecasting results compared to ARIMA models.

Using Korean's stock data index, Lee et al., (2007) compared the forecasting performance of both ARIMA and the ANNs; the ARIMA model generates more accurate forecasting results compared to ANNs. Forecasting the Indian stock index, Merh et al., (2010) tested the performance of hybrid ARIMA and the ANNs. They suggested that in most prediction cases, ARIMA model provided better results than ANNs. Also, Wijaya et al., (2010) contrast the performance of ANNs with ARIMA models on forecasting the Indonesian stock exchange. The authors argue that ANNs generate better forecasting results than ARIMA model.

The main contribution of this chapter is to investigate whether the U.S. S&P stock market follows a random walk hypothesis as required by market efficiency. The approach adopted is using the random walk with *drift* as a naïve model. Then compare the forecasts from the naïve model with those generated from ARIMA models, moving average and exponential smoothing models, and the random walk without *drift*. To our knowledge, there is little evidence that compares ARIMA models against the random walk with and without *drift*. In other words, there is limited evidence whether ARIMA models behave like a random walk with *drift*; this chapter fills this gap in the literature. For example, using daily data, Darrat and Zhong (2000) examined whether the Chinese stock exchanges (Shanghai and

Shenzhen) follow a random walk process. The authors used a variance ratio tests and compared the forecasts with ARIMA model, GARCH, and the artificial neural network (ANN). Their results reject the random walk hypothesis in both Chinese stock markets i.e., the ARIMA model, GARCH, and the artificial neural network (ANN) do not follow a random walk hypothesis. But the authors found evidence to support the ANN as useful tool to predict stock prices in emerging markets. Similarly, Halkos and Kevork (2006) suggest that the random walk with *drift* behaves like ARIMA (0,2,1) model if its parameter θ is close to (-1).

However, the authors did not indicate which ARIMA model is tested; or used only ARIMA (0,2,1) against the random walk process. As a result, their findings did not offer a conclusive empirical evidence as to whether ARIMA models follow a random walk process. Instead, our work focuses on several issues linked to the macroeconomics forecasting problem, in particular, the stock returns predictability. First, our work contributes to the out-of-sample stock returns forecasting problem and investigate its econometric underpinnings and predictability. Second, our work tests several ARIMA models (1,0,0; 0,1,0; 2,0,0; and 0,1,1) against the random walk hypothesis. Finally, our work focuses on the most important stock market globally, which is the S&P 500 index as it accommodates large numbers of companies.

4.3. Proposed Methodology

In this section, we obtain forecasts from the naïve model (random walk with *drift*) if the *drift* term is statistically significant. The estimation of the drift *term* is conducted by regressing the change in percentage of the U.S. S&P 500 index returns i.e., the difference between the first and the last values in the series on a constant term (Meese and Rogoff 1983). Then we test the random walk with *drift's* ability to forecast the out-of-sample S&P 500 stock market returns; and compare the results with those obtained from the alternative models (random walk without *drift*; moving average and exponential smoothing models; and ARIMA models 1,0,0; 0,1,0; 2,0,0; 0,1,1). Since the main intention is to investigate the superiority of one model over the other, we use numerous metrics to measure the predictive power of each mode such as: 6

- Box-Pierce test for excessive autocorrelation **AUTO**
- Root mean square error **RMSE**
- Mean absolute percentage error **MAPE**
- Mean absolute error **MAE**
- Akaike information criterion **AIC**
- Hannan-Qinn information criterion **HQC**
- Schwarz-Bayesian information criterion **SBIC**
- Test for excessive runs up and down **RUN**
- Test for excessive runs above and below median **RUNM**
- Test for difference in mean 1st half to 2nd half **MEAN**
- Test for difference in variance 1st to 2nd **VAR**

4.3.1. Random Walk Model and Notations

The random walk model is known to have *drift* or no *drift* depending on the distribution of the step sizes having a zero mean or a non-zero mean (Pesaran and Pick, 2008). For example, considering period n, the k-step-ahead forecast, which the random walk model without *drift* provides for the variable X is:

$$\hat{X}_{n+k} = X_n \tag{4.1}$$

This is to say that the random walk model is able to predict that almost all future values will equal the last observed value. However, along this line, it is not expected that all the forecasted values will be the same as the observed values, but they are likely expected to be higher or lower. Thus; statistically, the random walk's long-term point forecast looks similar to that of the mean model with the exception that they always re-anchored on the last observed values but not the mean of the historical data.

Considering the random walk model with *drift*:

$$\mathcal{X}_t = \mathcal{X}_{t-1} + \mu_t + \varepsilon_t, \qquad \varepsilon_t \sim \text{i.i.d.}(0,\sigma_t^2). \tag{4.2}$$

We can define $\mathcal{Y}_t = \mathcal{X}_t - \mathcal{X}_{t-1}$ and then have the following model;

$$\mathcal{Y}_t = \mu_t + \varepsilon_t \tag{4.3}$$

And this is defined over the sample period $t = 1, 2, \dots, T$, with a *drift* coefficient, μ_t, and volatility, σ_t, which subject to a single break at time $t = \mathrm{T}_b (1 < \mathrm{T}_b < \mathrm{T})$

$$\mu_t \begin{cases} \mu_1, \forall t \le \mathrm{T}_b \\ \mu_2, \forall t > \mathrm{T}_b \end{cases}, \tag{4.4}$$

$$\sigma_t \begin{cases} \sigma_1, \forall t \le \mathrm{T}_b \\ \sigma_2, \forall t > \mathrm{T}_b \end{cases}.$$

However, the aim is to forecast the U.S. S&P 500 index, which defined as $\chi_{\mathrm{T}+1}, or, \mathcal{Y}_{\mathrm{T}+1}$ based on the observations, $\mathcal{Y}1, \mathcal{Y}2, \dots \mathcal{Y}\mathrm{T}$. The estimation of the *drift* in the random walk model could be very tricky; and the best way of estimating it is by using the average period-to-period change observed in the past (Nau, 2014). Put it differently, it is the difference between the first and the last values in the series divided by $n - 1$;

$$\hat{d} = \frac{\chi_n - \chi_1}{n-1} \tag{4.5}$$

This represents the slope of the line between the first and last data point but not the slope of the trend line fitted to the data. To predict the first difference of the series, it may seem like using the random walk with *drift* is the same as using the mean model. However, in fact, we should be very careful when estimating the *drift*, as its very sensitive to the size of historical data fitted in the model.

4.3.2. ARIMA (p, d, q) Models

In ARIMA models, which also called Box and Jenkins (1970) methodology, the non-stationarity of the data transformed into stationary by adding-up finite differencing to the data points. Using lag polynomial, ARIMA (p, d, q) can be expressed as below:

$$y(\Psi)(1-\Psi)^d\ \Upsilon_t = \Phi(\Psi)\varepsilon_t \tag{4.6}$$

This can be written as:

$$\left(1-\sum_{i=1}^{p} y_i\ \Psi^i\right)(1-\Psi)^d\ \Upsilon_t\ = \left(1+\sum_{i=1}^{p} \Phi_j\, \Psi^j\right)+\varepsilon_t \tag{4.7}$$

Where p is the integer of autoregressive term, d is the non-seasonal differences integer and q is the forecast error term. Therefore, the Box-Jenkins ARIMA model is a univariate method because it uses the historical information of a single value to forecast the future outcome (Reagan, 1984). In this case, the value of interest is the U.S. S&P 500 index, which should be separated by spaced time interval (equally) in order to apply the Box-Jenkins approach.

For example, let a discreet time series n equally spaced observation over time as;

$$x_t = x_1, x_2, x_3, x_4 \dots\dots\dots\dots\dots x_{n-1}, x_n \tag{4.8}$$

The intuition of Bok-Jenkins approach that it reflects on the observed time series x_t to be an outputs of an unobserved black box process (Paretkar, 2008). The black box inputs are series of independent random shocks b_t, as in Figure 4.1. below.

Figure 4.1 Black Box Process (Box-Jenkins Method)

In statistical terms, the random shocks assumed to be normally distributed having zero mean and a constant variance, which refers to as a white noise (Box et al., 2015). Therefore, time series in the Box-Jenkins approach is the result of a white noise transformation process through a black box (linear filter). The ARIMA models, in particular, assumes the outputs depend on:

a) Previous and current outputs (random shocks and white noise);

b) And the previous output values of time series $x_{t-1}, x_{t-2}, \ldots \ldots$, in different proportion. Thus, the Box-Jenkins method introduces a simple linear form for the observed time series values (Reagan, 1984; Paretkar, 2008).

$$x_t = \varrho_1 x_{t-1} + \varrho_2 x_{t-2} + \cdots + \varrho_p x_{p-1} + b_t - \theta_1 b_{t-1} - \theta_2 b_{t-2} \ldots - \theta_q b_{t-q} \qquad (4.9)$$

$$\text{Or, } \Psi\,(\Lambda)(1-\Lambda)^d\, x_t = \Theta(\Lambda) b_t \qquad (4.10)$$

Where $\Psi(\Lambda) = (1 - \varrho_1 \Lambda - \varrho_2 \Lambda^2 - \cdots - \varrho_p \Lambda^p)$, $\Theta(\Lambda) = \left(1 - \theta_1 \Lambda - \theta_2 \Lambda^2 - \cdots \theta_p \Lambda^q\right)$, $\Lambda x_t = x_{t-1}$, Λ is the backward shift operator ($\Lambda x_3 = x_2, \Lambda x_9 = x_8 \ldots$) and d = order of differencing. Therefore, according to the above-mentioned definition, the ARIMA models can be expressed as:

1) Autoregressive (AR) models:

If the value of the output x_t depends on p prior outputs and the current output (random shock) b_t, the ARIMA model takes the form of

$$x_t = \varrho_1 x_{t-1} + \varrho_2 x_{t-2} + \cdots + \varrho_p x_{t-p} + b_t \qquad (4.11)$$

Thus; it is called an autoregressive model of order p known by AR (p) or ARIMA (p, 0, 0).

2) Moving Average Models:

If the current output x_t, depends on the current output and q prior inputs, the ARIMA model takes the form of

$$x_t = b_t - \theta_1 b_{t-1} - \theta_2 b_{t-2} \dots \theta_q b_{t-q} \tag{4.12}$$

And it is called the moving average model of order q, known by MA (q) or ARIMA (0, 0, q) (Paretkar, 2008).

4.3.3. Dataset

The data applied in this chapter is the U.S. S&P 500 index over the period (2/01/2014 – 02/01/2020), which consists of daily adjusted close prices. The daily stock prices data are extensively applied in academic studies (Kim 2003; Brownlees and Gallo, 2006; Ariyo et al., 2014; Henrique et al., 2018). The reason for selecting the U.S. S&P 500 index is due to its large market capitalisation and high activity level. This is because studies revealed that less traded markets are not suitable for testing efficiency as they lack liquidity and the smooth transfer of information (Darrat and Zhong 2000). The daily data selected are for the period of five years with 1511 observations, obtained from DataStream. The adjusted closing prices are chosen because they represent the daily behavioural activities of the index.

4.4. Empirical Application and results

In this section, we consider an application based on forecasting the U.S. daily S&P 500 index, which illustrates the methodology discussed in section 4.3.1. The random walk model with *drift* is used as a naïve model, which performance is tested against different set of competing models including;

(A) Random walk

(B) Random walk with *drift* = 0.000381239

(C) Constant mean = 7.75628

(D) Linear trend = 7.49225 + 0.000174738 t

(E) Simple moving average of 2 terms

(F) Simple exponential smoothing with alpha = 0.9815

(G) Brown's linear exp. smoothing with alpha = 0.4907

(H) Holt's linear exp. smoothing with alpha = 0.9062 and beta = 0.0016

(I) ARIMA(1,0,0)

(J) ARIMA(0,1,0)

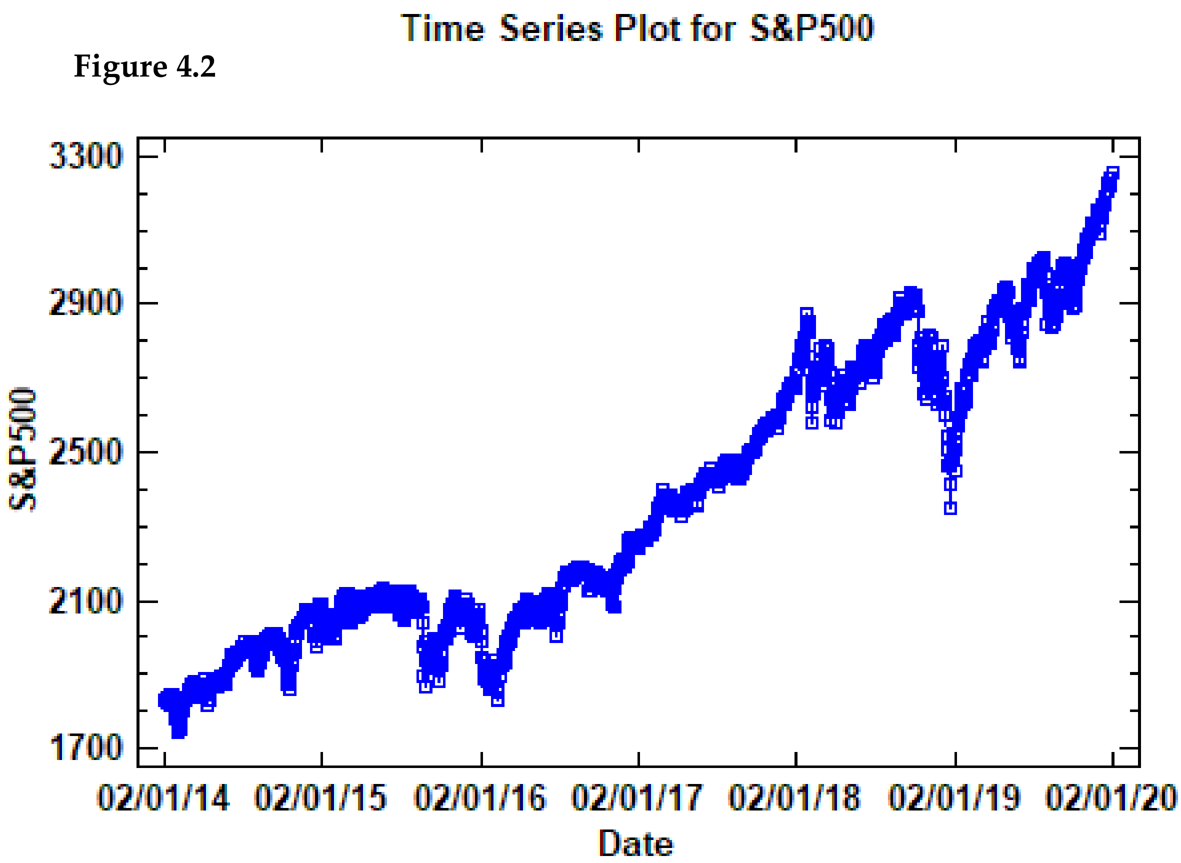
(K) ARIMA(2,0,0)

(L) ARIMA(0,1,1)

First, it is vital to highlight that the standard-error of the 1-step-ahead forecast is the most significant parameter for the random walk model. This is due to the square root of time, which indicates that the confidence interval is wider for a k-period-ahead random walk forecast than that of a 1-period-ahead forecast (Alexander, 1998; Pesaran and Pick, 2008). Thus, for the random walk with *drift* model, the 1-step-ahead standard error considered, is the standard deviation of the differenced series. And for the random walk *without drift* model, the 1-step forecast error is the root mean square of the differenced series. More specifically, the critical value of the t-distribution used to calculate the confidence interval (based on the forecast and standard error) is quite different. For the random walk with *drift* model the critical t-value is based on $n - 2$ degrees of freedoms, where n is the sample size. The critical t-value for the random walk without *drift* is based on $n - 1$ degrees of freedoms.

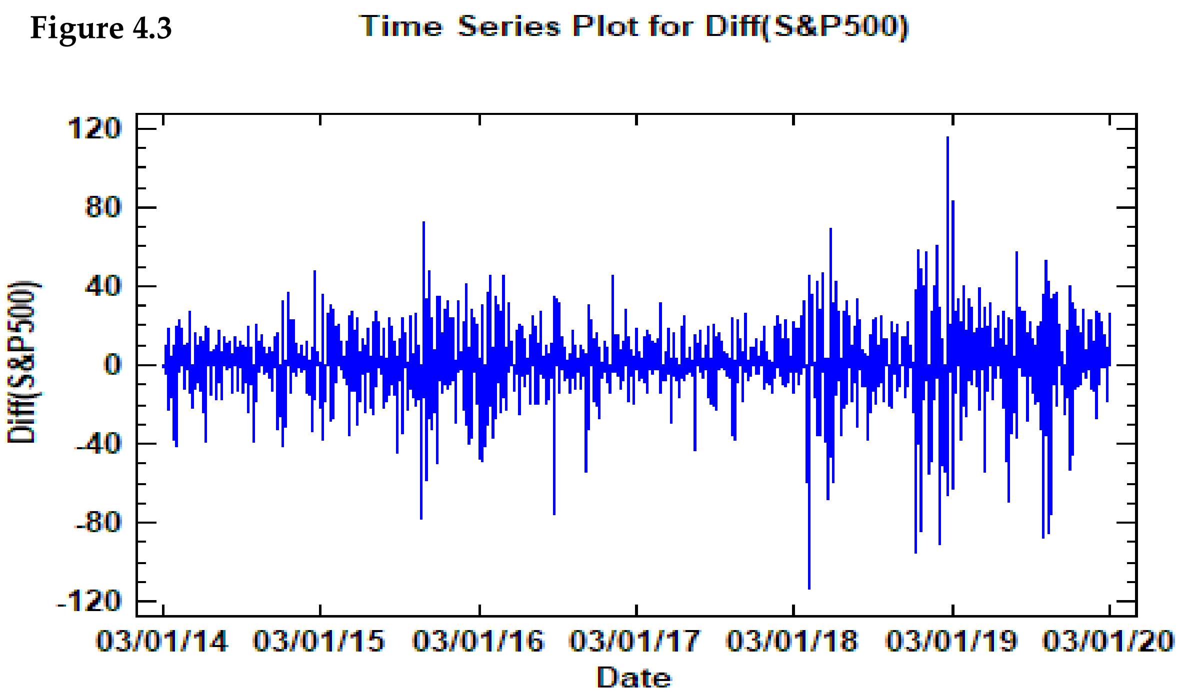
Since the sample size we use is large, the difference of the critical value of the t-distribution is inconsequential; figure 4.2 shows the time series plot for S&P 500 index and the data spans from 2/01/2014 to 2/01/2020 with 1511 observations. The steps we use to forecast the U.S. S&P 500 index follow the logical progression of the time series data applied here.

Figure 4.2



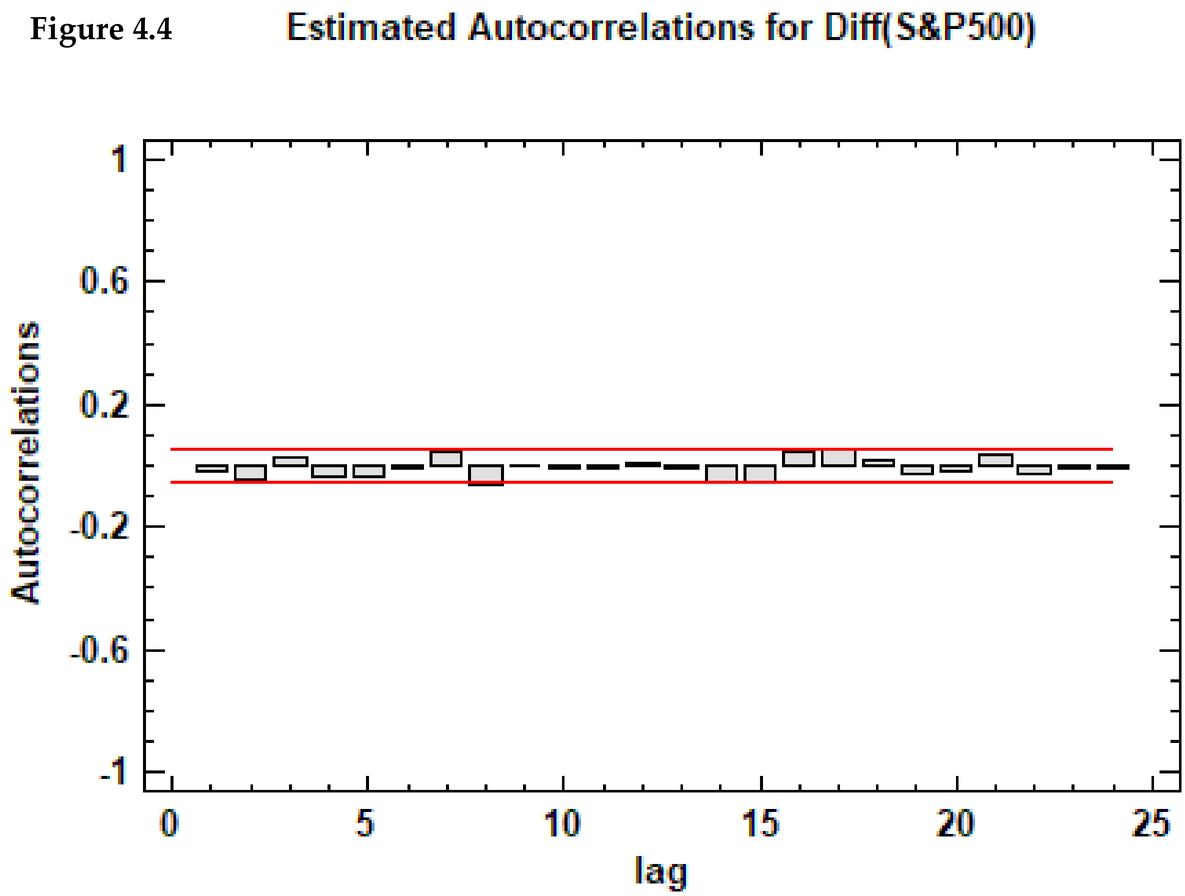
First, we begin by looking at the time series plot of the data (as in figure 4.2 above) including it is first difference. The plot reflects a pattern of non-linear growth with upward trend (from beginning to end) with short-term volatility.

Figure 4.3



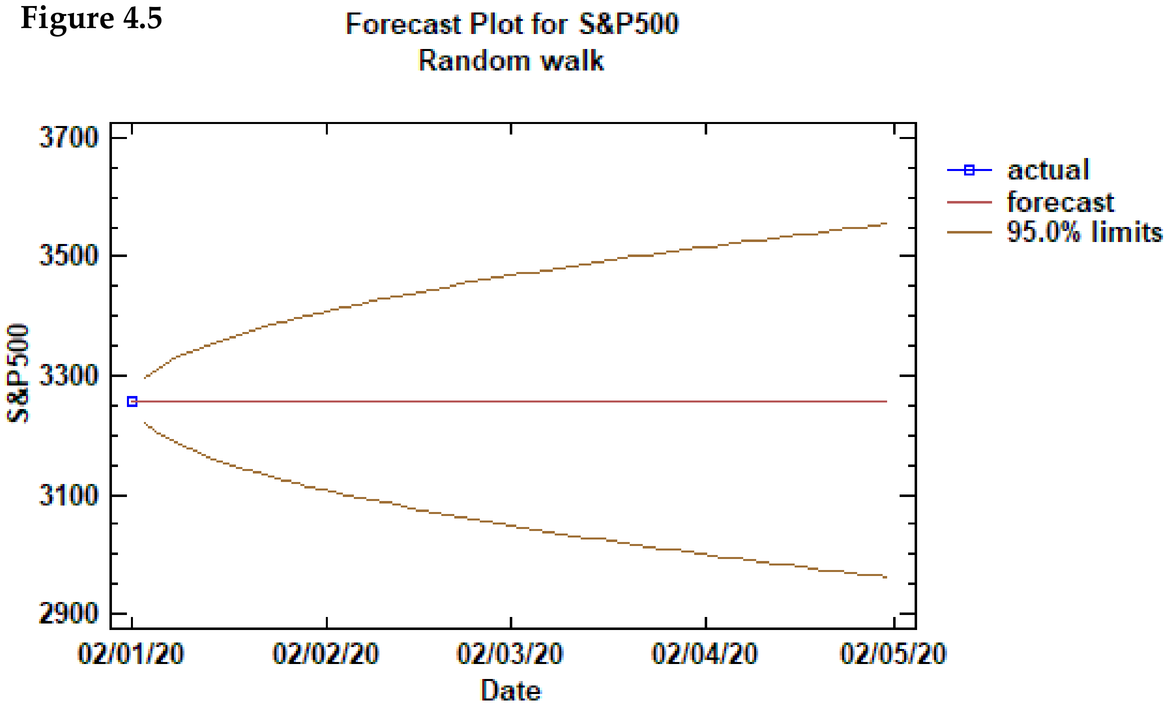
We then checked the first difference (daily changes), which looks very much like a noise as it appears in figure 2 above. However, the plot of the first difference (figure 4.3) does not clearly indicate whether the daily changes are statistically independent with zero mean. In other words, does it show a random walk without *drift*? To answer this question, we estimate the autocorrelations for S&P 500 index, which shown in figure 4.4, using Statgraphics.

Figure 4.4



Since the red lines represent the 95% limits for testing the significance, the autocorrelations are not significant because they all appear within the limits. From statistical viewpoint, the S&P 500 index series appear to be a prefect random walk without *drift*. Figure 4 shows the forecasts and confidence limits for the next 5 years (60 forecasts).

Figure 4.5



It is clear that the point forecast is constant at 3250, which is the last actual value. Also, for a longer horizon forecasts, the 95% confidence limits widen as they go further out. Given the model above, the 95% confidence interval for the rate five years are 2950 and 3550. This is an indication that the result is sensitive to the modelling assumptions such as the amount of past data that considered to be relevant. Up to this point, we have analysed the forecasting performance of the random walk without *drift* using absolute changes for the S&P 500 index. Next, we will apply the random walk model with *drift* to measure the daily volatility of the S&P 500 series in terms of percentage changes.

Another reason for considering the random walk with *drift* is that the natural logarithm of the variable is expected to walk the random walk, which in most cases, a random walk with *drift* (Pesaran and Pick, 2008; Nau, 2014). This is to say that the natural log changes (the percentage changes) from one period to another, is expected to be independent and identically normally distributed. Thus, the geometric random walk model's k-step-ahead forecasting equation is same as that of the random walk with *drift* model. The exception that it is applied to LY(X) rather than X, (see Branch and Evans, 2006; Nau, 2014), which can be expressed as:

$$LN(\hat{X}_{n+k}) = LN(X_n) + Kr \tag{4.13}$$

In this case r represents the *drift* measure in log units, which interpreted as a periodical percentage increase. Put it differently, it is the prediction that the series is undergoing multiple growth factor of (1+r) per period such as;

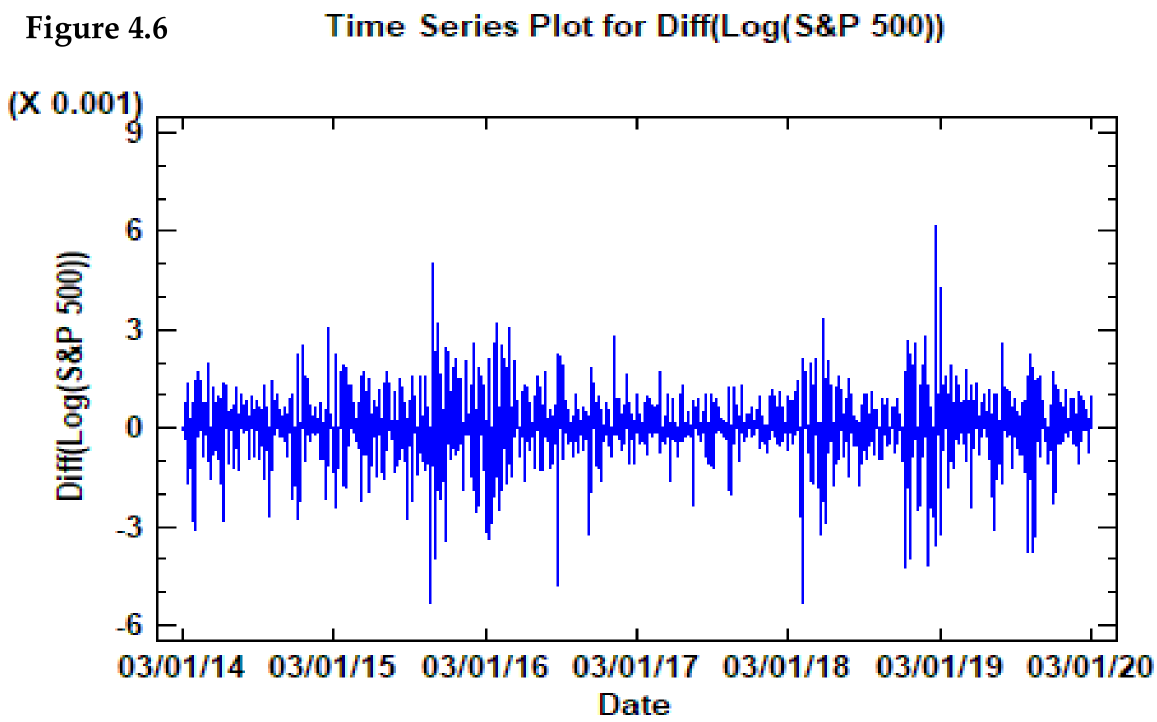
$$\hat{X}_{n+k} = X_n\,(1+r)^k \tag{4.14}$$

For instance, if the *drift* in log unit estimation represented by $\hat{r}$ = 0.019 then the corresponding growth rate will be 1.9% per period, and that is a per-period compound growth factor of 1.019. That means if the logged series has a first difference of X_LN_DIFF1, the 1-step forecast standard error in log units for the geometric random walk model is:

$$SE_{fcst(1)} = STDEV(X\_LN\_DIFF1) \tag{4.15}$$

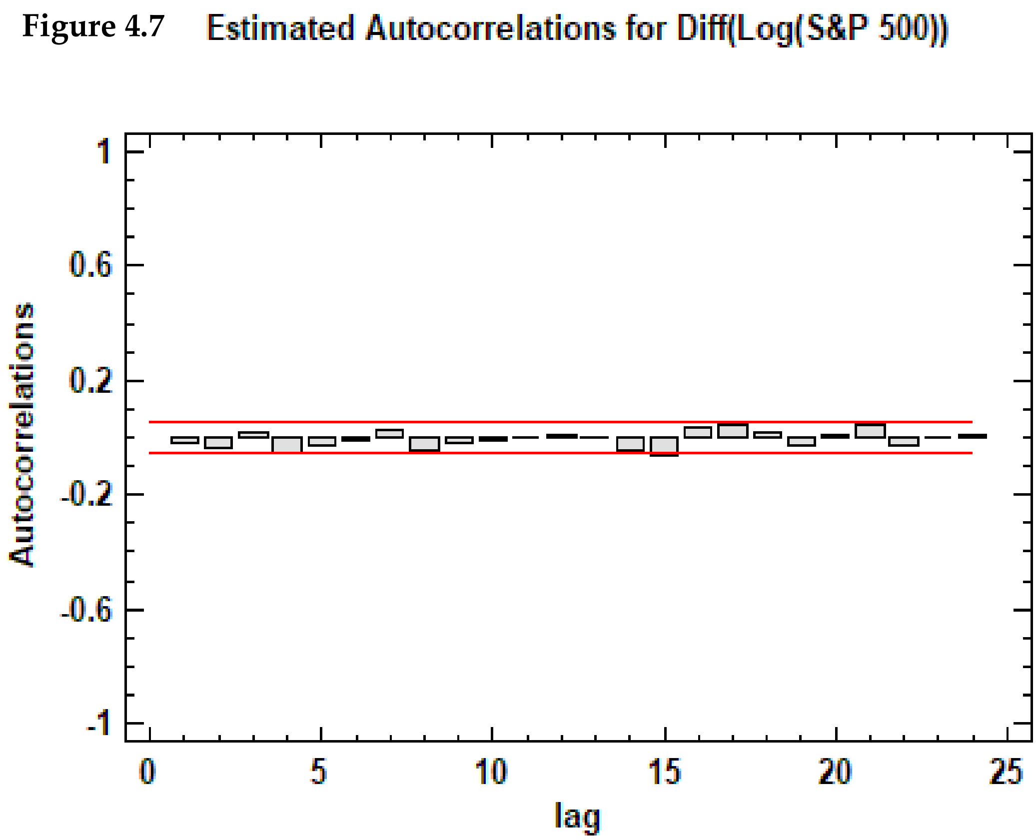
Using Statgraphics, the K-step-ahead forecasts standard error is obtained by the factor of SQRT(K). The confidence intervals in logged units for the forecasts are calculated using the point forecasts plus-or-minus an appropriate number of the standard error. And finally, the confidence limits in their original units for the series and the point forecasts are calculated by using the EXP function. Figure 4.6 shows the first difference of the logged series, which reflects a period of lower and higher volatility. Also, the diff-logs are interpreted as a percentage changes showing steady stream of the daily changes on the order of -/+3 percent. Thus, the pattern is relatively consistent over the whole period of my sample (02/01/2014 to 02/01/2020). Of course, realistically, the results show to some extent, periods of high and low volatility. However, it worth looking at the daily percentages' autocorrelations (Figure 4.7) to see whether they are random.

Figure 4.6



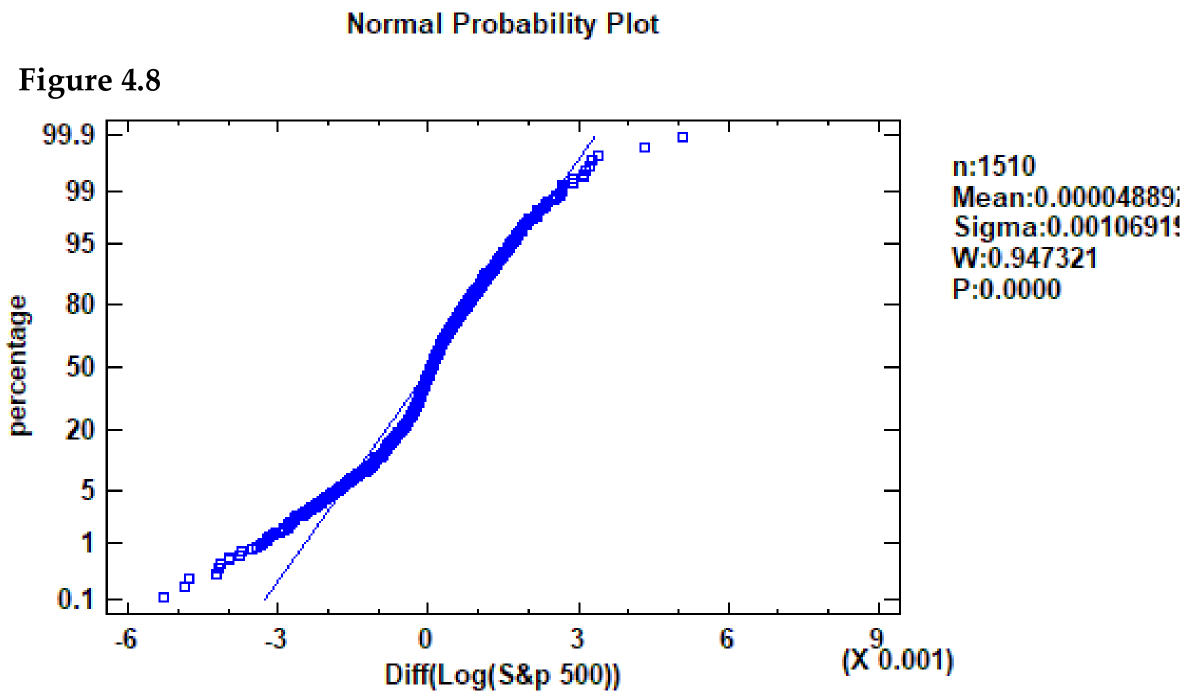
The autocorrelations show insignificant pattern, which means the daily changes seem to be statistically independent and identically distributed.

Figure 4.7



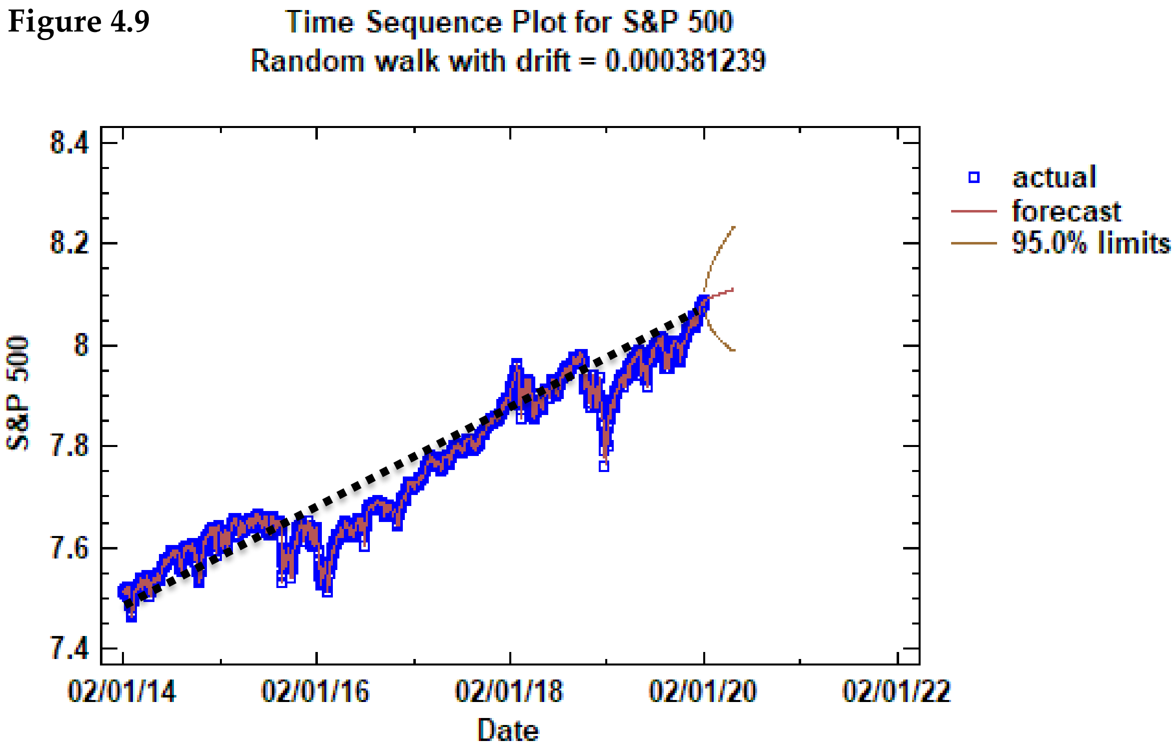
In addition, the autocorrelations also show that the U.S. S&P 500 daily index is almost a perfect random walk. Finally, the random walk confidence intervals' forecasts are built on the assumption that the steps are normally distributed and i.i.d. Therefore, it is worth checking whether the daily percentage changes follow a normal distribution patten. We have tested the hypothesis of normality by drawing the normal probability plot of the Diff-Logged series, which demonstrated in Figure 4.8.

Figure 4.8



Having a same mean and standard deviation, the normal probability plot showcases the values against the percentiles of the normal distribution. We can say that the sample data is normally distributed when the points lie along the straight line. Figure 4.9 shows that the plotted points bend to the left at the bottom of the plot, which means the distribution is skewed to the left. This is because there are big values in the lower tail of the distribution than otherwise if the distribution is normal. Nevertheless, the distribution of the daily percentage changes still not far from being normal. Given the analysis and observations produced above, it is suitable to use the random walk with *drift* model to predict the logged S&P 500 index, which yields the following result in Figure 4.9.

Figure 4.9



We generate this forecasting plot by using the [user-specified] forecasting process in Statgraphics. The random walk with *drift* is used along with 60 forecasts, which correspond to a five years daily values of the U.S. S&P 500 index. Then following Nau (2014), the black dashed-line, which we drawn myself, is to show that; the future point forecasts are extrapolation of straight line drawn between the first and last data points. Also, it is significant to consider other source of information in order to estimate the trend properly when fitting a random walk with *drift* models.

4.4.1. Assessing the forecasting ability of different models

We now compare how the forecasting models shown in Table 7, perform against the random walk with *drift* model. The key forecasting steps performed in Statgraphics as follows:

A. we have manually applied the ''natural'' log transformation to the input variable.

B. The input data specified as daily data.
C. The starting date is specified to be 01/01/50, which has no effect on the analysis
D. And we have used 60 forecasts, which is five years' worth of forecasts.

Table 8: Forecasting models

(A) Random walk without *drift*

(B) Random walk with drift = 0.000381239

(C) Constant mean = 7.75628

(D) Linear trend = 7.49225 + 0.000174738 t

(E) Simple moving average of 2 terms

(F) Simple exponential smoothing with alpha = 0.9815

(G) Brown's linear exp. smoothing with alpha = 0.4907

(H) Holt's linear exp. smoothing with alpha = 0.9062 and beta = 0.0016

(I) ARIMA(1,0,0)

(J) ARIMA(0,1,0)

(K) ARIMA(2,0,0)

(L) ARIMA(0,1,1)

Using the above procedure, we forecast the future values of S&P 500 and the data covers 1511 time periods. We use Akaike Information Criterion AIC, root mean square error RMSE, mean absolute percentage error MAPE, and other important loss-functions to evaluate these out-of-sample forecasts. Table 9 reports the forecast estimation of the selected models. Followed by Table 10, which summarises the results of five tests run on the residuals to determine whether each model is adequate for the data. Each of the statistics is based on the one-ahead forecast errors, which are the differences between the data value at time t and the forecast of that value made at time t-1. The first three statistics measure the magnitude of the errors and a better model will give a smaller value.

An OK means that the model passes the test. One * means that it fails at the 95% confidence level. Two *'s means that it fails at the 99% confidence level. Three *'s means that it fails at the 99.9% confidence level. It is worth noting that the current selected model, model B (random walk with *drift*), passes 5 tests. This is because the random walk with *drift* model (B) has the lowest value of the Akaike Information, which has been used to generate the forecasts. Since no tests are statistically significant at the 95% or higher confidence level, the random walk with *drift* model is adequate for the data. The random walk with *drift* model assumes that the best forecast for future data is given by the last available data value plus a constant *drift* up or down. These results are unambiguously support the random walk with drift model as a dominant forecasting model for the U.S. S&P 500 index. Considering Table 9, the naïve model (model B) consistently generates overall the best out-of-sample forecasts in the U.S. S&P 500 market. This indicates that the random walk with *drift* model (Naïve model) outperforms the competing models in table 10 including the random walk without *drift*, and ARIMA models (1,0,0; 0,1,0; 2,0,0; and 0,1,1). This result is inconsistent with the finding of (Moosa and Burns, 2016) who found that the random walk without *drift* outperforms the random walk with *drift* model.

Moreover, the empirical results provided here emphatically indicate that the U.S. S&P 500 stock market do follow a random walk process. This means, the results support the random walk hypothesis, which has significant implications for testing market efficiency as well as understanding the stock market forecastability (Rapach and Zhou, 2013).

Table 9: Estimation period

Model	RMSE	MAE	MAPE	ME	MPE	AIC	HQC	SBIC
(A)	0.00827637	0.00572501	0.0739552	-3.32332E-16	0.00483203	-9.5887	-9.5887	-9.5887
(B)	0.00827032	0.0057045	0.0736954	0.000381239	-0.0000851541	-9.58884	-9.58753	-9.58532
(C)	0.159233	0.143374	1.84594	2.76687E-14	-0.0419647	-3.67345	-3.67214	-3.66993
(D)	0.0458711	0.0367355	0.475388	2.79767E-14	-0.00345081	-6.16119	-6.15857	-6.15415
(E)	0.00919481	0.00643202	0.0830689	0.000569693	0.00722256	-9.37691	-9.3756	-9.37339
(F)	0.00827505	0.00571776	0.0738609	0.000388067	0.00491865	-9.5877	-9.58639	-9.58418
(G)	0.00907435	0.0062921	0.0812646	0.0000071858	0.0000816231	-9.40328	-9.40197	-9.39976
(H)	0.00830268	0.0057012	0.0736547	-0.000241945	-0.00324965	-9.57971	-9.57708	-9.57266
(I)	0.00827035	0.00570969	0.0737598	0.000211751	0.00264687	-9.58883	-9.58752	-9.58531
(J)	0.00827637	0.00572501	0.0739552	0.000381239	0.00483203	-9.5887	-9.5887	-9.5887
(K)	0.00826894	0.00569662	0.0735939	0.00000577397	-0.0000100899	-9.58785	-9.58523	-.958081
(L)	0.00827779	0.00572149	0.0739091	0.000388549	0.00492475	-9.58703	-9.58572	-9.58351

Table 10: Model results

Model	*RMSE*	*RUNS*	*RUNM*	*AUTO*	*MEAN*	*VAR*
(A)	0.00827637	OK	OK	OK	OK	OK
(B)	0.00827032	OK	OK	OK	OK	OK
(C)	0.159233	***	***	***	***	***
(D)	0.0458711	***	***	***	***	***
(E)	0.00919481	***	***	***	OK	OK
(F)	0.00827505	OK	OK	OK	OK	OK
(G)	0.00907435	***	*	***	OK	OK
(H)	0.00830268	*	OK	**	OK	OK
(I)	0.00827035	OK	OK	OK	OK	OK
(J)	0.00827637	OK	OK	OK	OK	OK
(K)	0.00826894	OK	OK	*	OK	OK
(L)	0.00827779	OK	OK	OK	OK	OK

Note:

RMSE = Root mean squared error; **RUNS =** Test for excessive runs up and down; **RUNM =** Test for excessive runs above and below median; **AUTO =** Box-Pierce test for excessive autocorrelation; **MEAN =** Test for difference in mean 1st half to 2nd half; **VAR =** Test for difference in variance 1st to 2nd half; **OK =** Not significant (p > =0.05); * = Marginally significant (0.01 < p < =0.05); ** = Significant (0.001 < p <=0.01); *** = Highly significant (p <=0.001).

4.5. Conclusion

The future of macroeconomic forecasting has been under extreme scrutiny, particularly, given the death of large-scale forecasting models (Diebold, 1998). While a huge number of models have been identified in the literature as forecasting tools of the stock market returns, the in-sample and out-of-sample predictability performed extremely poorly (Welch and Goyal 2008). One of the major issues is whether the stock market returns follow a random walk process and the models that would provide accurate predictability.

This chapter provides novel evidence on this matter (for which there is little evidence) by investigating the U.S. S&P 500 stock market using a large amount of data (1511 obs) and the random walk with *drift* as a naïve model. Then, we compare the *ex* post forecasts with those of ARIMA models (1,0,0; 0,1,0; 2,0,0; and 0,1,1), moving average and exponential smoothing models and the random walk without *drift*. Using 60 forecasts, which corresponds to five years' worth of forecasts, the results from the model's comparison (Tables 9 – 10) decisively accept the random walk hypothesis in the U.S. S&P 500 stock market. The results also highlight that the random walk with *drift* is the best model to provide accurate prediction for the U.S. S&P 500 stock market; Fig. 4.9 displays the forecasting results. Although the random walk with *drift* outperformed the alternative models in this chapter, the random walk without *drift* (Table 9, model A) also demonstrates good fits to the underlying data. This result is inconsistent with the finding of (Moosa and Burns 2016) who argued, the random walk without *drift* outperformed the random walk with *drift*.

Another important evidence demonstrated in this chapter that the predictive model (random walk with *drift*) provides successful out-of-sample forecasts. Further, Tables 9-10 report that ARIMA (1,0,0; 0,1,0; and 0,1,1), and the Simple exponential smoothing models also demonstrate good fit for the data. This implies that the ARIMA models mentioned above and the simple exponential smoothing models behave like a random walk with *drift*. Nonetheless, the random walk with *drift* decisively outperformed the alternative models in this chapter and it is hard to beat based on the metrics (RMSE, MAE, MAPE, ME, MPE, and AIC) shown above. This result offers significant insights to investors concerning wealth allocation as well as avenue for future research.

5

The dynamic behaviour of credit, house prices, GDP, consumption and loans to the private sector in G7 Economies: A robust PVAR Analysis

5.1. Introduction

In recent years, advanced modern economies undergone a massive surge of credit growth resulted in an extraordinarily increases in house prices, especially during the time preceded the great recession. As a consequence, the role of credit on the level of asset prices, particularly, house price becomes centre stage in the finance and economic debates (Milan and Sufi 2009; Brunnermeier 2012). Thus far, several questions remain unanswered mainly, those concerns the multidirectional links between the important macroeconomic variables such as credit, house prices, GDP, consumption, and loans to the private sector. There is extensive literature studied the dynamic behaviour between credit and house prices (Khandani et al., 2009; Glaeser et al., 2010; Favilukis et al., 2010; Pavlov and Wachter, 2010; Mayer, 2011). Other study considered the households' consumption behaviours in an individual and social levels (e.g., Baiocchi and Minx, 2010; Yadav and Pathak 2016;Yang et la., 2016; and Li et al., 2019).

Nonetheless, the multidirectional links between credit, house prices, consumption, GDP, and loans from central banks to the private sector is under-researched. Overall, this chapter is the first work (to our knowledge) to provides extensive study of the aforementioned variables by answering the following questions: What is the interrelated nature between the dynamic behaviour of credit availability, house prices, GDP, consumption and the loans from central banks to the private sector? If any, does it play a significant role in advanced modern economies, concerning money lending qualities, credit creation, investment decisions, consumption and real output?

An empirical but robust response to these questions is of great importance to countercyclical macroprudential policy and global financial stability. Simply because the recent financial crisis delivered the lesson on how a persistent increase in house prices accompanied by rapid credit growth, intersect the dynamics behaviour of macroeconomic performance phenomenally. This is due to the strong correlation between credit and house prices, which may increase through housing wealth and collateral effects on credit supply and credit demand, adding to it the consequences of credit supply on house prices (Goodhart and Hofmann 2008). In this sense, the dynamic behaviour of credit, house prices, GDP, consumption and loans to the private sector in advanced modern economies takes different forms: First, it poses direct influences to the business cycle mechanisms via the aggregate expenditure, particularly when expenditure exceeds supply causing sharp increase in house prices through excess demand. Second, it also poses threats to the performance of the financial cycle through its effects on the profitability determinants[28] of financial institutions. Finally, since house purchases (in most cases) require mortgage financing, the cost of mortgages' credit comes into play with different forms of availabilities to shape the dynamics behaviour of house prices. This implies the correlated nature of the multidirectional links between credit availability and the house prices, which from a policy point of view, affects the performance of the financial institutions. Hence, in this chapter, we analyse the dynamic behaviour of credit and house prices on advanced modern economies from the supply side of the

[28] Yao et al., (2018) advocate that credit quality, operational efficiency, banking sector development, inflation, and industry concentration are negatively and significantly related to the profitability of banks.

economy. It is because, as financial indicators, the rapid growth in credit and house prices would outperform prominently any other indicators (Borio and Lowe, 2002). Most importantly, this chapter also provides an extensive set on analyses on the response of consumption to the fall or rise in house prices in advanced modern economies. Like wise we also examine the casual relationship between the GDP growth and the loans from central banks to the private sector on the G7's country level.

The ramifications of credit and house prices, GDP, loans to private sector and consumption in the macroeconomic activity received extensive attention after the recent financial crisis (Whittle et al., 2014). Until now, it is unclear how to measure house prices' changes or what are the difficulties averting the conventional economic modelling from providing an adequate estimate to such a significant phenomenon (Watkins and MCmaster, 2011). However, final posteriori estimation approaches still under investigation as to whether a rapid growth in credit and house prices can provide accurate results to predict the financial crisis. Considering the neoclassical economics approach, the supply and demand of housing widely affect the dynamic behaviour of credit availability and most importantly, money lending qualities in the housing markets. This is because homeowners, and those who still yet to pay off their mortgages, have easy access to more credit via home collateralisation.

Such a situation boosts the confidence level between borrowers and most importantly, lenders, leading to substantial credit creation, and boosting loans to the private sector, thus; house prices and the cost of credit skyrocketed. It is, however, there is no doubt that the dynamic behaviour of credit availability and house prices' increase can be seen as significant predictors of the financial crises. Time and again, the history of global housing markets, especially within advanced modern economies, yield almost identical scenarios, summarised in a rapid surge in property prices followed by crash or crisis. For example, during the late 1980s, the UK housing market experienced a massive house prices surge due to increasing financial liberalisation. Most recently, the U.S. subprime mortgage crisis where between the year 2000 and 2005 the house prices increased by over 61 percent, causing financial havoc. Similar situations also affected different housing markets in advanced modern economies such as France, 1996-2008 and Japan's housing bubble burst in late 1990.[29] These are good reasons to believe that the dynamic behaviour of credit and house prices, consumption, GDP, and loans to the private sector in advanced modern economies require an in-depth analysis. Also, for the same reasons, the sample of the variables mentioned above, which investigated in this study are collected from the G7 countries over the last three decades.

In light of these issues, this chapter studies the dynamic behaviour of credit, house prices, consumption, GDP, and loans to the private sector in advanced modern economies, G7 countries, using annual data over the period 1980-2017. Our choice of this time period is to investigate changes to the underlying variables across numerous economic events including pre and post the recent financial crisis. As far as the author knows, this is the first attempt to investigate the dynamic behaviour of the aforementioned variables collectively to address all the relevant questions raised above. Therefore, this chapter provides two main contributions to the relevant literature. The study examined the dynamic behaviours of the underlying variables from two different perspectives:

First, it highlights the correlated nature of interdependence between credit availability, house prices, GDP, consumption and the loans to the private sector, using the system-GMM method. Our findings show that an increase in house prices in the G7 economies will not affect consumption, whereas house prices positively cause credit, which indicates house prices will increase by 8.6 percent when credit availability increase by 1 percent. This result is in line with the arguments that asset prices influencing credit creation and output growth (Aikman et al., 2014; Borio,

[29] At the end of 1990, the housing market in Japan plunged into severe depression due to a burst in property prices (Oizumi, 1994).

2014). From a macroprudential point of view, this result supports the Loan-to-value (LTV) caps policy, which adopted by many countries recently. Based on these results, it can be argued that the dynamic behaviours of credit and house prices directly affect the macroeconomic performance of the G7 countries concerning money lending qualities, credit creation, investment decisions, consumption and real output.

Second, the orthogonalised impulse response functions (OIRFs) outcome, which shows how the VAR residuals helps isolating the response of house prices, credit, GDP, and loans from central banks to the private sector to a shock on each variable. By implementing this method, we are able to obtain a clear picture of the dynamic behaviours of the underlying variables in the G7 economies. This chapter provides convincing results that the dynamic behaviour of credit, house prices, GDP, consumption, and the loans to the private sector play significant role in shaping the macroeconomic performance in advanced modern economies, in this case, G7 countries.

Finally, this chapter is structured as follows: Section 5.2. reviews the related literature. Section 5.3 lays out the empirical methodology. Section 5.4 describes and discusses the data using a fixed-effects method. The PVAR results provided in section 5.5. Section 5.6 concludes.

5.2. Related Literature

This chapter relates to well-established empirical literature analysing the relationship between credit, house prices, GDP, consumption, loans to the private sector, asset prices and the macroeconomy. Vast studies concerning these areas confirmed the link between credit growth, asset prices (mainly house prices) and the macroeconomy. The literature further intensified as the recent financial crisis revealed the consequences of rapid credit growth and house prices increase to the macroeconomy. However, before the recent financial crisis, there has been growing interest to determine the dynamic movement of house prices and real estate. Engle et al., (1985) presented a model for house prices' determination based on Kalman filtering and smoothing. They examined house prices using monthly data over the period 1973 – 1980 and concluded that the main factors of house prices increase are the fall of capitalisation rates which caused by rental inflation, tax and mortgage rates.

Goodhart (1995) examines the surge of house prices on bank lending in the UK and the U.S. using historical data, and he finds that unlike the U.S., the credit growth in the UK is significantly affected by house prices. Quigley (2001) argues that the economic fundamental as crucial as they are can only explain 10 to 40 percent of house prices changes. Farlow (2004) finds that the dramatic increase in house price is not due to the usual demand and supply fundamentals; instead, it is due to the behaviour of consumers and banks. Tsatsaronis and Zhu (2004) argue that the house prices dynamic is due to three variables related to mortgage finance, including bank credit, short-term interest rates and spreads. They also suggest that an increase in interest rates may cause a surge in house price over time. Goodhart et al., (2006) analyse the relationship between bank lending and property prices based on a multivariate empirical framework and find that causality does, in fact, seems to go in both directions, but that the effect of property prices on credit appears to be stronger than the effect of credit on property prices.

Wheaton and Nechaye, (2008) investigate the house prices' inflation over the period 1998 – 2005, they revealed that the intense level of excess price increase is significantly due to the availability of the risky mortgage credit and the purchases of houses for investment purposes.

A study by Mendoza and Terrones (2008) proposed a method for measuring credit boom in industrial and emerging economies over the last four decades. The authors concluded that not all credit booms yield financial crisis; however, most emerging markets' crises were associated with credit booms. They further argue that the large capital inflows often antecedent credit booms in emerging economies. Mian and Sufi (2009) find credit expansion is the primary source of household debt and that the year 2002 – 2005 is the only period during which income and mortgage credit growth is negatively correlated. Schularick and Taylor (2012) presented evidence that excessive credit growth may be regarded as a good predictor for both financial and banking crises. Favara and Imbs (2015) assessed the U.S. banks deregulation; they advocate that house prices are well inflicted by the credit expansion induced by deregulation. Recently, Justiniano et al., (2019) argue that the credit supply associated with looser lending constraints, caused the housing boom that preceded the great recession.

There are broad existing studies in this subject, although none of them addressed all the relevant questions we have raised above. Most of the studies confirmed the link between credit and house prices; however, they tend to focus on one direction, which is the effect of house prices on credit. Others believe that house prices changes are only partially affected by economic fundamentals but strongly affected by consumers and bank behaviour. As stated the introduction, the analysis of this chapter is intended to close this gap by examining the dynamic behaviour of credit, house prices, GDP, consumption, and the loans to the private sector in the G7 economies.

5.3. Empirical Methodology

5.3.1. Panel Vector Autoregression (PVAR)

Known as longitudinal or cross-sectional time-series data, the behaviour of the panel data entities can be observed over time. The advantage of panel data that it allows the control over variables those are difficult to observe or measure such as cultural factors. In addition, panel data also accounts for individual heterogeneity which provides control for variables that change over time, for example, national policies, international agreements and federal regulations. Besides, PVAR is widely applied in the macroeconomics' literature, Canova and Ciccarelli (2013) summarised several PVAR advantages as follows:

> (a) They are able to capture both static and dynamic interdependencies, (b) treat the links across units in an unrestricted fashion, (c) easily incorporate time variation in the coefficients and in the variance of the shocks, and (d) account for cross-sectional dynamic heterogeneities (Canova and Ciccarelli, 2013: p. 2).

This chapter aims to investigate the dynamic behaviour of credit, house prices, consumption, GDP, and the loans to the private sector on the G7 economies. in particular, the response of one variable to orthogonal shocks in another variable. To identify the effect of one shock at a time while holding other shocks constant, following the literature, we apply the panel vector autoregression (PVAR) model developed by Love and Zicchino (2006). Specially, we use the system-GMM method developed by Arellano and Bover (1995), which builds on the work of Bond (1988).

The PVAR framework allows all the variables in the system to affect each other simultaneously. In other words, how changes in house prices (positive or negative) affect credit availability and vice versa. This is because, in the PVAR system, all variables are treated endogenously and independently (Ramey and Shapiro, 1998). That being said, this study follows a similar methodological approach conducted by Assenmacher-Wesche and Gerlach (2008); and Goodhart and Hofmann (2008) who applied PVAR to examine the relationships between real GDP, credit growth, house prices and inflation.

Following Abrigo and Love (2016), in this study, we take the form of G-variant PVAR of order p with a panel-specific fixed effect which can be expressed as follows:

$$\Psi_{it} = \Psi_{it-1}\,\mathrm{B}_1 + \Psi_{it-2}\mathrm{B}_2 + \cdots + \Psi_{it-p+1}\mathrm{B}_{p-1} + \mathrm{X}_{it}C + U_{it} + e_{it} \tag{4.1}$$

$$i \in \{1,2,\dots,N\},\, t \in \{1,2,\dots,T_i\}$$

Where Ψ_{it} is a $(1\ x\ G)$ vector of dependent variables; and X_{it} is a $(1xl)$ vector of the exogenous variable (credit, house prices, GDP, consumption, and LtoPS), and i is the country index; u_i and e_{it} are $(1\ x\ G)$ vectors of dependent variable-specific fixed effects and idiosyncratic error, respectively. The $(1\ x\ G)$ matrix B and the (GxG) matrices $\Psi_1, \Psi_2,\ \dots,\ \Psi_{p-1}, \Psi_p$ are parameters to be estimated, assuming that innovations are represented in the following characteristics: $0, E\ [e'_{it}e_{it}] = \Sigma\ and\ E[e'_{it}e_{is}] = 0\ for\ all\ t > s.$

The parameters described above can be estimated in connection with the fixed effects. It can also be estimated independently without the fixed effect (after some transformation) using ordinary least square (OLS). However, Holtz-Eakin et al., (1988) criticised the fixed effect estimator as being severely bias when used with panels that have lagged endogenous variables, especially if the time dimension is small. Since the data used in this study spans from 1980 to 2017, the bias problem is not a significant issue.

In addition, to enhance the reliability of the results, we apply the generalised method of moment (GMM) estimator as an auxiliary tool to address the bias problem. The GMM estimator is extensively discussed in the recent macroeconomic literature (Love and Zicchino, 2006; Tiwari, 2011; Gravier-Rymaszewska 2012; and Feyen et al., 2014). This is because, using equation-by-equation approach, the GMM estimator can provide a consistent estimation to the PVAR analysis; however, applying the system of equations may provide a more accurate result (Abrigo and Love, 2016; Holzt-Eaking et al., 1988). Thus, in this study, I apply the system of equations to estimate the panel VAR.

For example, let the standard set of $\llcorner \geq \mathrm{K}\rho + l$ given by the row vector, $\mathbb{Z}_{it}$, where, $X_{it} \in \mathbb{Z}_{it}$, to address this problem and based on equation (1) represented in a different form as follows:

$$\Psi^{*}_{it} = \Psi^{*}_{it}\ \mathrm{B} + {}_{e^{\ *}_{it}} \tag{4.2}$$

$$\overline{\Psi^{*}_{it}} = [{}_{\Psi_{it}}^{1*}\quad {}_{\Psi_{it}}^{2*} \ldots {}^{k-1*}_{\Psi_{it}}\quad {}^{k*}_{\Psi_{it}}]$$

$$\Psi^{*}_{it} = [\Psi^{*}_{it-1}\ \Psi^{*}_{it-2} \ldots \Psi^{*}_{it-p+1}\quad \Psi^{*}_{it-p}\quad \mathrm{X}^{*}_{it}]$$

$$e^{*}_{it} = [e^{1*}_{it}\ e^{2*}_{it} \ \ldots e^{k-1*}_{it}\quad e^{k*}_{it}]$$

$$\mathrm{B}' = [B_1{}'\ \ B_2{}'\ \ \ldots\ B'_{p-1}\ \ B'_p\ \ B'\ ]$$

The asterisk represents some of the transformations of the original variables, however, assuming the original variable as n_{it} the transformation first difference indicates that $n^{*}_{it} = n_{it}$ - n_{it-1}, whereas, the forward orthogonal deviation is $\overline{n^{*}_{it}}$ = $(n_{it} - n_{it})\ T_{it} / \sqrt{(T_{it}+1)}$, where T_{it} is the future observations available for the panel i at a time t, and $\overline{n_{it}}$ is its average. That being said, stacking the observations over panels as well as overtime then the GMM estimator represented as follows:

$$B = (\overline{\Psi^{*\prime}}\ Z\,\widehat{W}\ Z'\ \overline{\Psi^{*}}\ )^{-1}(\ \overline{\Psi^{*\prime}}\ Z\,\widehat{W}\ Z'\ \Psi^{*}\ ) \tag{4.3}$$

Where $\widehat{W}$ is a $(L\ X\ L)$ weighting non-singular matrix, asymmetric and positive-semi definite. Let E $[Z'\ e]$ = 0, and rank E $[\ \Psi^{*\prime}\ Z] = kp + l$ then the GMM estimator is consistent. However, to choose the optimal lag order for the PVAR specification and moment condition, we apply the consistent model and moment selection criteria[30] (MMSC) developed by Andrews and Lu (2001).

[30] For more elaboration on the model and moment selection criteria (MMSC), see (Hansen, 1982; Andrews and Lu, 2001; and Abrigo and Love, 2016).

5.3.2. Impulse Response

To identify the behavioural interdependence between the underlying variables variables, we apply the impulse response function (IRF). The impulse response function allows the identification of how the shock in one variable, for instance, credit or house prices is propagating to other variables (consumption, GDP, LtoPS) and whether the effect is large or small. The interpretation of the impulse responses in the PVAR is generally more straightforward than in factor models (Canova and Ciccarelli, 2013), that is, if all the models of the companion matrix $\bar{\mathbb{A}}$ are strictly less than one, then the VAR model is stable, (Hamilton, 1994; and Lütkepohl, 2005). The companion matrix can be expressed as follows:

$$\bar{\mathbb{A}} = \begin{bmatrix} \mathbb{A}_1 & \mathbb{A}_2 & & \mathbb{A}_p & \mathbb{A}_{p-1} \\ I_k & O_k & \cdots & O_k & O_k \\ O_k & I_k & & O_k & O_k \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ O_k & O_k & \cdots & I_k & O_k \end{bmatrix} \tag{4.4}$$

The above stability indicates that the PVAR is invertible with infinite –order vector moving average (VMA) representation (Abrigo and Love, 2016). The vectors moving average (VMA) representation facilitate the estimation of impulse response functions and the forecast-error decompositions. A simple impulse function Ω_i can be written in the form of infinite vector moving-average, where Ω_i represents the VMA parameters as follows:

$$\Omega_i = \begin{cases} I_k \;, \; i = 0 \\ \sum_{j=1}^{i} \Omega_{t-j} \mathbb{A}_{j,} \, i = 1,2,.. \end{cases} \tag{4.5}$$

As the innovations e_{it} are contemporaneously correlated, the shock in one variable is highly likely to be associated with shocks to other variables.

5.3.3. Forecast-error Variance Decomposition (FEVD)

The h-step-ahead forecast-error is expressed as follows:

$$\Psi_{it+h} - \mathrm{K}[\Psi_{it+h}] = \sum_{i-0}^{h-1} e_{i(t+h-i)\Phi_i} \tag{4.6}$$

Where Ψ_{it+h} is the observed vector at a time $t + h$ and $\mathrm{K}[\Psi_{it+h}]$ is the h-step-ahead predicted vector made at the time t (Abrigo and Love, 2016).

5.4. Data

The sample in this study includes the G7 advanced economies: Germany, France, Canada, Japan, UK, US, and Italy, over the period 1980 – 2017. The financial variables under investigation are house prices, credit, GDP, consumption and the Loans from central banks to the private sector (LtoPS); which represent the fundamental of financial intermediation Claessens et al., (2011b). To measure credit, we use the aggregate claims on the private sector by deposit money banks, which is widely applied in recent literature.[31] The house prices, GDP, and consumption series are collected from the organisation for economic co-operation and development (OECD) and credit series collected from the international financial statistics (IFS). Table 11 presents the summary statistics for the underlying variables across the seven countries, using ordinary least square (OLS) regression, which fits the data well at the 0.5 significant level and P< 0.008. The p-values shown in table 7 are the results of the t-tests for the individual variables.

[31] Mendoza and Terrones, 2008; and Claessens et al., (2011).

Table 11: OLS Regression (House prices, consumption, GDP, credit, and LtoPS)

HouseCost	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Consumption	-.1705718	.0399787	-4.27	0.000	-.2490182	-.0921254
GDP	.1591935	.033528	4.75	0.000	.0934046	.2249823
Credit	-.0763475	.0336947	-2.27	0.024	-.1424635	-.0102314
LtoPS	.1963821	.042934	4.57	0.000	.1121367	.2806275
cons	41297.55	3129.872	13.19	0.000	35156.09	47439

No of observations = 1,064
Prob > F = 0.000
Root MSE = 29208
R – squared = 0.0572
AJ R- squared = 0.0536

The pooled OLS test of the underlying variables yields initial stimulating results about the multidirectional links between the variables. To ensure the robustness of the findings, we perform empirical exercises to analyse further the panel data applied in this study, such as the fixed-effects (FE) model. A significant advantage of the fixed-effects model that, it investigates the impact of the underlying variables, which varies over time. It also explores the relationship between the predictor and outcome variables within an entity. Each entity has individual characteristics, which may or may not influence the predictor variables. For example, credit in the G7 economies could influence the behaviour of new-build houses and house prices, and vice-versa.

However, when applying the FE model, the underlying assumption lies within the individual may impact or even bias the predictor or outcome variables which should be under careful control (Torres-Reyna, 2007). This is the rationale behind the assumed correlation between the entity's error-term and the predictor variables. The FE model removes the effect of those time-variant characteristics and provides a clear assessment of the net effect of the predictors on the outcome variable[32]. Table 12 reports the fixed-effects results for the variables applied in this study.

[32] See Torres-Reyna (2007); and Park (2011) for in-depth analysis and discussions.

For example, the results show that the dynamic behaviour of house prices has a significant influence on the credit behaviour. This is because the two-tail (p>|t|) p-values results, which shown in table 8, test the hypothesis that each coefficient is different from zero, and to reject this, the p-values has to be lower than 0.05. In addition, the coefficient of the regressors indicates how much credit changes when the house prices change, see table 12. This means there is negative relationship between house prices and credit. However, this is a robust indication that the panel data applied in this study is appropriate.

Table 12: Fixed-effects test results

HouseCost	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Consumption	-.1304078	.0379383	-3.44	0.001	-.2048511	-.0559645
GDP	.1795677	.0313918	5.72	0.000	.1179702	.2411652
Credit	-.1017155	.032714	-3.11	0.002	-.1659076	-.0375235
LtoPS	.1028064	.042175	2.44	0.015	.0200499	.185563
Country						
2	-6505.241	3108.962	-2.09	0.037	-12605.71	-404.7749
3	28451.17	3094.303	9.19	0.000	22379.47	34522.88
4	-5322.008	3112.384	-1.71	0.088	-11429.19	785.1715
5	-9314.73	3325.73	-2.80	0.005	-15840.54	-2788.918
6	1655.606	3130.407	0.53	0.597	-4486.94	7798.152
7	6115.863	3128.78	1.95	0.051	-23.48911	12255.21
_cons	40843.48	3581.972	11.40	0.000	33814.86	47872.09

No of observations = 1,064
Prob > F = 0.000
R – squared = 0.2052
Root MSE = 26893
AJ R – squared = 0.1977

Further, we test the data for a cross-sectional dependence correlation using Breusch-Pagan's Lagrange Multiplier (1980) test of independence. Since the data applied in this study is over 20 years, in macro-panel data, it is a source of cross-section -dependency problem. Table 13 reports the result of Breush Pagan's LM test of independence, which shows no cross-section dependence. This is because the null hypothesis in the B-P/LM test of independence means the residuals across entities are not correlated,[33] which in this case, (pr = 0.000), see Table 13.

Table 13: Breush Pagan's test of independence

Correlation matrix of residuals:

	e1	__e2	__e3	__e4	__e5	__e6	__e7
e1	1.000						
e2	-0.506	1.000					
e3	-0.667	0.122	1.000				
e4	-0.241	-0.095	0.070	1.000			
e5	-0.380	0.041	0.293	-0.105	1.000		
e6	0.430	-0.502	0.215	-0.108	-0.240	1.000	
e7	-0.090	-0.165	-0.372	-0.107	-0.243	-0.465	1.000

Breusch-Pagan LM test of independence: chi2 (21) = 77.666, Pr = 0.000

5.4. PVAR Results

This section provides the empirical results for this chapter, generated from the system generalised method of movement (PVAR), the forecast error variance decomposition and the analysis of the impulse response functions.

5.5.1. Panel data balance

As mentioned in the data section above, the variables under investigation (GDP, house prices, consumption, loan to the private sector (LtoPS) and credit) are from

[33] For an in-depth analysis of the B-P/LM test of independence and how to implement it in Stata, see Breusch and Pagan (1980); and Torres-Reyna (2007).

the G7 economies. Before estimating the PVAR, we perform a data balance test to prepare STATA to handle the panel data by using the command *xtset.* Since we have a quarterly data, we transformed the year to a *qdate* to avoid the problem of repeated time values within panel. This is because panel data defined by identifier variable as well as time variable. Table 14 reports the result of the test where it shows the country is strongly balanced.

Table 14: Xtset qdate Year

```
xtset qdate Country

        panel variable:  qdate (strongly balanced)
         time variable:  Country, 1 to 7
                 delta:  1 unit
```

Notes: Country represents panels i and the year represents the time variable t.

Strongly balanced means that countries have the data for all the years under investigation, in this study, the G7 Countries; however, if a Country misses a data for one year, then the data is unbalanced.

5.5.2. PVAR Lags Selection Order Criteria

To establish an appropriate lag-order for the PVAR analysis, in this study, we use the moment and model selection criteria (MMSC). The MMSC is developed by Andrews and Lu (2001), based on Hansen's (1982) J statistic of over-identifying restrictions. Table 15 shows the overall coefficients of determination (CD), corresponding J-p-value, Bayesian information criteria (MBIC), Akaike's (1969) information criterion (MAIC), and Hannan and Quinn (1979) information criterion (MQIC). Based on the selection criteria mentioned above, the first-order PVAR is the appropriate model for this study, as it has relatively small MAIC, MBIC and MQIC.

Table 15: PVAR moment model lag selection criteria (Sample: 1984-2016)

lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	.9988094	274.6702	1.46e-24	-154.1068	124.6702	13.15287
2	.9999361	223.7297	7.89e-24	-62.12168	123.7297	49.3848
3	.9998726	127.1441	1.19e-15	-15.78156	77.14413	39.97168

Notes: Number of observations 304, panels 7, and average T number is 2.000

In order to infer the joint behaviour of credit, house prices, consumption and the loan to the private sector on the G7 economies; we estimate the model using sample data from the G7 countries over the period 1980-2017. In this case, we end up with a global sample of 7 countries observed over 37 years. Nevertheless, the sample is diverse and includes developed countries from different regions around the world and different financial systems.

We also address the issue regarding the presence of unit roots in the series, which significant to avoid reducing the time span of our sample. Table 16 presents the results of the Levin-Lin-Chu unit-root test, where the null hypothesis means all series are non-stationary and the alternative hypothesis is that at least one of the series in the panel is stationary. The Levin-Lin-Chu tests reject the presence of unit roots for all the variables. The header of the output summarises the test, which performed by using xtunitroot. The test also includes fitting of the augmented dicky-fuller regression for each panel and the number of the 6 lags selected based on the AIC. In addition, the estimation of the long run variance of the series is performed by xtunitroot, which is by default, uses the Bartlett kernel using 6 lags as selected by the method proposed by Levin et al (2002).

Table 16: Levin-Lin-Chu unit-root test

Ho: Panels contain unit roots		AR parameter: Common
Ha: Panels are stationary		Panel means: Included
ADF regressions: 1 lag		Asymptotics: N/T -> 0
LR variance: Bartlett kernel, 6.00 lags average (chosen by LLC)		
Variable	Adjusted t^*	p-value
HouseCost	-29.3701	0.000
Consumption	-6.8411	0.000
Credit	-24.0155	0.000
LtoPS	-98.8741	0.000
GDP	-3.4771	0.000

It is clear that all the Levin-Lin-Cho bias-adjusted t statistics are significant at all usual testing levels. Thus, we reject the null hypothesis and conclude that the series are stationary.

To this end, we estimate the homogenous PVAR model via the system generalised method of moment (GMM)[34] approach to enhance the quality of the model's coefficients. As shown in Table 14, the datasets utilised in this study is a strongly balanced panel with $N > T$ which helps to avoid the proliferation problem and allows for a consistent GMM estimation. Table 17 reports the casual relationships between credit, house-prices, consumption, GDP and the loans to the private sector (LtoPS) for the G7's economies, implemented by system-GMM.[35]

The system-GMM estimation results shown in Table 17 are robust since the numbers of observations included in the estimation are the same as that in the dataset, i.e., the results do not impose additional restrictions. That is because, by default, the PVAR drops from estimation observations with missing data. In such cases, applying the system-GMM instrument proposed by (Holtz-Eakin et al., 1988) improves the

[34] The Technical application of GMM PVAR is based on the Stata codes proposed by Abrigo and Love, (2016).

[35] For more details about the PVAR codes implemented in this study, see Abrigo and Love, (2016).

estimation by replacing any missing values with zero, which results in a more efficient estimation.

The system-GMM results (table 17) show that the house prices do not cause consumption. This implies that an increase in house prices in the G7 economies will not affect consumption, which is inconsistent with the finding of (Berger et al, 2018), who found that consumption response on impact, to a permanent house prices shock. However, the result is in line with the findings of (Ganong and Noel, 2017) that households with high marginal propensity to consumes (MPCs) tend to have little response to a house price shocks. In addition, house prices positively cause credit, which indicates house prices will increase by 8.66% when credit availability increase by 1%. As Favara and Imbs (2015) put it, high demand in credit increases commercial banks' lending which also increases the demand for houses, and consequently house prices increase. These results provide significant insights to behavioural economists concerning house prices' changes relevant to the contemporaneous difficulties of providing economic modelling, which explains changes in house prices (Watkins and McMaster, 2011). The result shows positive correlation between house prices and GDP. That means house prices will increase by 3.99% when GDP increases. These empirical evidences support the work of (Chan and Woo, 2013) that there is a bi-directional link between credit and GDP. Also, the house prices cause the loans from central banks to the private sector and the relationship is negative. Therefore, house prices will decrease by 3.17% when loans from central banks to private sectors increase by 1%.

Moreover, consumption causes house prices with a negative relationship, which implies that a 1% increase in house prices will decrease consumption by 15.74%. This result is also consistent with the findings of (Kaplan et al, 2015) who found that the long-term drop of house price in the U.S. can be explain by the collapse of the aggregate consumption. Attanasio al (2009) suggest that the non-homeowners hoping to purchase a house in the future, an increase in prices might lead to a reduction in their overall level of consumption. Consumption also causes credit and the relationship is negative. This implies that a 1% increase in consumption will lead to a decrease in credit by 5.23% and this result is consistent with the findings of (Antzoulatos,1996) who found that a predictable growth in consumer credit is significantly related to the consumption growth.

Table 17: Estimated causality results from the dynamic panel SYS-GMM

	Dependent Variables				
Independent Variables	HousePrice	Consumption	Credit	GDP	LtoPS
HousePrice	0.272	-1.16	8.66***	3.99***	-3.17**
	(0.33)	(0.247)	(0.00)	(0.00)	(0.002)
Consumption	-15.74***	-9.52***	-5.23***	2.63*	2.47***
	(0.00)	(0.00)	(0.00)	(0.008)	(0.013)
Credit	1.38***	9.42***	3.65	-6.96***	-0.80**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.42)
GDP	14.83***	11.26***	2.94**	-16.88***	-11.3***
	(0.00)	(0.00)	(0.003)	(0.00)	(0.00)
LtoPS	12.37***	15.29***	6.20***	-1.65	-4.87***
	(0.00)	(0.00)	(0.00)	(0.100)	(0.00)

Notes: Instruments : l(1/4).(HouseCost Consumption Credit GDP LtoPS), observations 304, panels 7, average T number is 2.000, and Q (b) = 904. Ave. no. of T = 5.000
Final GMM Criterion Q(b) = .686; No. of obs = 760
Initial weight matrix: Identity; GMM weight matrix: Robust
No. of panels = 152

The result also supports the permanent income theory; which suggests that people are willing to spend their money at a level consistent with their long-term average income. It is clear that consumption also causes the loan to the private sector and the relationship is positive. This indicates that an increase by 1% in consumption will cause the loan from central banks to the private sectors to increase by 2.47%.

In addition, credit causes house prices and the relationship is positive; which means a 1% increase in credit will lead to approximately 1.38% increase in the house prices. This result is consistent with the findings of (Goodhart and Hofmann, 2008) that credit influences money and house prices. The result also in line with the work of (Adelino et al, 2012) who found that easier access to credit can significantly increase house prices. Credit also cause consumption but with a position relationship. This implies that an increase by 1% in credit will increase consumption by 9.42%. This causal relationship between credit and consumption supports the argument of (Ludvigson, 1999) that predictable growth in consumer credit is significantly related to consumption growth. There is also a negative correlation between credit and GDP, an indication that an increase in credit by 1% will result in a decreasing GDP by 6.86%. This result is also in line with the findings of (Repullo and Saurina, 2011) who argue that credit gap might not be appropriate for the buffer because it moves countercyclically with the GDP growth. More importantly, there is a negative relationship between credit and the loans from central banks to the private sector. This indicates that a 1% increase in credit will lead to a decrease in the loans from central banks to the private sector. Also, GDP causes house prices and the relationship is positive. It implies that a 1% increase in the GDP will cause house prices to increase by 14.83%, which is in line with the finding of (Leung, 2003) that the increase in house prices is the consequences of persistent economic growth. The relationship between GDP and consumption is also positive. This indicates that a 1% increase in GDP causes an increase in consumption by 11.26%. This result is just a resemblance of the fact that GDP viewed as a measure of aggregate economic well-being (Dynan and Sheiner, 2018).

Moreover, GDP and credit also have positive relation, which means a surge in GDP by 1% will lead to an increase in credit by 2.94%. The result is consistent with the argument that higher credit demand means higher domestic demand for goods and services (Ermişoğlu et al, 2013). The loan from central banks to the private sector also cause house prices and the relationship is positive. It implies that a 1% increase in the loan from central banks to the private sector will lead to an increase in house prices by 12.37%. This result reminds us with the recent U.S. housing market crisis; where the easy access to credit accompanied by reduced cost of credit were the central factors that fuelled the increase in housing prices (Aelino et al, 2012). Loans from central banks to the private sector cause consumption with positive correlation. It means, a 1% increase in the loans from central banks to the private sector will lead to increasing consumption by 15.29%. It also causes credit and the relationship is positive, which indicates that the increase of loans from central banks to the private sector by 1% will result in a surge in credit by 6.20%. However, the result shows that the loans from central banks to the private sector does not cause GDP. Thus, the increase or decrease in the loans from central banks to the private sector does not have a positive or positive effect on the gross domestic products in the G7 economies.

5.5.3. Forecast Variance Decomposition

This section provides the forecast error variance decomposition for the dynamic behaviour of credit, house prices, GDP, consumption and the loans from central banks to the private sector. At the G7 country level, a shock to house prices amounts of 0.004%, 0.019%, 0.012%, and 0.031% of the variances in consumption, credit, GDP and loans from central banks to the private sector (LtoPS), respectively for a 10-years period ahead. These results indicate that a positive or negative shock to house prices in the G7's economies significantly affect consumption expenditure, credit availability, GDP, and the loans from central banks to the private sector, in both short and long run. The shock to Credit at the G7's level, amounts to 0.009%, 0.167%, 0.055%, and 0.001% of the variance in house prices, consumption, GDP, and the loans from central banks to the private sector (LtoPS), respectively, for a 10-years period ahead. Likewise, at the G7's level, a shock to the GDP amounts to 0.001%, 0.046%, 0.005% and 0.022% of the variance in house prices, consumption, credit and the loans from central banks to the private sector (LtoPS), respectively, for a 10-years period ahead. Again, these results are evident and consistent with the causality tests provided in Table 17 however, Table 18 showcases more details concerning the variance decomposition and figures (5.1 & 5.2) visualises the results.

Table 18: Variance Decomposition at a Group of Seven (G7) Level

Forecast horizon	Impulse variable				
	HouseCost	Consumption	Credit	GDP	LtoPS
HouseCost					
0	0	0	0	0	0
1	1	0	0	0	0
2	.9606492	.0042449	.0198254	.012116	.0031644
3	.9478346	.0045927	.0196281	.0246514	.0032932
4	.9411449	.0065668	.0195657	.0287902	.0039322
5	.9387306	.0076216	.0195267	.0297797	.0043413
6	.9380639	.007963	.0195221	.0299526	.0044984
7	.9379237	.0080433	.0195227	.0299702	.0045402
8	.9379021	.0080566	.019523	.0299701	.0045482
9	.9378998	.008058	.0195231	.0299699	.0045492
10	.9378996	.008058	.0195231	.0299701	.0045493
Consumption					
0	0	0	0	0	0
1	.0592792	.9407208	0	0	0
2	.1564475	.8184204	.0178618	.0040492	.003221
3	.1622022	.8075476	.0183176	.0076554	.0042773
4	.1618439	.8048931	.0182825	.0107128	.0042677
5	.1621729	.8032359	.0182545	.0119171	.0044195
6	.1624446	.8025497	.0182475	.0122248	.0045334
7	.1625534	.8023404	.0182467	.0122814	.0045779
8	.162582	.8022931	.0182469	.0122881	.0045899
9	.1625872	.8022852	.018247	.0122884	.0045922
10	.1625878	.8022843	.0182471	.0122884	.0045924
Credit					
0	0	0	0	0	0
1	.0090359	.1679294	.8230346	0	0
2	.008264	.1745207	.7613265	.0557255	.0001633
3	.0083141	.1724733	.7422397	.0759247	.0010482
4	.0127573	.1732164	.7298895	.0819678	.0021691
5	.0157046	.1737009	.724372	.0833205	.002902

6	.0167153	.1739033	.7226985	.0835015	.0031815
7	.0169667	.1739549	.7223191	.0835039	.0032554
8	.0170118	.1739635	.7222563	.083499	.0032695
9	.0170169	.1739642	.7222494	.0834982	.0032713
10	.0170171	.1739641	.722249	.0834984	.0032714

(Continued on next page)

Table 18: (Continued)

GDP					
0	0	0	0	0	0
1	.0013236	.0461711	.0005881	.9519171	0
2	.1130371	.1123233	.0010395	.7515554	.0220447
3	.1619215	.1347528	.0028315	.6659034	.0345907
4	.177284	.141702	.0035946	.6382223	.0391971
5	.1812353	.1433666	.0038108	.6311087	.0404785
6	.1819914	.1436544	.0038587	.629751	.0407445
7	.1820848	.1436837	.0038662	.6295832	.0407821
8	.1820883	.1436834	.0038668	.6295769	.0407845
9	.1820877	.1436831	.0038668	.629578	.0407843
10	.1820881	.1436833	.0038668	.6295773	.0407844
LtoPS					
0	0	0	0	0	0
1	.1381954	.0127204	.0335821	.0148902	.8006119
2	.1425216	.0609313	.0385943	.0143465	.7436062
3	.1512644	.0636806	.0380127	.0156235	.7314187
4	.1512049	.0635786	.0379791	.0171897	.7300477
5	.1512132	.0636549	.0379327	.0180314	.7291678
6	.1513518	.0637767	.0379104	.018302	.728659
7	.1514309	.0638343	.037903	.018363	.7284687
8	.1514571	.0638513	.0379013	.0183726	.7284176
9	.1514631	.0638549	.0379011	.0183734	.7284075
10	.1514641	.0638555	.037901	.0183734	.728406

Figure 5.1

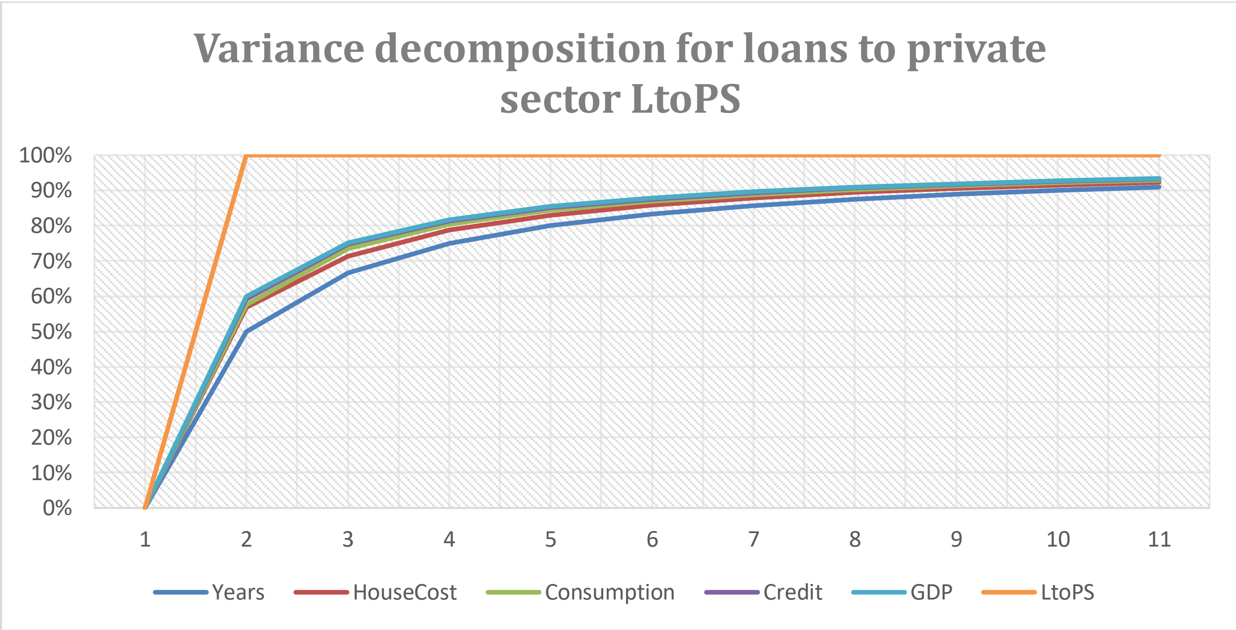
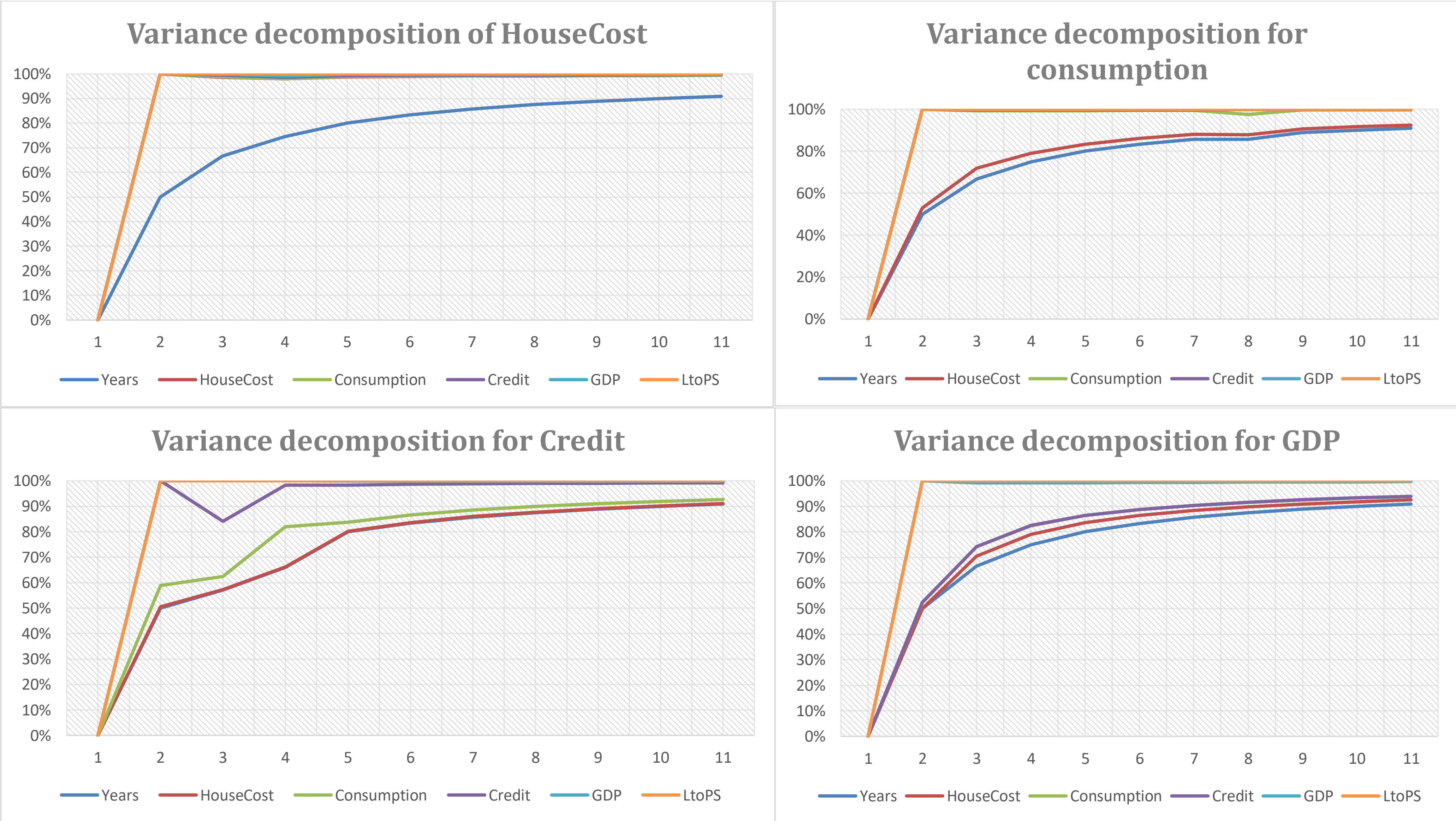
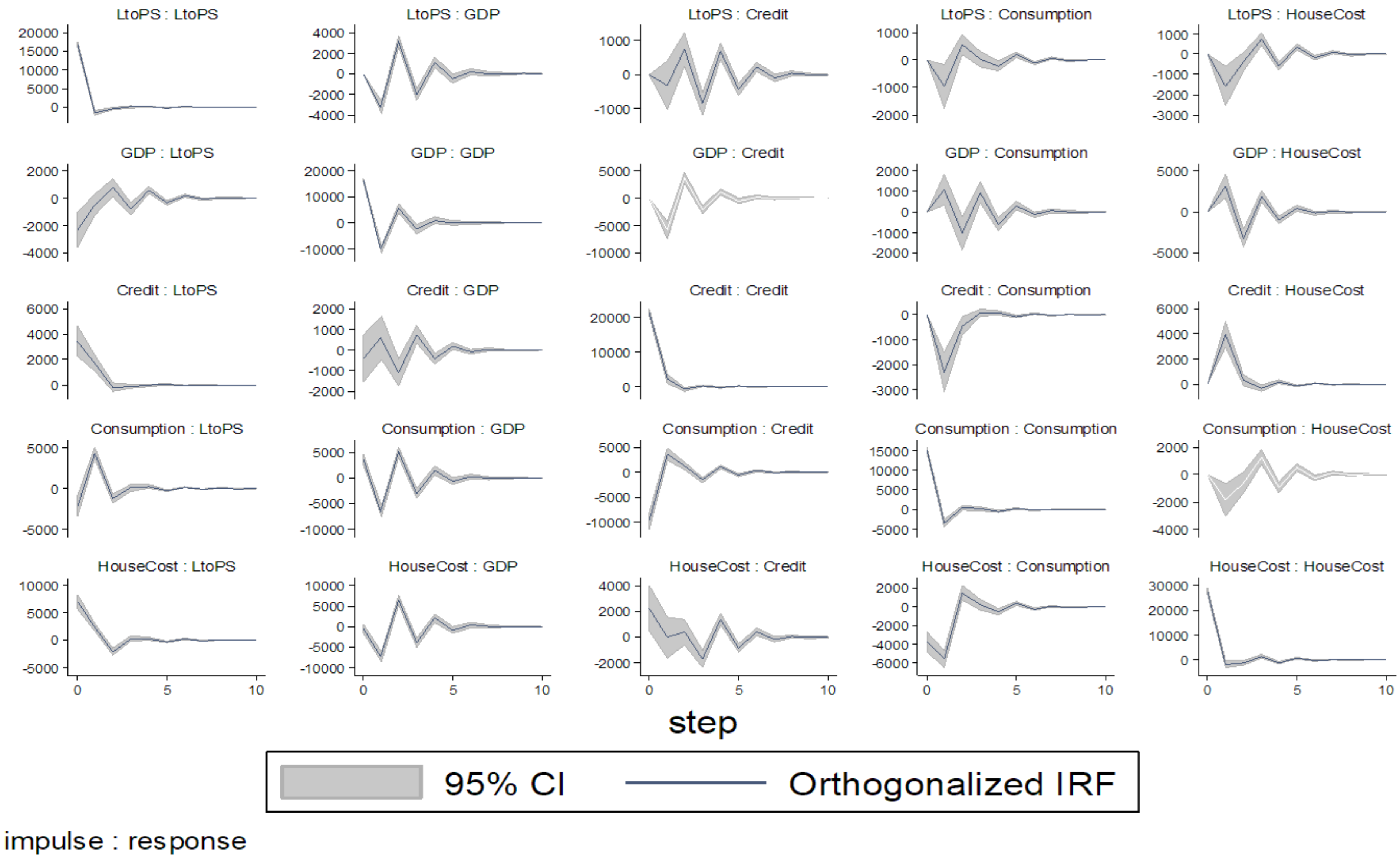

Variance decomposition for loans to private sector LtoPS
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
1
2
3
4
5
6
7
8
9
10
11
Years
HouseCost
Consumption
Credit
GDP
LtoPS

Figure 5.2



Variance decomposition of HouseCost
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
1 2 3 4 5 6 7 8 9 10 11
Years HouseCost Consumption Credit GDP LtoPS
Variance decomposition for consumption
100%
80%
60%
40%
20%
0%
1 2 3 4 5 6 7 8 9 10 11
Years HouseCost Consumption Credit GDP LtoPS
Variance decomposition for Credit
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
1 2 3 4 5 6 7 8 9 10 11
Years HouseCost Consumption Credit GDP LtoPS
Variance decomposition for GDP
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
1 2 3 4 5 6 7 8 9 10 11
Years HouseCost Consumption Credit GDP LtoPS

Figure 5.3: Impulse



5.5.4. Impulse Response Analysis

In this section, we present the impulse response functions results and the 95% confidence intervals band, which generated based on 200 Monte Carlo simulations. we also show how the orthogonalization of the VAR residuals helps to isolate the response of house prices, credit, GDP and loans from central banks to private sector to a shock on each variable. This will help obtaining a clear picture of the dynamical behaviour of the house prices, credit, GDP, consumption, and LtoPS in the G7 economies. Thus, Fig. 5.3 reports the Impulse Response Function(IRF) of house prices, credit, GDP, consumption, and the LtoPS to a shock on each variable in the G7 economies.

It is clear that a positive shock to credit in the G7 economies initially increases the house prices but later decreases marginally and stabilises in the long-run reaching zero effect level. The results in Fig. 1 also show a negative relationship between house prices and the loans from central banks to the private sector (LtoPS) in the G7 economies. This implies that the negative shock to house prices initially decreases to amount of loans from central banks to the private sector then increases marginally and stabilises in the long-run.

Moreover, the positive innovation to credit availability in the G7 economies is originating from the central banks loans to the private sector with a significant positive and negative effect in the long-run. On the other hand, a negative shock to the credit availability significantly decreases consumption expenditure but later stabilises in the long-run.

The stability graph Fig. 5.4 shows that PVAR satisfies the stability conditions.

However, the VAR model is stable if all the companion matrixes are strictly less than one (Abrigo and Love, 2015; Hamilton, 1994). Thus, the VAR model is stable if all the eigenvalues lie in the unit circle. From the roots of the companion matrix Fig. 5.4, all the eigenvalues lie in the unit circle.

In other words, the roots of the companion matrix show that there is no eigenvalue greater than 1, i.e., there is no explosive root. This indicates that the PVAR models are stable and the results are good for forecasting and valid for policy recommendations.

Figure. 5.4: The Stability Graph

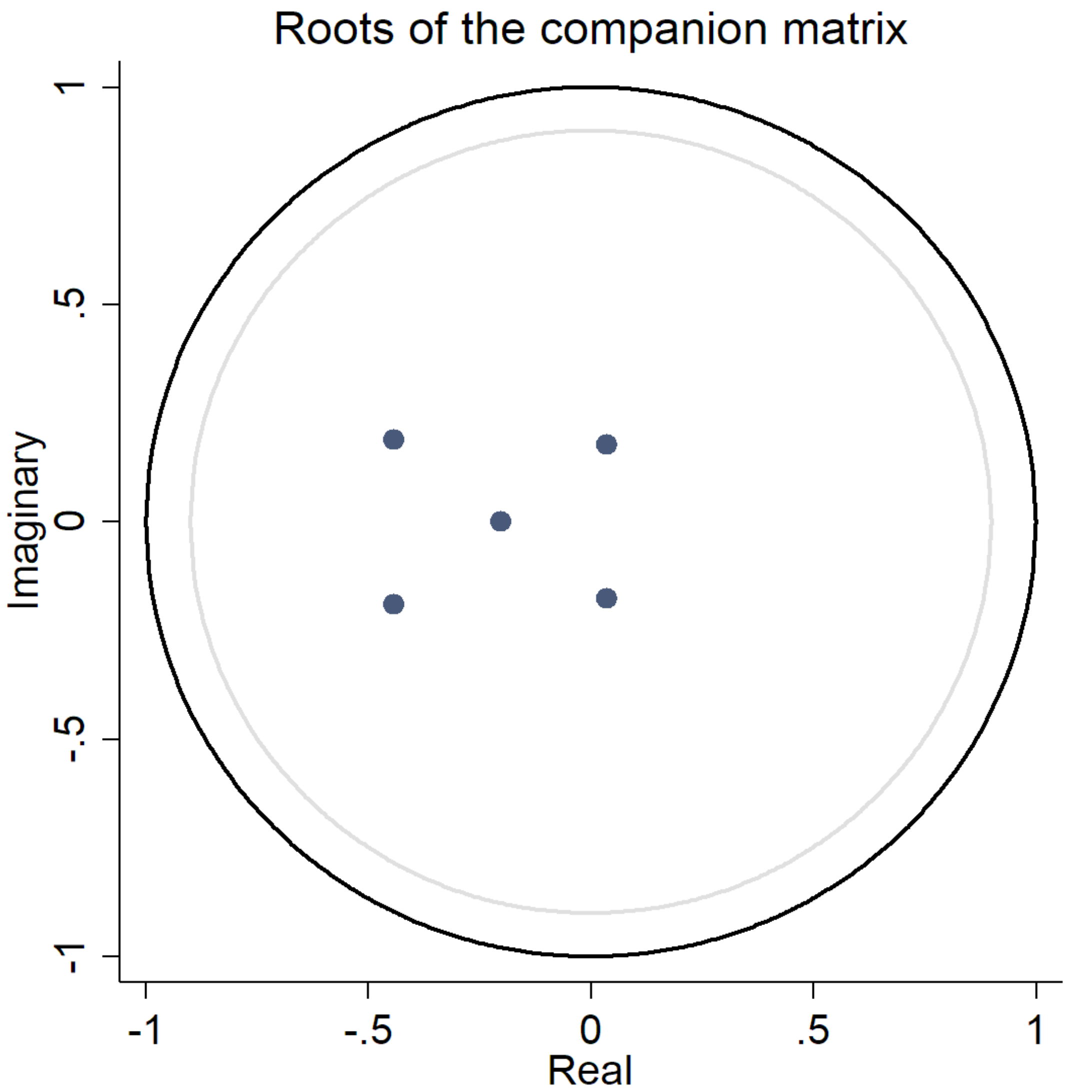


Table 19: Eigenvalue Stability Condition

Real	Imaginary	Modulus
.4424088	-.1892608	.4811914
.4424088	.1892608	.4811914
.2011325	0	.2011325
.0370678	-.1770597	.1808981
.0370678	.1770597	.1808981

Notes: All the eigenvalues lie inside the unit circle; PVAR satisfies stability condition.

5.5.5. Robustness Check

In this section, we use the panel granger causality test to help determining the robustness of the causality results generated by the system generalised method of moment (system-GMM) shown in Table 17. As shown in Table 15, the causality direction established between the variables (house prices, consumption, credit, GDP, and loans from central banks to the private sector) using the panel granger causality is consistent with the direction of causality presented in Table 17.

As displayed in Table 17, house prices unidirectionally causes consumption, credit, GDP, and the loans from central banks to the private sector (LtoPS) without feedback relationship. Likewise, consumption also unidirectionally causes house prices, credit, GDP, and the LtoPS, and that is also true for credit, GDP and LtoPS as shown in Table 15. As might be expected, the results are supportive to the argument discussed in the introduction section. That the behavioural activities of house prices, credit, GDP, consumption, and the loans from central banks to the private sector (LtoPS); play a significant role in modern developed economies in terms of money lending qualities, credit creation, investment decisions, consumption and real output. Most importantly, the co-movement between house prices, credit, consumption, GDP, and LtoPS shown in this study is a dynamic that provides accuracy for making sounds policy recommendations.

Table 20: Panel Granger Causality Results

Equation \ Excluded	chi2	df	Prob > chi2
HouseCost			
Consumption	1.340	1	0.247
Credit	75.002	1	0.000
GDP	15.939	1	0.000
LtoPS	10.052	1	0.002
ALL	115.239	4	0.000
Consumption			
HouseCost	247.697	1	0.000
Credit	27.380	1	0.000
GDP	6.937	1	0.008
LtoPS	6.113	1	0.013
ALL	565.624	4	0.000
Credit			
HouseCost	1.907	1	0.167
Consumption	88.828	1	0.000
GDP	48.484	1	0.000
LtoPS	0.646	1	0.421
ALL	135.838	4	0.000
GDP			
HouseCost	219.816	1	0.000
Consumption	126.826	1	0.000
Credit	8.670	1	0.003
LtoPS	127.904	1	0.000
ALL	591.714	4	0.000
LtoPS			
HouseCost	152.912	1	0.000
Consumption	233.884	1	0.000
Credit	38.486	1	0.000
GDP	2.712	1	0.100
ALL	388.904	4	0.000

Notes: Ho: Excluded variable does not Granger-cause Equation variable

Ha: Excluded variable Granger-causes Equation variable

The empirical findings presented here are robust evidence that the collective behaviour of house prices, credit, consumption, GDP, and LtoPS have significant repercussions on modern developed economies, in this case, G7 economies.

5.6 Conclusion

In the aftermath of the 2008 financial crisis, the dynamic behaviour of the house prices, credit, GDP, consumption expenditure, and the loan from central banks to the private sector (LtoPS) is now the focus of the arena in the macroprudential policy debates. Thus, in this study, for the first time, we apply system-GMM PVAR to examine the dynamic causal relationship between house prices, credit, GDP, consumption, and the loans from centra banks to the private sector (LtoPS). As shown in the PVAR results section, the empirical analysis of this study attempts to offer some contribution to the contemporaneous issues affecting the macroeconomic performance. This is achieved by investigating the significance of dynamic behaviour of the critical variables mentioned above.

Using fixed-effects, panel VAR methods and data sample spanning the period 1980 – 2017 from G7 countries. The results indicate that shocks to the house prices, credit, GDP, consumption and the loans from central banks to the private sector (LtoPS) will yield to severe consequences on the macroeconomic performance. In particular, a shock on house prices strongly affects credit, which may explain the feedback effects on credit growth regarding mortgage lending qualities and lending for investments. Such dynamic relationship may very well explain how the US housing bubbles' burst in 2006, causing severe consequences on the housing markets and the global financial systems. This implies that the dynamic behaviour of credit and house prices may provide accurate results concerning the build-up of financial crises (Borio and Lowe, 2002; Mendoza and Terrones, 2008; Goodhart and Hofmann, 2008). As a result, close monitoring to the dynamic development of house prices should always remain the focus of prudential authority particularly when the increase of property prices associated with rapid credit growth (Tsatsaronis and Zhu, 2004).

The study further highlights the orthogonalised impulse response functions' (OIRFs) result, which actively demonstrates the macro-finance interconnectedness. The result also shows that shock on credit significantly affects the dynamic behaviour of house prices. This implies that a rapid surge in credit creation or a loose lending strategy may cause disastrous consequences to the housing markets and the macroeconomy. This is because, a positive credit growth boosts financing availability, which increases investments, consumption, real output and the overall economic growth (Levine, 2005). The results presented in this study are strong evidence that the dynamic behaviour of credit and house prices play a significant role in shaping the macroeconomic performance in advanced modern economies, in this case, G7 countries. The recent financial crisis documented the significance of rapid credit growth, which contributes to the build-up of systemic risks to the financial stability and may also materialise into systemic banking crises, (Alessi and Detken, 2018). Finally, the results presented here are substantial evidence that negative credit growth and house prices booms affect lending qualities, credit creation, investment decisions, consumption and real output in the G7 economies.

6

Conclusion

This chapter recaps the main findings generated from this thesis, in particular from the three chapters devoted to studying the financial markets (foreign exchange and stock market forecast). And the dynamic behaviour of credit, house prices, GDP, consumption and the loans from central banks to the private sector. Chapter 3, *Measuring Intra-Foreign Exchange Market Return and Volatility Spillover across Developed and Developing Countries*, investigates whether the effect of returns and volatility spillover is bidirectional between developed and developing countries. Chapter 4, *Time Series Modelling and Forecasting: Challenges of Stock forecasting* investigates the out-of-sample forecasting of the stock market returns. And finally, Chapter 5 studies *the dynamic behaviour of credit availability, house prices, GDP, loans from central banks to the private sector, consumption in the G7 economies*.

The added value of chapter 3 to the relevant literature is the transmission of return and volatility spillovers between developed and developing countries, which documented in two main points. On the one hand, developed countries found to be a receiver as well as a transmitter of volatility spillovers, dominated by the British pound, Australian dollar, and the euro. On the other hand, developing countries did not show evidence of volatility transmission; instead, they are a net receiver of volatility spillovers from developed countries. However, as expected, there is evidence of significant bidirectional volatility spillover among the European region (Eurozone and non-Eurozone currencies). This is due to the interdependent nature of the financial markets and trades between the countries in the European region, which featured in the single European market. A further insight of chapter 2 results supports the recent arguments that currency crises tend to be regional (Glick and Rose 1998; and Yarovaya et al., 2015) especially in the European region where significant volatility spillovers documented during crises periods.

Chapter 4 provides novel contribution to the contentious issue of the stock returns forecasting, especially the out-of-sample (OOS) forecast. This because the recent financial crisis tested the validity of numerous macroeconomic models where the majority of the forecasting models performed poorly. Therefore, this chapter provides strong evidence that the out-of-sample forecast is an effective way of predicting the stock market returns. Applying daily data, the results show that the U.S. S&P stock exchange follow a random walk process, which required by market efficiency. We also use the random walk with *drift* as a naïve model and compared the ex post forecast from the naïve model with those of alternative models such as ARIMA, random walk without *drift*, and simple exponential smoothing models.

Our results also highlight that the random walk with *drift* is the best model to provide accurate prediction for the U.S. S&P 500 stock market. Based on our finding, it can be argued that ARIMA (1,0,0; 0,1,0; and 0,1,1), and the Simple exponential smoothing models demonstrate good forecasting results. However, the random walk with *drift* decisively outperformed the alternative models in this chapter and it is hard to beat based on all the metrics considered in this study such as RMSE, MAE, MAPE, ME, MPE, and AIC.

Finally, Chapter 5 addresses the dynamic behaviour of credit, house prices, GDP, consumption, and the loans from central banks to the private sector in advanced modern economies from three different perspectives. First, it highlights the correlated nature of interdependence between credit availability, house prices, GDP, consumption and the loans to the private sector, using the system-GMM method. Our findings show that an increase in house prices in the G7 economies will not affect consumption, whereas house prices positively cause credit, which indicates house prices will increase by 8.6 percent when credit availability increase by 1 percent.

Our finding is in line with the arguments that asset prices influencing credit creation and output growth (Aikman et al., 2014; Borio, 2014). From a macroprudential point of view, this chapter supports the Loan-to-value (LTV) caps policy, which adopted by many countries recently. Based on these results, it can be argued that the dynamic behaviours of credit and house prices directly affect the macroeconomic performance of the G7 countries concerning money lending qualities, credit creation, investment decisions, consumption and real output.

Second, the orthogonalised impulse response functions (OIRFs) outcome in this chapter document convincing results that the dynamic behaviour of credit, house prices, GDP, consumption, and the loans to the private sector play significant role in shaping the macroeconomic performance in advanced modern economies, in this case, G7 countries.

Finally, the empirical results provided in this thesis should be accounted for when conducting trade policies between among developed countries, in particular, the eurozone economic area. This is because our results show there is strong level of interconnectedness within this region in terms of return and volatility spillover. This thesis also provides valuable policy recommendations concerning credit availability, house prices, GDP growth, consumption and the loans from central banks to the private sector. The thesis merits the attention as it illustrates the strong multidirectional links between the aforementioned variables in advanced modern economies. As a result, this thesis archived its objective as stated in the introduction, to mitigate the spillover risk in the financial markets and to advance stock market returns predictability.

6.1. Research Implications and Future Research

The benefits of understanding the interconnectedness of the financial markets are widely acknowledged in the literature, especially to maintain financial stability after the recent global economics integrations at all levels. Chapter 3 contributes emphatically to this literature by studying the financial spillovers between developed and developing countries. In this chapter, we performed a static and dynamic analysis of return and volatility spillovers transmission between developed and developing countries using the Diebold and Yilmaz (2009, 2012) methodology. The modelling approach of the spillover index is that it provides an analysis of the transmitted information between asset classes. Using this method, we provide empirical evidence of return and volatility spillovers between developed and developing countries. We also applied the time-varying volatility, net volatility and net pairwise volatility spillover.

A significant challenge, however, it is not clear how to measure or define a positive volatility spillover between the asset classes. The spillover index model cannot identify whether the spillover (return or volatility) is the negative or positive spillover. For example, the spillover index model collects vital transmitted information between two asset classes during a crisis period; therefore, the spillover of information during such time assumed to be negative. This is because the transmission of information during a crisis period could be dangerous or at least can cause disastrous situations to other asset classes or a particular market (foreign exchange, stock market, bond market). This means a major caveat of this study is that the spillover of return and volatility are assumed to be negative. A functional area for future research is to investigate the magnitude and extent of the volatility spillover from the default of systemically important financial institutions. The results in this thesis and other findings in the literature show that volatility spillover significantly associated with the financial crises and economic events.

However, in chapter 4, we present the stock returns forecasting steps, especially the out-of-sample (OOS) forecast. Nevertheless, the out-of-sample forecasting results still under extreme scrutiny. This is due to the nature of the stock prices, which are incredibly dependent on newly revealed information; therefore, they are naturally unpredictable for long-term. Also, the results provided in this chapter show that the random walk with *drift* as a naïve model, outperformed the random walk without *drift*. However, there extensive studies, which found that the random walk without drift outperformed the random walk with *drift*. That means, still, there is no wide consistencies in the forecasting literature in terms of best performing models. Therefore, the literature in the stock returns forecast remain unconclusive and the forecasting models available may not be of great benefits for the in-time investors.

Finally, chapter 5 investigates the dynamic behaviour of credit, house prices, GDP, consumption, and the loans to the private sector in advanced modern economies, G7 countries. And the empirical analysis of this chapter provides evidence of a strong link between the aforementioned variables.

As the first attempt to investigate such a problem, there are several caveats. First, to measure credit, we used the aggregate claims on the private sector by deposit money banks, the results would be more precise by using a dataset from institutions involved in the crises episodes or domestic credit cycle, (Detken et al., 2014). That means, the availability of appropriate data is significantly important for a fruitful research outcome.

Second, an adverse credit in this study means a rapid growth in credit, although the study does not define what precisely an adverse credit is. For example, is the money made through homes collateralisation (homeowners' leverage) lending can be classed as bad credit or bad loans which used for property investments and speculations?

In addition, it is difficult to define which credit may feed into rapid credit growth and to finance which consumption. To conclude, the findings of this thesis highlight a fruitful research area to study the dynamic behaviour of credit and house prices in emerging economies. In particular, to investigate the factors which contribute significantly to negative credit creation and it is effects on the dynamic behaviour of house prices' changes. This will provide a considerable contribution to the efforts of measuring house price changes which are currently under investigation. Also, this thesis used the random walk with *drift* as a naïve model, which outperformed the alternative models. It would be interesting to investigate the random walk under *drift* instability as a naïve model, according to my knowledge, there is only one study in this area.

Bibliography

Abrigo, M.R. and Love, I., 2016. Estimation of panel vector autoregression in Stata. *The Stata Journal*, *16*(3), pp.778-804.

Adams, Z., Roland F., and Reint, G. (2014) "Spillover Effects among Financial Institutions: A State Dependent Sensitivity Value at Risk Approach (SDSVar)," Journal of Financial and Quantitative Analysis, 49(3): 575-598.

Adebiyi, A.A., Adewumi, A.O. and Ayo, C.K., 2014. Comparison of ARIMA and artificial neural networks models for stock price prediction. *Journal of Applied Mathematics*, *2014*.

Adelino, M., Schoar, A. and Severino, F., 2012. *Credit supply and house prices: evidence from mortgage market segmentation* (No. w17832). National Bureau of Economic Research.

Adelman, I., & Adelman, F. L. (1959). The dynamic properties of the Klein-Goldberger model. *Econometrica: Journal of the Econometric Society*, 596-625.

Adhikari, R. and Agrawal, R.K., 2013. An introductory study on time series modeling and forecasting. *arXiv preprint arXiv:1302.6613*.

Agrawal, G., Srivastav, A.K., and Srivatava, A. (2010) A study of Exchange Rates Movement and Stock Market Volatility," *International Journal of Business and Management* 5 (12), 62–73.

Aikman, D., Haldane, A., Nelson, B. (2010) "Curbing the credit cycle", Paper presented at the Columbia University Centre on Capitalism and Society Annual Conference, New York, November.

Aikman, D., Haldane, A.G. and Nelson, B.D., 2014. Curbing the credit cycle. *The Economic Journal*, *125*(585), pp.1072-1109.

Aikman, D., Lehnert, A., Liang, N. and Modungno, M., 2020. Credit, financial conditions, and monetary policy transmission. *62nd issue (June 2020) of the International Journal of Central Banking*.

Akaike, H., 1969. Fitting autoregressive models for prediction. *Annals of the institute of Statistical Mathematics*, *21*(1), pp.243-247.

Alessi, L. and Detken, C., 2018. Identifying excessive credit growth and leverage. *Journal of Financial Stability*, *35*, pp.215-225.

Alexander, C., 1998. Volatility and correlation: measurement, models and applications. *Risk management and analysis*, *1*, pp.125-171.

Alexander, C., 2001. Market models. *A Guide to Financial Data Analysis*, *1*.

Alizadeh, S., Brandt, M. W., and Diebold, F. X (2002) "Range-Based Estimation of Stochastic Volatility Models," *Journal of Finance*, Vol. 57 (3), PP. 1047-92.

Andersen, T. G., and Bollerslev, T. (1998) “Answering the Skeptics: yes, Standard Volatility Models do Provide Accurate Forecasts,” *International Economic Review* 39, 885–905.

Anderson, T. G., Bollerslev, T., Diebold, F. X., and Labys, P. (2001) “The Distinction of Realised Exchange Rate Volatility,” *Journal of the American Statistical Association* 96, 42-55.

Andrews, D.W. and Lu, B., 2001. Consistent model and moment selection procedures for GMM estimation with application to dynamic panel data models. *Journal of Econometrics*, *101*(1), pp.123-164.

Andrikopoulos, A., Angelidis, T., and Skintzi, V. (2014) “Illiquidity, Return and Risk in G7 Stock Markets: Interdependencies and Spillovers”, *International Review of Financial Analysis*, 35, 118-127.

Ang, A., Goetzmann, W.N. and Schaefer, S.M., 2011. The efficient market theory and evidence: implications for active investment management. *Foundations and Trends® in Finance*, *5*(3), pp.157-242.

Antonakakis, N. (2012) “Exchange Return Co-movement and Volatility Spillovers before and after the Introduction Euro”, *Journal of International Financial Markets, Institutions and Money* 22, 1091-1109.

Antonakakis, N., Breitenlechner, M., and Scharler, J. (2015) “Business Cycle and Financial Cycle Spillovers in the G7 Countries,” *The Quarterly Review of Economics and Finance*, 58 PP. 154-162. ISSN, 1062-9769.

Antzoulatos, A.A., 1996. Consumer credit and consumption forecasts. *International Journal of Forecasting*, *12*(4), pp.439-453.

Anundsen, A.K., Gerdrup, K., Hansen, F. and Kragh-Sørensen, K., 2016. Bubbles and crises: The role of house prices and credit. *Journal of Applied Econometrics*, *31*(7), pp.1291-1311.

Apergis N, Rezitis A (2001) Asymmetric Cross-market Volatility Spillovers: Evidence from Daily Data on Equity and Foreign Exchange Markets. Manchester Sch 69:81–96.

Ariyo, A.A., Adewumi, A.O. and Ayo, C.K., 2014, March. Stock price prediction using the ARIMA model. In *2014 UKSim-AMSS 16th International Conference on Computer Modelling and Simulation* (pp. 106-112). IEEE.

Armada, M.J.R., Sousa, R.M. and Wohar, M.E., 2015. Consumption growth, preference for smoothing, changes in expectations and risk premium. *The Quarterly Review of Economics and Finance*, *56*, pp.80-97.

Arouri, M. E. H., Lahiani, A., and Nguyen, D. K. (2011) "Return and Volatility Transmission between World Oil Price and Stock Markets of the GCC Countries", *Economic Modelling*, 28, 1815-1825.

Attanasio, O.P., Blow, L., Hamilton, R. and Leicester, A., 2009. Booms and busts: Consumption, house prices and expectations. *Economica*, *76*(301), pp.20-50.

Attanasio, O.P., Blow, L., Hamilton, R. and Leicester, A., 2009. Booms and busts: Consumption, house prices and expectations. *Economica*, *76*(301), pp.20-50.

Baiocchi, G. and Minx, J.C., 2010. Understanding changes in the UK's CO2 emissions: A global perspective.

Bakker, M.B.B., Dell'Ariccia, M.G., Laeven, M.L., Vandenbussche, J., Igan, D. and Tong, H., 2012. *Policies for macrofinancial stability: How to deal with credit booms*. International Monetary Fund.

Balli, F., Hajhoj, H. R., Basher, S. A., and Ghassan, H. B. (2015) "An Analysis of Returns and Volatility Spillovers and their Determinants in Emerging Asian and Middle Eastern Countries", *International Review of Economics and Finance*, 39, 311-325.

Bank for International Settlements (2013) "Triennial Centre Bank Survey," available from http://www.bis.org/publ/rpfx13fx.pdf [Accessed 17th July 2016].

Barro, R.J. and Ursúa, J.F., 2017. Stock-market crashes and depressions. *Research in Economics*, *71*(3), pp.384-398.

Baruník, J., Kočenda, E. and Vácha, L., 2017. Asymmetric volatility connectedness on the forex market. *Journal of International Money and Finance*, *77*, pp.39-56.

Bascand, G., 2018. Financial stability–risky, safe, or just right?

Basher, S.A., Hassan, M.K. and Islam, A.M., 2007. Time-varying volatility and equity returns in Bangladesh stock market. *Applied Financial Economics*, *17*(17), pp.1393-1407.

Bazilevskaya, G.A., Cliver, E.W., Kovaltsov, G.A., Ling, A.G., Shea, M.A., Smart, D.F. and Usoskin, I.G., 2014. Solar cycle in the heliosphere and cosmic rays. *Space Science Reviews*, *186*(1-4), pp.409-435.

Beer F, Hebein F (2011) An Assessment of the stock market and exchange rate Dynamics in industrialized and emerging markets. Int Busi Econ Research J 7(8):59–70.

Beirne, J., Caporale, G. M., Schulze-Ghattas, M., and Spagnolo, N. (2009) "Volatility Spillovers and Contagion from Mature to emerging Stock Markets," *International Monetary Fund* WP08-286 and European Central Bank: WP1113.

Bekiros, S. D., and Diks, C. G. H. (2008) "The Nonlinear Dynamic Relationship of Exchange Rates: Parametric and Nonparametric Causality Testing," *Journal of Macroeconomics*, 30, 1641-1650.

Berger, D., Guerrieri, V., Lorenzoni, G. and Vavra, J., 2018. House prices and consumer spending. *The Review of Economic Studies*, *85*(3), pp.1502-1542.

Berger, D., Guerrieri, V., Lorenzoni, G. and Vavra, J., 2018. House prices and consumer spending. *The Review of Economic Studies*, *85*(3), pp.1502-1542.

Bickel, P.J. and Bühlmann, P., 1996. What is a linear process?. *Proceedings of the National Academy of Sciences*, *93*(22), pp.12128-12131.

Billah, B., King, M.L., Snyder, R.D. and Koehler, A.B., 2006. Exponential smoothing model selection for forecasting. *International journal of forecasting*, *22*(2), pp.239-247.

Billio, M., Getmansky, M., Andrew, L., and Pelizzon, L. (2012) "Econometric Measures of Connectedness and Systemic Risk in the Finance and Insurance Sectors," *Journal of Financial Economics*, 104(3): 535-559.

Boero, G., Silvapulle, P., and Tursunalieva, A. (2011) "Modelling the Bivariate Dependence Structure of Exchange Rates Before and After the Introduction of the Euro: A Semi-parametric Approach," *International Journal of Finance and Economics* 16 (4), 357–374.

Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. *Journal of econometrics*, *31*(3), pp.307-327.

Bollerslev, T., Engle, R.F. and Nelson, D.B., 1994. ARCH models. *Handbook of econometrics*, *4*, pp.2959-3038.

Bollerslov, T. (1990) "Modelling the Coherence in Short-run Nominal Exchange Rates: A Multivariate Generalised ARCH Model," *Review of Economics and Statistics*, 72, 498-505.

Borio, C. (2013) "Macroprudential Policy and the Financial Cycle: Some Stylized Facts and Policy Suggestions", Speech Given at the "Rethinking Macro Policy II: First Steps and Early Lessons" hosted by the IMF in Washington, DC.

Borio, C. and Lowe, P., 2002. Assessing the risk of banking crises. *BIS Quarterly Review*, *7*(1), pp.43-54.

Borio, C., 2014. The financial cycle and macroeconomics: What have we learnt?. *Journal of Banking & Finance*, *45*, pp.182-198.

Borio, C., Lowe, P., (2002) "Assessing the risk of banking crises". BIS Quarterly Review December, 43–54.

Bouveret, A., 2018. *Cyber risk for the financial sector: a framework for quantitative assessment*. International Monetary Fund.

Box, G. E., Jenkins, G. M., & Reinsel, G. (1970). Time series analysis: forecasting and control Holden-day San Francisco. *BoxTime Series Analysis: Forecasting and Control Holden Day1970*.

Box, G.E., Jenkins, G.M., Reinsel, G.C. and Ljung, G.M., 2015. *Time series analysis: forecasting and control*. John Wiley & Sons.

Branch, W.A. and Evans, G.W., 2006. A simple recursive forecasting model. *Economics Letters*, *91*(2), pp.158-166.

Breusch, T.S. and Pagan, A.R., 1980. The Lagrange multiplier test and its applications to model specification in econometrics. *The review of economic studies*, *47*(1), pp.239-253.

Brown, W.O., Huang, D. and Wang, F., 2016. Inflation illusion and stock returns. *Journal of Empirical Finance*, *35*, pp.14-24.

Brown, W.O., Huang, D. and Wang, F., 2016. Inflation illusion and stock returns. *Journal of Empirical Finance*, *35*, pp.14-24.

Brownlees, C.T. and Gallo, G.M., 2006. Financial econometric analysis at ultra-high frequency: Data handling concerns. *Computational Statistics & Data Analysis*, *51*(4), pp.2232-2245.

Brownlees, C.T., Engle, R.F. (2010) "Volatility, Correlation and Tails for Systemic Risk Measurement," Mimeo, New York University.

Brunnermeier, Markus K., Eisenbach, T., and Sannikov, Y. (2012) Macroeconomics with Financial Frictions: A Survey. Working Paper.

Bubák, V., Kocenda, E., and Zikes, F. (2011) "Volatility Transmission in European Foreign Exchange Markets", *Journal of Banking and Finance*, 35, 2829-2841.

Burnside, C., Eichenbaum, M. and Rebelo, S., 2016. Understanding booms and busts in housing markets. *Journal of Political Economy*, *124*(4), pp.1088-1147.

CAI, F., Howorka, E., and Wongswan, J. (2008) "Informational Linkages across Trading Regions: Evidence from Foreign Exchange Markets", *Journal of International Money and Finance* 27, 1215–1243.

Campbell, J.Y. and Vuolteenaho, T., 2004. Inflation illusion and stock prices. *American Economic Review*, *94*(2), pp.19-23.

Canova, F. and Ciccarelli, M., 2013. Panel Vector Autoregressive Models: A Survey☆ The views expressed in this article are those of the authors and do not necessarily reflect those of the ECB or the Eurosystem. In *VAR Models in Macroeconomics–New Developments and Applications: Essays in Honor of Christopher A. Sims* (pp. 205-246). Emerald Group Publishing Limited.

Cao, L.J. and Tay, F.E.H., 2003. Support vector machine with adaptive parameters in financial time series forecasting. *IEEE Transactions on neural networks*, *14*(6), pp.1506-1518.

Castro, C., and Ferrari, S. (2014) “Measuring and Testing for the Systemically Important Financial Institutions." Journal of Empirical Finance, 25: 1-14.

Cesa-Bianchi, A., Cespedes, L.F. and Rebucci, A., 2015. Global liquidity, house prices, and the macroeconomy: Evidence from advanced and emerging economies. *Journal of Money, Credit and Banking*, *47*(S1), pp.301-335.

Chan, H.L. and Woo, K.Y., 2013. Studying the dynamic relationships between residential property prices, stock prices, and GDP: lessons from Hong Kong. *Journal of Housing Research*, *22*(1), pp.75-89.

Chen, A.S., Leung, M.T. and Daouk, H., 2003. Application of neural networks to an emerging financial market: forecasting and trading the Taiwan Stock Index. *Computers & Operations Research*, *30*(6), pp.901-923.

Chiang, M., Sing, T. F., and Tsai, I. (2016) “Spillover Risks in REITs and Other Asset Markets”, *Journal of Real Estate Finance and Economics*, doi: 10.1007/s11146-015-9545-9.

Choi DF, Fang V, Fu TY (2010) Volatility spillovers between New Zealand stock market returns and exchange rate changes before and after the 1997 Asian financial crisis. Asian J Finan Acc 1(2):106–117.

Choudhry, T., and Jayasekera, R. (2014) “Returns and Volatility Spillover in the European Banking Industry during Global Financial Crisis: Fight to Perceived Quality or Contagion?” *International Review of Financial Analysis*, 36, 36-45.

Choudhry, T., and Jayasekera, R. (2014) “Returns and Volatility Spillover in the European Banking Industry during Global Financial Crisis: Fight to Perceived Quality or Contagion?” *International Review of Financial Analysis*, 36, 36-45.

Claessens, S., Kose, M. A., and Terrones, M. E. (2011b) “How do Business and Financial Cycle Interact?” IMF Working Paper: WP/11/88.

Clark, T.E. and McCracken, M.W., 2006. The predictive content of the output gap for inflation: Resolving in-sample and out-of-sample evidence. *Journal of Money, Credit and Banking*, pp.1127-1148.

Clessens, S., Kose, M., and Terrones, M. (2011a) "Financial Cycles: What? How? When?" IMF Working Paper, No WP/11/76.

Cochrane, J.H., 2008. The dog that did not bark: A defense of return predictability. *The Review of Financial Studies*, *21*(4), pp.1533-1575.

Darrat, A.F. and Zhong, M., 2000. On testing the random-walk hypothesis: a model-comparison approach. *Financial Review*, *35*(3), pp.105-124.

Darrat, A.F. and Zhong, M., 2000. On testing the random-walk hypothesis: a model-comparison approach. *Financial Review*, *35*(3), pp.105-124.

De Jonghe, O. (2010) "Back to Basics in Banking? A Micro-Analysis of Banking System Stability," Journal of Financial Intermediation 19, 387-417.

Dell' Arriccia, Igan, D., Laeven, L., Tong, H. (2012) "Policies for Macro-financial Stability": How to Deal with Credit Booms. IMF Discussion Note, April.

DeMiguel, V., Garlappi, L. and Uppal, R., 2009. Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy?. *The review of Financial studies*, *22*(5), pp.1915-1953.

Demirguc K, A., and Huizinga, H. (2010) "Bank Activity and Funding Strategies," Journal of Financial Economics: *98, 626-650.*

Detken, C and Smets, F. (2004) "Asset price booms and monetary policy," ECB Working Paper Series, no 364.

Detken, C., Weeken, O., Alessi, L., Bonfim, D., Boucinha, M.M., Castro, C., Frontczak, S.,

Diebold, F. X., and Nerlove, M. (1989) "The Dynamics of Exchange Rate Volatility: A Multivariate Latent-Factor ARCH Model," *Journal of Applied Econometrics,* 4, 1-22.

Diebold, F., and Yilmaz, K. (2009) "Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets", *Economic Journal*, 119, 158-171.

Diebold, F., and Yilmaz, K. (2012) "Better to Give Than to Receive: Predictive Measurement of Volatility Spillovers", *International Journal of Forecasting*, 28, 57-66. different?', *World Bank Policy Research Working Paper*, No. 6783.

Diebold, F.X., 1998. The past, present, and future of macroeconomic forecasting. *Journal of Economic Perspectives*, *12*(2), pp.175-192.

Diebold, F.X., Gardeazabal, J. and Yilmaz, K., 1994. On cointegration and exchange rate dynamics. *The Journal of Finance*, *49*(2), pp.727-735.

Do, H. X., Brooks, R., and Treepongkaruna, S. (2015) "Realised Spillover Effects between Stock and Foreign Exchange Market: Evidence from Regional Analysis", *Global Finance Journal*. http://dx.doi.org/10.1016/j.gfj.2015.11.003.

Dow, C.H., 1920. Scientific Stock Speculation (The Magazine of Wall Street, New York, NY).

Dungey, M., and Martin, V. L. (2004) "A Multifactor Model of Exchange Rates with Unanticipated Shocks: Measuring Contagion in the East Asian Currency Crisis," *Journal of Emerging Market Finance,* 3, 305-330. economic growth and CO2 emissions of Europe and Eurasian countries: A PVAR.

Dynan, K. and Sheiner, L., 2018. GDP as a measure of economic well-being. *Work. Pap*, *43*.

Edwards, S., and Susmel, R. (2001) "Volatility Dependence and Contagion in Emerging Equity Markets", *Journal of Development Economics* 66, 505-532.

Ehrmann, M., Fratzscher, M., and Rigobon, R. (2005) "Stocks, Bonds, Money Markets and Exchange Rates: Measuring International Financial Transmission," Working Paper No. 452, European Central Bank, Frankfurt.

Ehrmann, M., Fratzscher, M., and Rigobon, R. (2011) "Stocks, Bonds, Money Markets and Exchange Rates: Measuring International Financial Transmission," *J. Appl. Econ*. 26, 948–974. http//dx.doi.org/10.1002/jae.1173.

Eickmeier, S. (2007) "Business cycle transmission from the US to Germany—A structural factor approach," *European Economic Review* 51, 521–551.

Engel, C. and Hamilton, J.D., 1990. Long swings in the dollar: Are they in the data and do markets know it?. *The American Economic Review*, pp.689-713.

Engel, C., 1994. Can the Markov switching model forecast exchange rates?. *Journal of international economics*, *36*(1-2), pp.151-165.

Engle, R. F., and Kroner, K. F. (1995) "Multivariate Simultaneous Generalised ARCH," *Econometric Theory*, 11, 122-150.

Engle, R. F., and Susmel, R. (1993) "Common Volatility in International Equity Markets", *Journal of Business and Economic Statistics*, Vol. 11, issue 2, pp. 167-176.

Engle, R. F., Ito, T., and Lin, W. L. (1990) "Meteor Showers or Heat Waves? Heteroskedastic Intra-Daily Volatility in the Foreign Exchange Market," *Econometrica*, 58, 525-542.

Engle, R.F., Focardi, S.M. and Fabozzi, F.J., 2012. ARCH/GARCH models in applied financial econometrics. *Encyclopedia of Financial Models*.

Engle, R.F., Lilien, D.M. and Watson, M., 1985. A dymimic model of housing price determination. *Journal of Econometrics*, *28*(3), pp.307-326.

Ermişoğlu, E., Akçelik, Y. and Oduncu, A., 2013. Nowcasting GDP growth with credit data: Evidence from an emerging market economy. *Borsa Istanbul Review*, *13*(4), pp.93-98.

European Central Bank (ECB) (2010) "Financial networks and financial stability," Financial Stability Review, 2010, 155–160.

Ezzati, P. (2013) "Analysis of Volatility Spillovers Effects: two-Stage Procedures Based on A Modified GARCH-M", *University of Western Australia*, Discussion Paper, 13-29.

Fama, E.F. and French, K.R., 1988. Dividend yields and expected stock returns. *Journal of financial economics*, *22*(1), pp.3-25.

Farooq, T., Guergachi, A. and Krishnan, S., 2007, October. Chaotic time series prediction using knowledge based green's kernel and least-squares support vector machines. In *2007 IEEE International Conference on Systems, Man and Cybernetics* (pp. 373-378). IEEE.

Favara, G. and Imbs, J., 2015. Credit supply and the price of housing. *American Economic Review*, *105*(3), pp.958-92.

Favara, G. and Imbs, J., 2015. Credit supply and the price of housing. *American Economic Review*, *105*(3), pp.958-92.

Favilukis,J., Ludvigson, S.C., and Nieuwerburgh, S. V. (2010) The Macroeconomic E_ects of Housing Wealth, Housing Finance, and Limited Risk-Sharing in General Equilibrium. NBER Working Paper, No. 15988.

Fayek, M.B., El-Boghdadi, H.M. and Omran, S.M., 2013. Multi-objective optimization of technical stock market indicators using gas. *International Journal of Computer Applications*, *68*(20).

Fedorova, E., and Saleem, K. (2010) "Volatility Spillovers between Stock and Currency Markets: Evidence from Emerging Eastern Europe", *Czech Journal of Economics and Finance* 60, 519-533.

Ferreira, M.A. and Santa-Clara, P., 2011. Forecasting stock market returns: The sum of the parts is more than the whole. *Journal of Financial Economics*, *100*(3), pp.514-537.

Feyen, E., Letelier, R., Love, I., Maimbo, S.M. and Rocha, R. (2014), 'The impact of funding

Filis, G., Degiannakis, S. and Floros, C., 2011. Dynamic correlation between stock market and oil prices: The case of oil-importing and oil-exporting countries. *International Review of Financial Analysis*, *20*(3), pp.152-164.

Forbes,K. J., and Rigobon, R. (2002) "No Contagion, Only Interdependence: Measuring Stock Market Comovements", *Journal of Finance*, 57, 2223-2261.

Fratzscher, M. (2003) "On Currency Crisis and Contagion," *International Journal of Finance and Economics*, 8 (2), 109e, 130.

Ganong, P. and Noel, P., 2017. The effect of debt on default and consumption: Evidence from housing policy in the great recession. *Unpublished Working Paper*.

Garman, M. B., and Klass, M. J. (1980) "On the Estimation of Security Price Volatilities from Historical data," *Journal of Business*, Vol. 53 (1) (January), PP. 67-78.

Gebka, B. (2012) "the Dynamic Relationship between Returns, Trading Volume, and Volatility: Lessons from Spillovers between Asia and the United States", *Bulletin of Economic Research*, 64, 65-90.

Georg, C, P. (2013) "The Effect of the Interbank Network Structure on Contagion and Common Shocks," Journal of Banking and Finance, 37-2216–2228.

Georgiadis, G. and Zhu, F., 2019. Monetary policy spillovers, capital controls and exchange rate flexibility, and the financial channel of exchange rates.

Ghosh, S. (2014) “Volatility Spillovers in the Foreign Exchange Market: the Indian Experience”, Macroeconomics and Finance in Emerging Market Economies 7 (1), 175-194.

Giordana, G., Giese, J., Jahn, N. and Kakes, J., 2014. *Operationalising the countercyclical capital buffer: indicator selection, threshold identification and calibration options* (No. 5). ESRB Occasional Paper Series.

Glaeser, E. L, Gottlieb, J., and Gyourko, J. (2010) Can Cheap Credit Explain the Housing Boom. NBER Working Paper, No. 16230.

Goodhart, C and Hofmann, B. (2008) "House Prices, Money, Credit, and the Macroeconomy", Oxford Review of Economic Policy, 24, 180–205.

Goodhart, C. and Hofmann, B., 2008. House prices, money, credit, and the macroeconomy. *Oxford Review of Economic Policy*, *24*(1), pp.180-205.

Goodhart, M.C., Basurto, M.A.S. and Hofmann, B., 2006. *Default, credit growth, and asset prices* (No. 6-223). International Monetary Fund.

Gravier-Rymaszewska, J. (2012), 'How aid supply responds to economic crises: A panel VAR

Greene, W.H., 2008. The econometric approach to efficiency analysis. *The measurement of productive efficiency and productivity growth*, *1*(1), pp.92-250.

Greiber, C. and Setzer, R., 2007. Money and Housing: Evidence for the Euro Area and the US.

Grobys K (2015) Are volatility spillovers between currency and equity market driven by economic states? Evidence from the US economy. Econ Lett 127:72–75.

Grobys, K. (2015) “Are Volatility Spillovers between Currency and Equity Market Driven by Economic States? Evidence from the U.S. Economy,” *Economics Letters* 127, 72–75.

Guresen, E., Kayakutlu, G. and Daim, T.U., 2011. Using artificial neural network models in stock market index prediction. *Expert Systems with Applications*, *38*(8), pp.10389-10397.

Halkos, G. and Kevork, I., 2006. Forecasting an ARIMA (0, 2, 1) using the random walk model with drift.

Halkos, G. and Kevork, I., 2006. Forecasting an ARIMA (0, 2, 1) using the random walk model with drift.

Hamilton, J.D., 1994. Time series analysis Princeton University Press Princeton. *NJ USA*.

Hamilton, J.D., 1994. *Time series analysis* (Vol. 2, pp. 690-696). Princeton, NJ: Princeton university press.

Hamilton, J.D., 1994. *Time series analysis* (Vol. 2, pp. 690-696). Princeton, NJ: Princeton university press.

Hannan, E.J. and Quinn, B.G., 1979. The determination of the order of an autoregression. *Journal of the Royal Statistical Society: Series B (Methodological)*, *41*(2), pp.190-195.

Hansen, J. V., McDonald, J. B., & Nelson, R. D. (1999). Time Series Prediction With Genetic-Algorithm Designed Neural Networks: An Empirical Comparison With Modern Statistical Models. *Computational Intelligence*, *15*(3), 171-184.

Hansen, L. P. (2013) "Challenges in Identifying and Measuring Systemic Risk", NBER Working Paper, No 18505.

Hansen, L.P., 1982. Large sample properties of generalized method of moments estimators. *Econometrica: Journal of the Econometric Society*, pp.1029-1054.

Henrique, B.M., Sobreiro, V.A. and Kimura, H., 2018. Stock price prediction using support vector regression on daily and up to the minute prices. *The Journal of finance and data science*, *4*(3), pp.183-201.

heteroskedastic stock returns. Journal of Financial Econometrics http://dx.doi.org/10.

Hipel, K.W. and McLeod, A.I., 1994. *Time series modelling of water resources and environmental systems* (Vol. 45). Elsevier.

Hochreiter, S. and Schmidhuber, J., 1997. Long short-term memory. *Neural computation*, *9*(8), pp.1735-1780.

Holtz-Eakin, D., Newey, W. and Rosen, H.S. (1988), 'Estimating vector autoregressions with panel

Holtz-Eakin, D., Newey, W. and Rosen, H.S., 1988. Estimating vector autoregressions with panel data. *Econometrica: Journal of the Econometric Society*, pp.1371-1395.

Holtz-Eakin, D., Newey, W. and Rosen, H.S., 1988. Estimating vector autoregressions with panel data. *Econometrica: Journal of the Econometric Society*, pp.1371-1395.

Hong, Y. (2001) "A test for Volatility Spillover with Application to Exchange Rates," *Journal of Econometrics*, 103-183-224.

Huang, Xin, Hao Zhou, and Haibin Zhu (2010) "Assessing the Systemic Risk of a Heterogeneous Portfolio of Banks during the Recent Financial Crisis," Working Paper, Federal Reserve Board.

Huynh, T.L.D., Nasir, M.A. and Nguyen, D.K., 2020. Spillovers and connectedness in foreign exchange markets: The role of trade policy uncertainty. *The Quarterly Review of Economics and Finance*.

Imbs, J. (2004) "Trade, Finance, Specialization, and Synchronisation," *The Review of Economics and Statistics* 86, 723–734.

Imbs, J. (2010) "The First Global Recession in Decades," IMF Economic Review 58, 327–354.

Ingaki, K. (2007) "Testing for Volatility Spillover Between the British Pound and the Euro," Research in International Business and Finance, 21, 161-174.

Ito, T., and Lin, W. (1993) "Price Volatility and Volume Spillovers between Tokyo and New York Stock Markets," working paper, The University of Wisconsin at Madison.

Jain, A. and Kumar, A.M., 2007. Hybrid neural network models for hydrologic time series forecasting. *Applied Soft Computing*, *7*(2), pp.585-592.

Jawadi, F., Louhichi, W., Idi Cheffou, K. (2015) "Intraday Bidirectional Volatility Spillover across International Stock Markets: Does the Global Financial Crisis Matter?" *Appl. Econ*. 45, 3633–3650.

Jayasinghe, P., and Tsui, A. (2008) "Exchange Rate Exposure of Sectoral Returns and Volatilities: Evidence from Japanese Industrial Sector", JPN. *World Economics* 20, 639-660.

Jegadeesh, N., 1991. Seasonality in stock price mean reversion: Evidence from the US and the UK. *The Journal of Finance*, *46*(4), pp.1427-1444.

Jouini, J., (2013) "Return and Volatility Interaction between Oil Prices and Stock Markets in Saudi Arabia", J. Policy Model 35, 1124-1144.

Jung, R., and Maderitsch, R. (2014) "Structural breaks in volatility spillovers between international financial markets: contagion or mere interdependence?" *Journal of Banking Finance* 47, 331–342.

Justiniano, A., Primiceri, G.E. and Tambalotti, A., 2019. Credit supply and the housing boom. *Journal of Political Economy*, *127*(3), pp.1317-1350.

Kamruzzaman, J. ed., 2006. *Artificial neural networks in finance and manufacturing*. IGI Global.

Kang SH, Yoon SM (2013) Revisited Return and Volatility Spillover Effect in Korea. Korea World Econ 14(1):121–145.

Kang, W., Ratti, R. A., and Yoon, K. H. (2014) "The Impact of Oil Price Shocks on U.S. Bond Market Returns," *Energy Economics*, 44, 248-258.

Kaplan, G., Mitman, K. and Violante, G., 2015. Consumption and house prices in the Great Recession: Model meets evidence. *Manuscript, New York University*.

Kaur, H., 2004. Time varying volatility in the Indian stock market. *Vikalpa*, *29*(4), pp.25-42.

Kearney, C., and Daly, K. (1998) "The causes of stock market volatility in Australia," *Applied Financial Economics*, 8, 597 – 605.

Khandani, A. E., Lo, A.W., and Merton, R.C. (2009) Systemic Risk and the Re_nanc- ing Ratchet E_ect. NBER Working Paper, No. 15362.

Khashei, M. and Bijari, M., 2010. An artificial neural network (p, d, q) model for timeseries forecasting. *Expert Systems with applications*, *37*(1), pp.479-489.

Kilian, L., 1999. Exchange rates and monetary fundamentals: what do we learn from long-horizon regressions?. *Journal of applied Econometrics*, *14*(5), pp.491-510.

Kim, J.H., 2003. Forecasting autoregressive time series with bias-corrected parameter estimators. *International Journal of Forecasting*, *19*(3), pp.493-502.

Kim, J.S., and Ryu, D. (2015) "Return and Volatility Spillovers and Cojump Behavior between the U.S. and Korean Stock Markets," Emerging Mark Finance Trade 51 (S1), 3–17.

Kim, K. (2003) "Dollar Exchange Rate and Stock Price: Evidence from Multivariate Cointegration and Error Correction Model," Review of Financial Economics 12, 301-313.

Kim, K.J., 2003. Financial time series forecasting using support vector machines. *Neurocomputing*, *55*(1-2), pp.307-319.

King, M., Sentana, E., and Wadhwani, S. (1994) "Volatility and Links Between National Stock Markets", Econometrica: *Journal of the Econometric Society*, 62, 901-933.

Kisman, Z., 2017. Model for Overcoming Decline in Credit Growth (Case Study of Indonesia with Time Series Data 2012M1-2016M12). *Journal of internet Banking and Commerce*, *22*(3), pp.1-11.

Kolmogoroff, A. (1941). Interpolation und extrapolation von stationaren zufalligen folgen. *Izvestiya Rossiiskoi Akademii Nauk. Seriya Matematicheskaya*, *5*(1), 3-14.

Kothari, S.P. and Shanken, J., 1997. Book-to-market, dividend yield, and expected market returns: A time-series analysis. *Journal of Financial economics*, *44*(2), pp.169-203.

Kotzé, K., and Kavli, K. (2014) "Spillovers in Exchange Rates and the Effects of Global Shocks on Emerging Market Currencies", *South African Journal of Economics*, Vol. 82, PP209-238.

Krause, T., and Tse, Y. (2013) "Volatility and Return Spillovers in Canadian and U.S. Industry ETFs", *International Review of Economics and Finance*, 25, 244-259.

Kumar, S., 2004. *Neural networks: a classroom approach*. Tata McGraw-Hill Education.

Lal, D., 2010. The great crash of 2008: causes and consequences. *Cato J.*, *30*, p.265.

Lee, C. K., Sehwan, Y., & Jongdae, J. (2007). Neural network model versus SARIMA model in forecasting Korean stock price index (KOSPI). *Issues in Information System*, *8*(2), 372-378.

Lee, Y. H. (2013) "Global and Regional Range-Based Volatility Spillover Effects," *Emerging Markets Review* 14, 1-10.

Leung, C.K.Y., 2003. Economic growth and increasing house prices. *Pacific Economic Review*, *8*(2), pp.183-190.

Levin, A., Lin, C.F. and Chu, C.S.J., 2002. Unit root tests in panel data: asymptotic and finite-sample properties. *Journal of econometrics*, *108*(1), pp.1-24.

Levine, R., 2005. Law, endowments and property rights. *Journal of Economic Perspectives*, *19*(3), pp.61-88.

Li, J., Zhang, D. and Su, B., 2019. The impact of social awareness and lifestyles on household carbon emissions in China. *Ecological Economics*, *160*, pp.145-155.

Lo, A.W. and MacKinlay, A.C., 1988. Stock market prices do not follow random walks: Evidence from a simple specification test. *The review of financial studies*, *1*(1), pp.41-66.

Lo, A.W. and MacKinlay, A.C., 1988. Stock market prices do not follow random walks: Evidence from a simple specification test. *The review of financial studies*, *1*(1), pp.41-66.

Lockwood, M., Owens, M.J., Barnard, L. and Usoskin, I.G., 2016. An assessment of sunspot number data composites over 1845–2014. *The Astrophysical Journal*, *824*(1), p.54.

Louzis, D.P. (2013) "Measuring Return and Volatility Spillovers in Euro Area Financial Markets," (Tech. Rep.), Bank of Greece.

Love, I. and Ariss, R.T., 2014. Macro-financial linkages in Egypt: A panel analysis of economic shocks and loan portfolio quality. *Journal of international financial markets, institutions and money*, *28*, pp.158-181.

Ludvigson, S., 1999. Consumption and credit: a model of time-varying liquidity constraints. *Review of Economics and Statistics*, *81*(3), pp.434-447.

Lütkepohl, H., 2005. *New introduction to multiple time series analysis*. Springer Science & Business Media.

Lyócsa, S., Vyrost, T., and Baumohl, E. (2015) "Return Spillovers around the Globe: A network Approach," Cornell University, Available at: https://arxiv.org/abs/1507.06242.

Maghyereh, A., Awartani, B., (2012) "Return and Volatility Spillovers between Dubai Financial Market and Abu Dhabi Stock Exchange in the UAE", *Applied Financial Economics* 22, 837-848.

Mankiw, N.G. and Shapiro, M.D., 1985. Trends, random walks, and tests of the permanent income hypothesis. *Journal of Monetary Economics*, *16*(2), pp.165-174.

Masih, R., Peters, S., and Mello, L. D. (2011) "Oil price Volatility and Stock Price Fluctuations in an E

Mayer, C. (2011) Housing Bubbles: A Survey. Annual Review of Economics, 3:55977.

McMillan, D. G., and Speight, E. H. (2010) "Return and Volatility Spillovers in Three Euro Exchange Rates," *Journal of Economics and Business*, 62, 79-93.

McMillan, D.G. and Speight, A.E., 2010. Return and volatility spillovers in three euro exchange rates. *Journal of Economics and Business*, *62*(2), pp.79-93.

Melard, G. and Pasteels, J.M., 2000. Automatic ARIMA modeling including interventions, using time series expert software. *International Journal of Forecasting*, *16*(4), pp.497-508.

Mendoza, E.G. and Terrones, M.E., 2008. *An anatomy of credit booms: evidence from macro aggregates and micro data* (No. w14049). National Bureau of Economic Research.

Merh, N., Saxena, V. P., & Pardasani, K. R. (2010). A comparison between hybrid approaches of ANN and ARIMA for Indian stock trend forecasting. *Business Intelligence Journal*, *3*(2), 23-43.

Mian, A. and Sufi, A., 2009. The consequences of mortgage credit expansion: Evidence from the US mortgage default crisis. *The Quarterly Journal of Economics*, *124*(4), pp.1449-1496.

Mian, A. and Sufi, A., 2010. The great recession: Lessons from microeconomic data. *American Economic Review*, *100*(2), pp.51-56.

Mishra, A. K., Swain, N., and Mahorta, D. K. (2007) "Volatility Spillover between Stock and Foreign Exchange Markets: Indian Evidence", *International Journal of Business* 12, 344-359.

Mohammed, W.A., 2020. Challenges of Stock Prediction. In *Valuation Challenges and Solutions in Contemporary Businesses* (pp. 234-252). IGI Global.

Mohanty, S., Nanhdi, M., Turkistani, A. Q., and Alaitani, M. Y. (2011) "Oil Price Movements and Stock Market Returns: Evidence from Gulf Cooperation Council (GCC) Countries", *Global Finance Journal* 22, 42-55.

Moosa, I. A., and K. Burns. 2014. "The Unbeatable Random Walk in Exchange Rate Forecasting: Reality or Myth?" Journal of Macroeconomics 40: 69–81. doi:10.1016/j. jmacro.2014.03.003.

Moosa, I. and Burns, K., 2016. The random walk as a forecasting benchmark: drift or no drift?. *Applied Economics*, *48*(43), pp.4131-4142.

Moosa, I. and Burns, K., 2016. The random walk as a forecasting benchmark: drift or no drift?. *Applied Economics*, *48*(43), pp.4131-4142.

Morales, L. De L. N. (2008) "Volatility Spillovers between Equity and Currency Markets: Evidence from Major Latin America Countries", *Caudernos De Economia*, 45, 185-215.

Morck, R., Shleifer, A., Vishny, R.W., Shapiro, M. and Poterba, J.M., 1990. The stock market and investment: is the market a sideshow?. *Brookings papers on economic Activity*, *1990*(2), pp.157-215.

Moshirian, F. (2011) "The Global Financial Crisis and the Evolution of Markets, Institutions and Regulation," *Journal of Banking and Finance*, 35, 502-511.

Mozumder, N., Vita, G. D., and Kyaw, K. S. (2015) "Volatility Spillovers between Stock Prices and Exchange Rates: New Evidence across the Recent Financial Crisis Period", *Journal of Economic Issues*, Vol. 20, part 1.

Murphy, J.J., 2009. *The visual investor: how to spot market trends* (Vol. 443). John Wiley & Sons.

Narayan, P.K. and Ahmed, H.A., 2014. Importance of skewness in decision making: evidence from the Indian stock exchange. *Global Finance Journal*, *25*(3), pp.260-269.

Nau, R., 2014. Notes on the random walk model. *Fuqua School of Business*.

Nayak, R.K., Mishra, D. and Rath, A.K., 2015. A Naïve SVM-KNN based stock market trend reversal analysis for Indian benchmark indices. *Applied Soft Computing*, *35*, pp.670-680.

Ngo, T.H., 2020. *Volatility Spillover of the Stock Market and Foreign Exchange: Evidence from Cee Countries [védés előtt]* (Doctoral dissertation, Budapesti Corvinus Egyetem).

Nier, E., Yang, J., Yorulmazer, T., and Alentorn, A. (2007) "Network Models and Financial Stability," *Journal of Economic Dynamics and Control*: 31, 2033–2060.

Nikkinen, J., Sahlstrom, P., and Vahamaa, S. (2006) "Implied Volatility Linkages A mong Major European Currencies," *Journal of International Financial Markets, Institute and Money*, 16- 87-103.

O'Donnell M, Morales L (2009) Volatility Spillovers Between Stock Returns and Foreign Exchange Rates: Evidence from Four Eastern European Countries. Int J Business 12:1–20.

Oberholzer N, Boetticher ST (2015) Volatility Spill-over between the JSE/FTSE Indices and the South African Rand. Proc Econ Finan 24:501–510.

Oizumi, E., 1994. Property finance in Japan: expansion and collapse of the bubble economy. *Environment and Planning A*, *26*(2), pp.199-213.

Okpara GC, Odionye JC (2012) The direction of volatility spillover between stock prices and exchange rate: evidence from Nigeria. Elix Finan 42:6410–6414.

Pai, P. F., & Lin, C. S. (2005). A hybrid ARIMA and support vector machines model in stock price forecasting. *Omega*, *33*(6), 497-505.

Paretkar, P.S., 2008. *Short-Term Forecasting of Power Flows over Major Pacific Northwestern Interties: Using Box and Jenkins ARIMA Methodology* (Doctoral dissertation, Virginia Tech).

Park, H.M., 2011. Practical guides to panel data modeling: a step-by-step analysis using stata. *Public Management and Policy Analysis Program, Graduate School of International Relations, International University of Japan*, pp.1-52.

Pavlov, A., and Wachter, S. (2011) Subprime Lending and Real Estate Prices. Real Estate Economics, 39: 117

Pérez-Rodrìguez, J. (2006) "The Euro and other Major Currencies Floating against the U.S. Dollar," *Atlantic Economic Journal* 34 (4), 367-384.

Pesaran, M.H. and Pick, A., 2008. Forecasting random walks under drift instability.

Phan, D.H.B., Sharma, S.S. and Narayan, P.K., 2015. Stock return forecasting: some new evidence. *International Review of Financial Analysis*, *40*, pp.38-51.

Pindyck, S. and Rubinfeld, L., 1998. Economentric models and economic forecasts. *United States of America: McGraw-Hill, Inc*.

Pontiff J, Schall LD. Book-to-market ratios as predictors of market returns. Journal of Financial Economics. 1998 Aug 1;49(2):141-60.

Poon, S.H., 2012. A practical guide for forecasting financial market volatility.

Poterba, J.M. and Summers, L.H., 1988. Mean reversion in stock prices: Evidence and implications. *Journal of financial economics*, *22*(1), pp.27-59.

Prediction. *Review of Financial Studies* 21:1455–508.

Quigley, J.M., 2001. Real estate and the Asian crisis. *Journal of Housing Economics*, *10*(2), pp.129-161.

Raicharoen, T., Lursinsap, C. and Sanguanbhokai, P., 2003, May. Application of critical support vector machine to time series prediction. In *Proceedings of the 2003 International Symposium on Circuits and Systems, 2003. ISCAS'03.* (Vol. 5, pp. V-V). IEEE.

Rajhans, R. K., and Jain, A. (2015) "Volatility Spillovers in Foreign Exchange Markets", *Paradigm*, Vol. 19, No 2, 137-151.

Ramey, V.A. and Shapiro, M.D., 1998, June. Costly capital reallocation and the effects of government spending. In *Carnegie-Rochester Conference Series on Public Policy* (Vol. 48, pp. 145-194). North-Holland.

Rapach, D. and Zhou, G., 2013. Forecasting stock returns. In *Handbook of economic forecasting* (Vol. 2, pp. 328-383). Elsevier.

Rapach, D.E., Strauss, J.K. and Zhou, G., 2010. Out-of-sample equity premium prediction: Combination forecasts and links to the real economy. *The Review of Financial Studies*, *23*(2), pp.821-862.

Reagan, K.M., 1984. *An evaluation of ARIMA(Box-Jenkins) models for forecasting wastewater treatment process variables* (Master's thesis, UCLA).

Reinhart, C.M. and Rogoff, K.S., 2009. The aftermath of financial crises. *American Economic Review*, *99*(2), pp.466-72.

Reinhart, C.M. and Rogoff, K.S., 2009. The aftermath of financial crises. *American Economic Review*, *99*(2), pp.466-72.

Repullo, R. and Saurina Salas, J., 2011. The countercyclical capital buffer of Basel III: A critical assessment.

Roll, R., 1986. The hubris hypothesis of corporate takeovers. *Journal of business*, pp.197-216.

Schiller, J. and Campbell, J., 1998. Valuation ratios and the long-run stock market outlook. *Journal of*.

Schularick, M. and Taylor, A.M., 2012. Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008. *American Economic Review*, *102*(2), pp.1029-61.

Schularick, M., and Taylor, A. (2009) "Credit booms gone bust: Monetary policy, leverage cycles, and financial crises," 1870-2008. NBER Working Paper 15512, forthcoming in the American Economic Review.

Schüler, Y.S., Hiebert, P. and Peltonen, T.A., 2017. Coherent financial cycles for G-7 countries: Why extending credit can be an asset. *Available at SSRN 2539717*.

Schwert, G.W., 2011. Stock volatility during the recent financial crisis. *European Financial Management*, *17*(5), pp.789-805.

Shapley, L.S. (1953) "A value for n-person games," In: Kuhn, H., Tucker, A. (Eds.), Contributions to the Theory of Games, vol. II, Annals of Mathematical Studies, vol. 28. Princeton University Press, pp. 307–317.

Shinagawa, Y. (2014) "Determinants of Financial Market Spillovers: the Role of Portfolio Diversification, Trade, Home Bias, and Concentration", *International Monetary Fund*, WP/14/187.

Smith, G. and Ryoo, H.J., 2003. Variance ratio tests of the random walk hypothesis for European emerging stock markets. *The European Journal of Finance*, *9*(3), pp.290-300.

Snowdon, B. and Vane, H.R., 2005. *Modern macroeconomics: its origins, development and current state*. Edward Elgar Publishing.

Sousa, R.M., Vivian, A. and Wohar, M.E., 2016. Predicting asset returns in the BRICS: The role of macroeconomic and fundamental predictors. *International Review of Economics & Finance*, *41*, pp.122-143.

Steiger, F., 2010. The validity of company valuation using Discounted Cash Flow methods. *arXiv preprint arXiv:1003.4881*.

Steland, A., 2005. Random walks with drift–a sequential approach. *Journal of Time Series Analysis*, *26*(6), pp.917-942.

Steland, A., 2005. Random walks with drift–a sequential approach. *Journal of Time Series Analysis*, *26*(6), pp.917-942.

Sterba, J. and Hilovska, K., 2010. The implementation of hybrid ARIMA neural network prediction model for aggregate water consumption prediction. *Aplimat—Journal of Applied Mathematics*, *3*(3), pp.123-131.

Stiroh, K. (2004) "Diversification in Banking: Is Noninterest Income the Answer?," Journal of Money, Credit and Banking *36, 853-882.*

Stiroh, K. (2006) "A Portfolio View of Banking with Interest and Noninterest Activities," Journal of Money, Credit, and Banking *38, 2131-2161.*

Tansel, I. N., Yang, S. Y., Venkataraman, G., Sasirathsiri, A., Bao, W. Y., & Mahendrakar, N. (1999). Modeling time series data by using neural netwroks and genetic algorithms. *Smart Engineering System Design: Neural Networks, Fuzzy Logic, Evolutionary Programming, Data Mining, and Complex Systems: Proceedings of the Intelligent Engineering Systems Through Artificial Neural Networks, 9, 1055-1060.*

Tarashev, N., Borio, C., and Tsatsaronis, K. (2010) “Attributing Systemic Risk to Individual Institutions,” Methodology and Policy Implications, BIS Working Paper. No: 308.

Tay, F.E. and Cao, L., 2001. Application of support vector machines in financial time series forecasting. *omega*, *29*(4), pp.309-317.

Ticknor, J.L., 2013. A Bayesian regularized artificial neural network for stock market forecasting. *Expert Systems with Applications*, *40*(14), pp.5501-5506.

Tiwari, A.K. (2011), 'Comparative performance of renewable and nonrenewable energy source on

Torres-Reyna, O., 2007. Panel data analysis fixed and random effects using Stata (v. 4.2). *Data & Statistical Services, Priceton University*.

Tsatsaronis, K. and Zhu, H., 2004. What drives housing price dynamics: cross-country evidence. *BIS Quarterly Review, March*.

Walid C, Chaker A, Masood O, Fry J (2011) Stock market volatility and exchange rates in emerging countries: A Markov-state switching approach. Emerg Market Rev 12(3):272–292.

Wall, K.D. and Stoffer, D.S., 2002. A state space approach to bootstrapping conditional forecasts in ARMA models. *Journal of Time Series Analysis*, *23*(6), pp.733-751.

Wang, J.J., Wang, J.Z., Zhang, Z.G. and Guo, S.P., 2012. Stock index forecasting based on a hybrid model. *Omega*, *40*(6), pp.758-766.

Watkins, C. and MCmaster, R., 2011. The behavioural turn in housing economics: reflections on the theoretical and operational challenges. *Housing, Theory and Society*, *28*(3), pp.281-287.

Watkins, C. and MCmaster, R., 2011. The behavioural turn in housing economics: reflections on the theoretical and operational challenges. *Housing, Theory and Society*, *28*(3), pp.281-287.

Welch, I., and A. Goyal. 2008. A Comprehensive Look at the Empirical Performance of Equity Premium

Westerlund, J., & Narayan, P. (2015a). Testing for predictability in conditionally

Wheaton, W. and Nechayev, G., 2008. The 1998-2005 Housing “Bubble” and the Current “Correction”: What’s Different This Time?. *Journal of real Estate research*, *30*(1), pp.1-26.

Whittle, R., Davies, T., Gobey, M. and Simister, J., 2014. Behavioural Economics and House Prices: A Literature Review. *Business and Management Horizons*, *2*(2), pp.15-28.

Wiener, N. (1942). The Extrapolation, Interpolation and Smoothing of Stationary Time Series with Engineering Applications: DIC Contract 6037, a Research Pursued on Behalf of the National Defense Research Council (Section D2) at the Massachusetts Institute of Technology. Massachusettes Insitute of Technology.

Wijaya, Y. B., Kom, S., & Napitupulu, T. A. (2010, December). Stock price prediction: Comparison of Arima and artificial neural network methods-an Indonesia stock's case. In *2010 Second International Conference on Advances in Computing, Control, and Telecommunication Technologies* (pp. 176-179). IEEE.

Wooldridge, J.M., 2010. *Econometric analysis of cross section and panel data*. MIT press.

Yadav, R. and Pathak, G.S., 2016. Young consumers' intention towards buying green products in a developing nation: Extending the theory of planned behavior. *Journal of Cleaner Production*, *135*, pp.732-739.

Yang, L. (2013) "Volatility among the U.S. and Asian Stock Markets: A Comparison between the Periods of Crisis and Subprime Credit Crisis," 26th Australasian Finance and Banking Conference, Available at: http://ssrn.com/abstract=2357345.

Yang, Z., Fan, Y. and Zheng, S., 2016. Determinants of household carbon emissions: Pathway toward eco-community in Beijing. *Habitat International*, *57*, pp.175-186.

Yao, H., Haris, M. and Tariq, G., 2018. Profitability determinants of financial institutions: evidence from banks in Pakistan. *International Journal of Financial Studies*, *6*(2), p.53.

Yarovaya, L., Brzeszczynski, ´ J., and Lau, C.K.M. (2016) "Intra- and Inter-Regional Return and Volatility Spill-overs across Emerging and Developed Markets: Evidence from Stock Indices and Stock Index Futures," *Journal of International Review of Financial Analysis*, 43, 96–114.

Yilmaz, K. M. (2009) "International Business Cycle Spillovers", Koc University-TUSIAD Economic Research Forum Working Papers 0903.

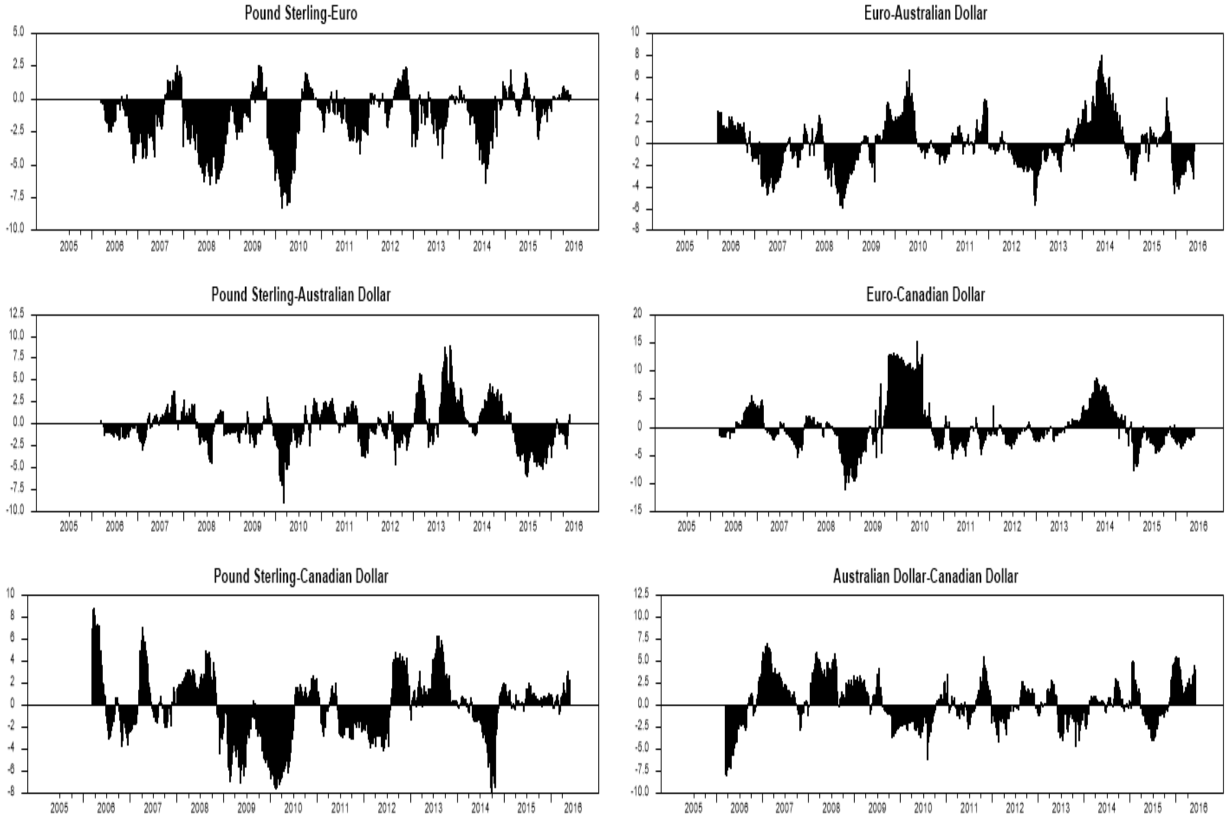
Zhang, G., Patuwo, B.E. and Hu, M.Y., 1998. Forecasting with artificial neural networks: The state of the art. *International journal of forecasting*, *14*(1), pp.35-62.

Zhang, G.P. and Qi, M., 2005. Neural network forecasting for seasonal and trend time series. *European journal of operational research*, *160*(2), pp.501-514.

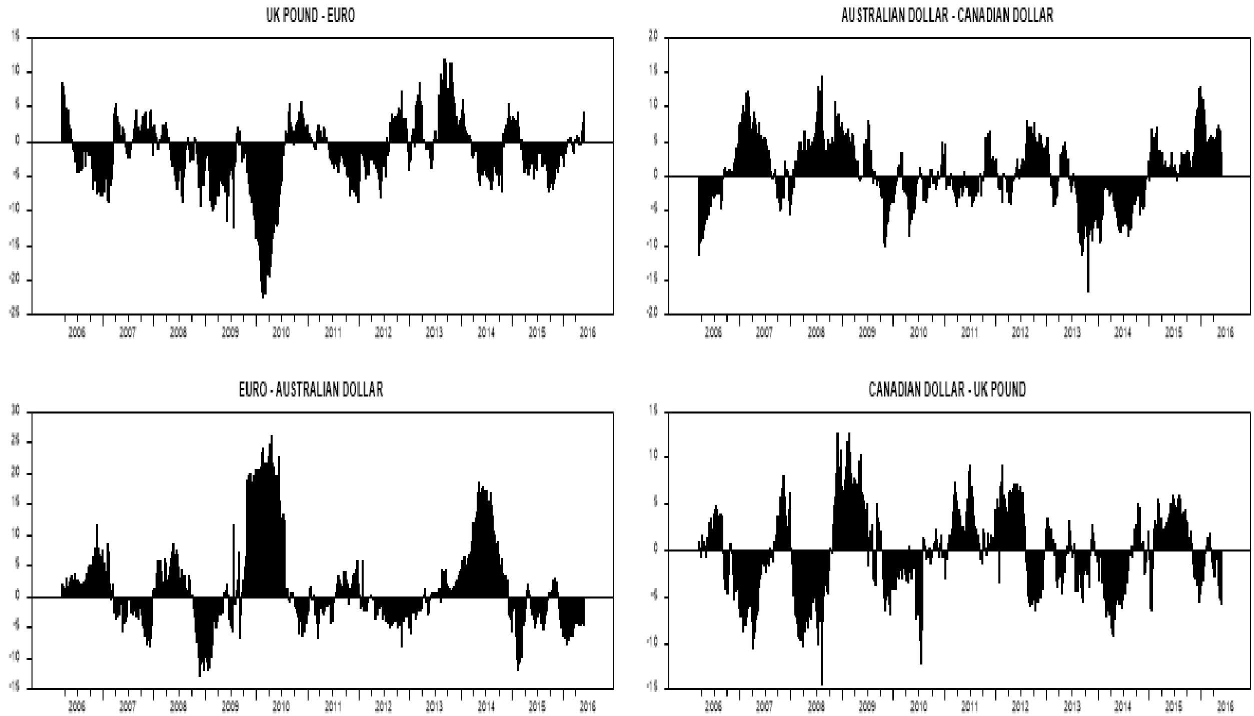
Zhang, G.P., 2003. Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing*, *50*, pp.159-175.

Zhou, Z. J., & Hu, C. H. (2008). An effective hybrid approach based on grey and ARMA for forecasting gyro drift. *Chaos, Solitons & Fractals*, *35*(3), 525-529.

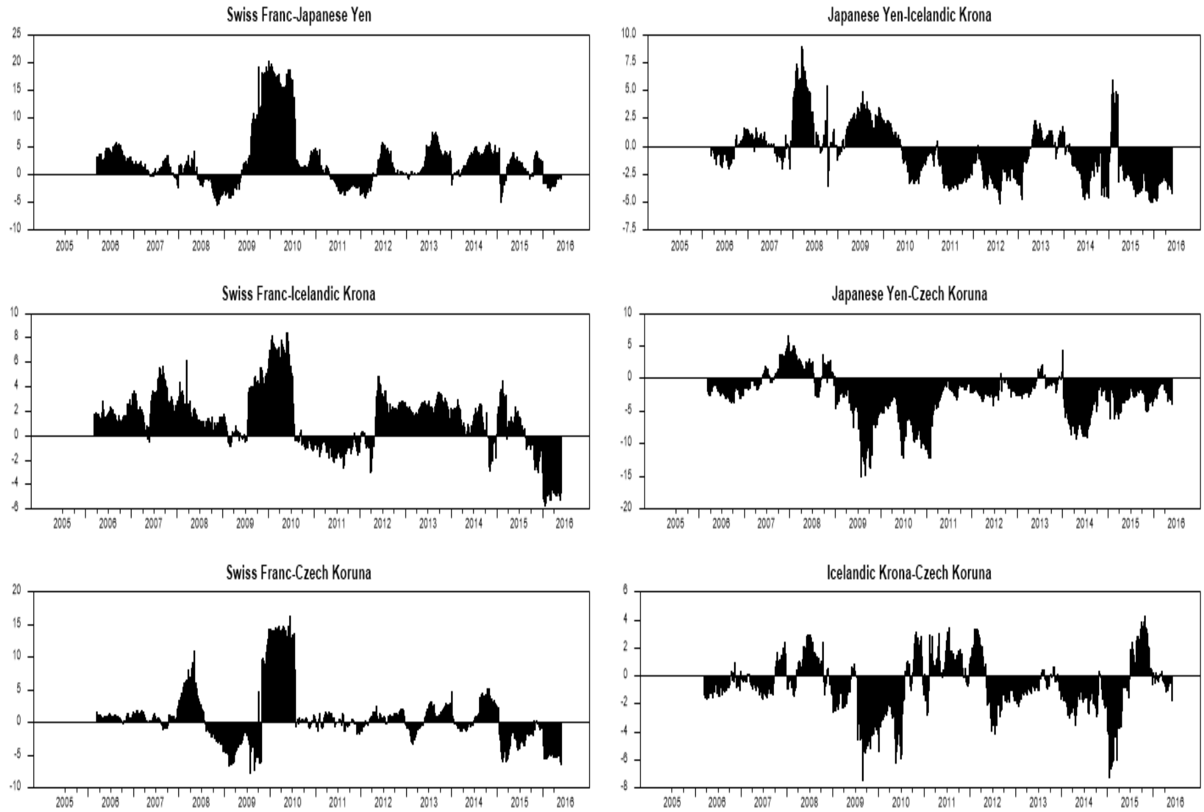
Net Pairwise Volatility Spillovers, GBP EUR AUD CAD



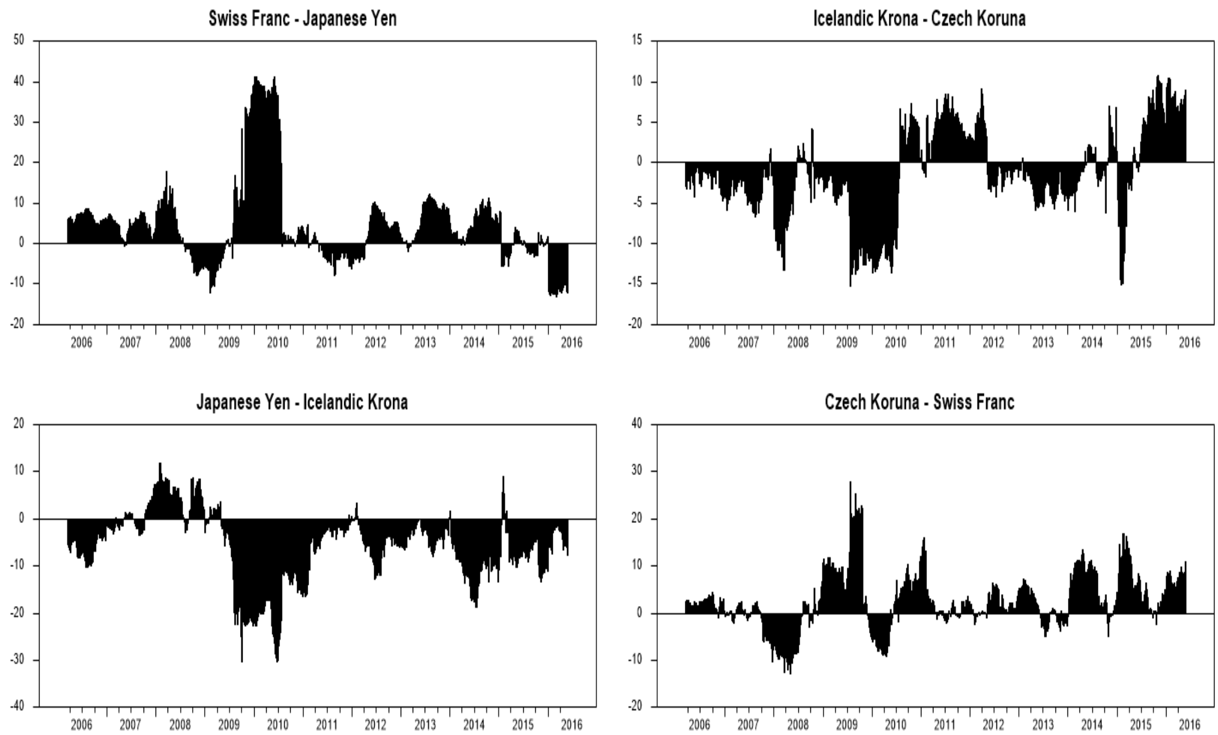
Net Volatility Spillovers, GBP EUR AUD CAD



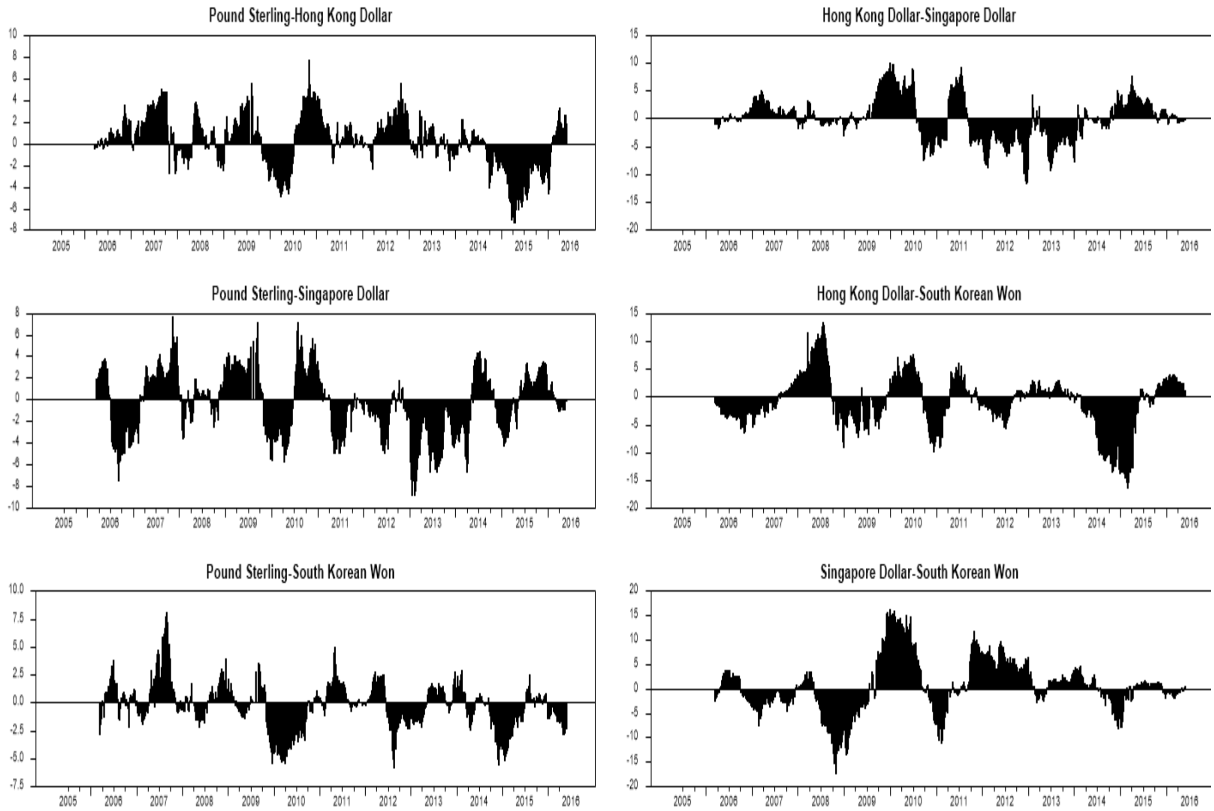
Net Pairwise Volatility Spillovers, CHF JPY ISK CZK



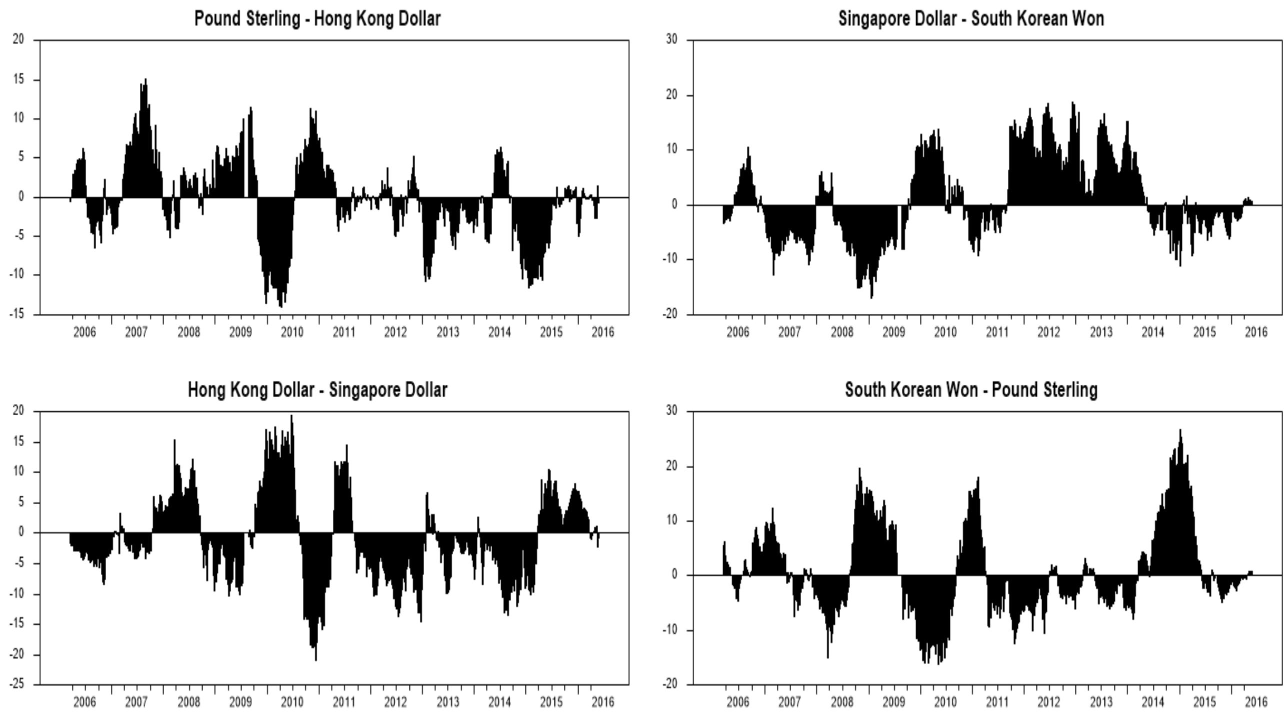
Net Volatility Spillovers, CHF JPY ISK CZK



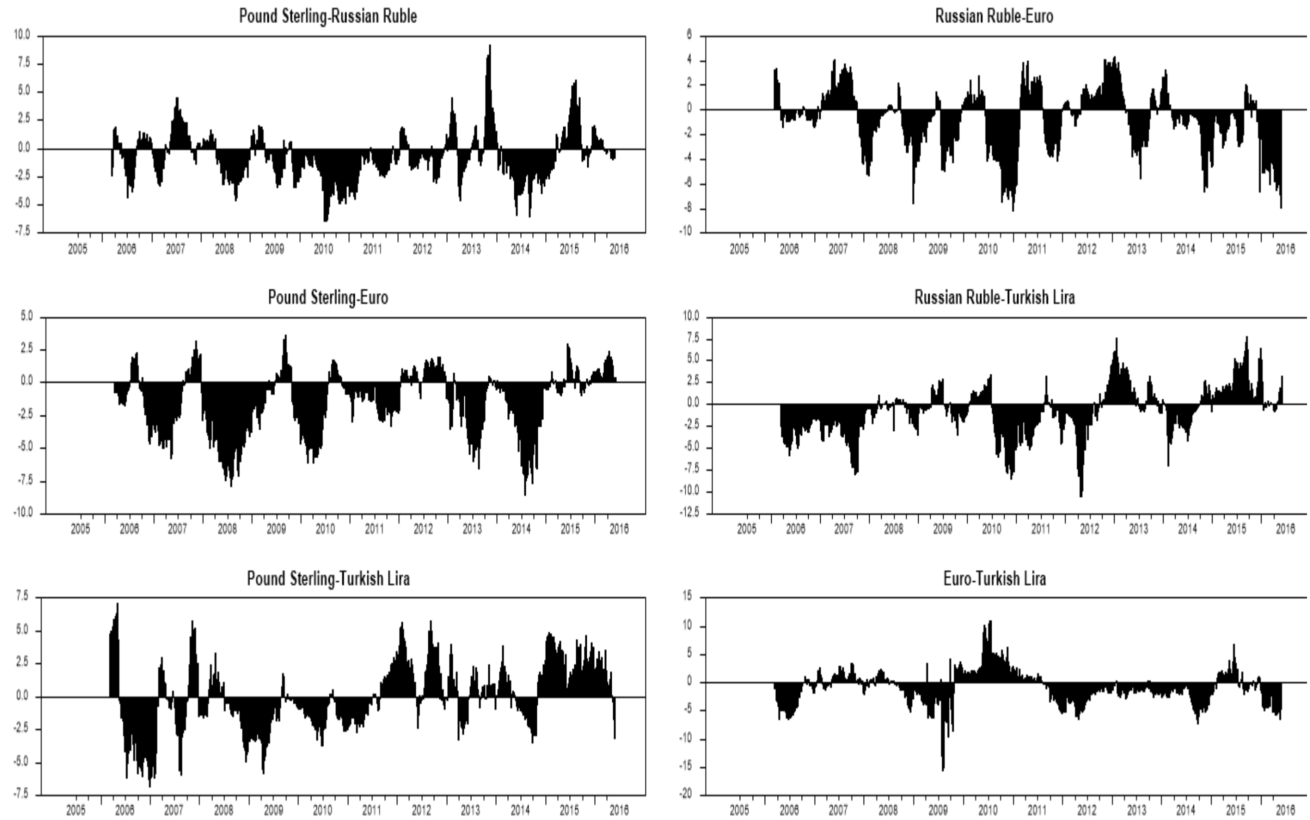
Net Pairwise Volatility Spillovers,GBP HKD SGD KRW



Net Volatility Spillovers, GBP HKD SGD KRW



Net Pairwise Volatility Spillovers,GBP RUB EUR TRY



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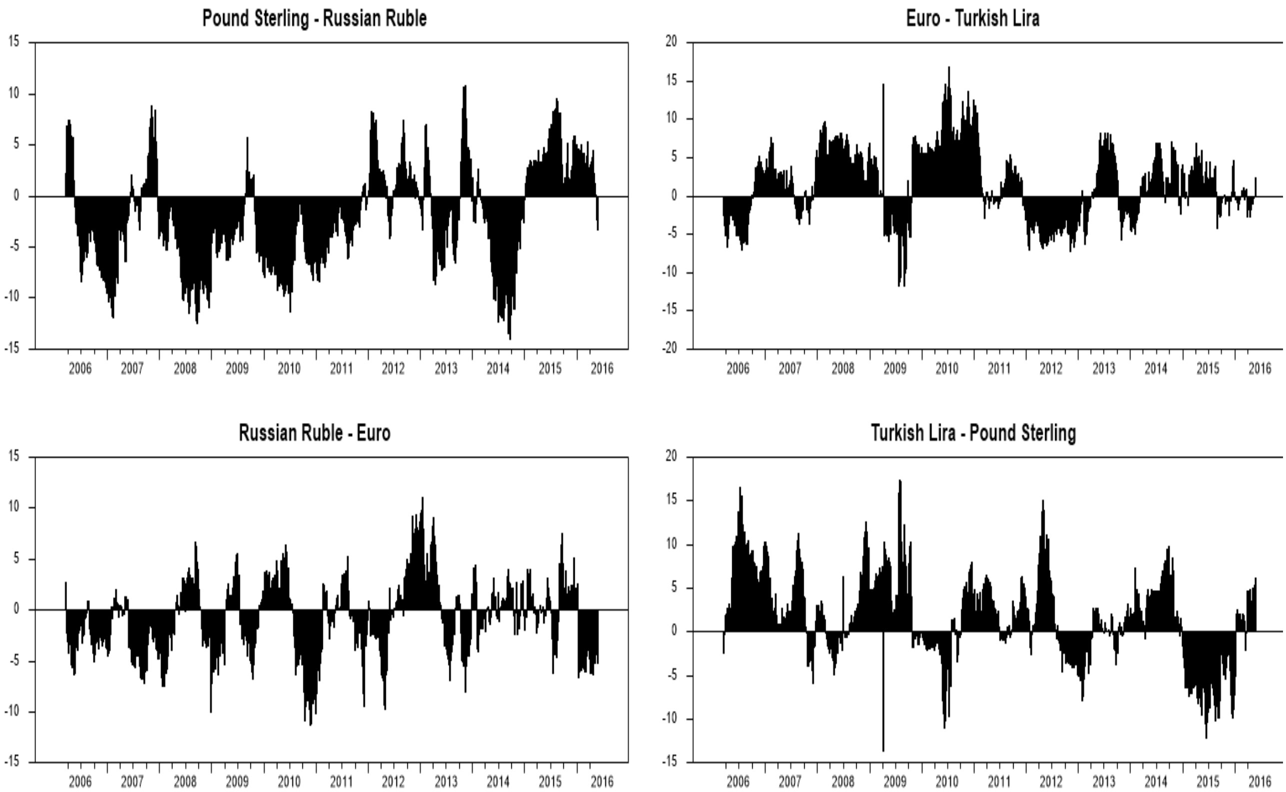
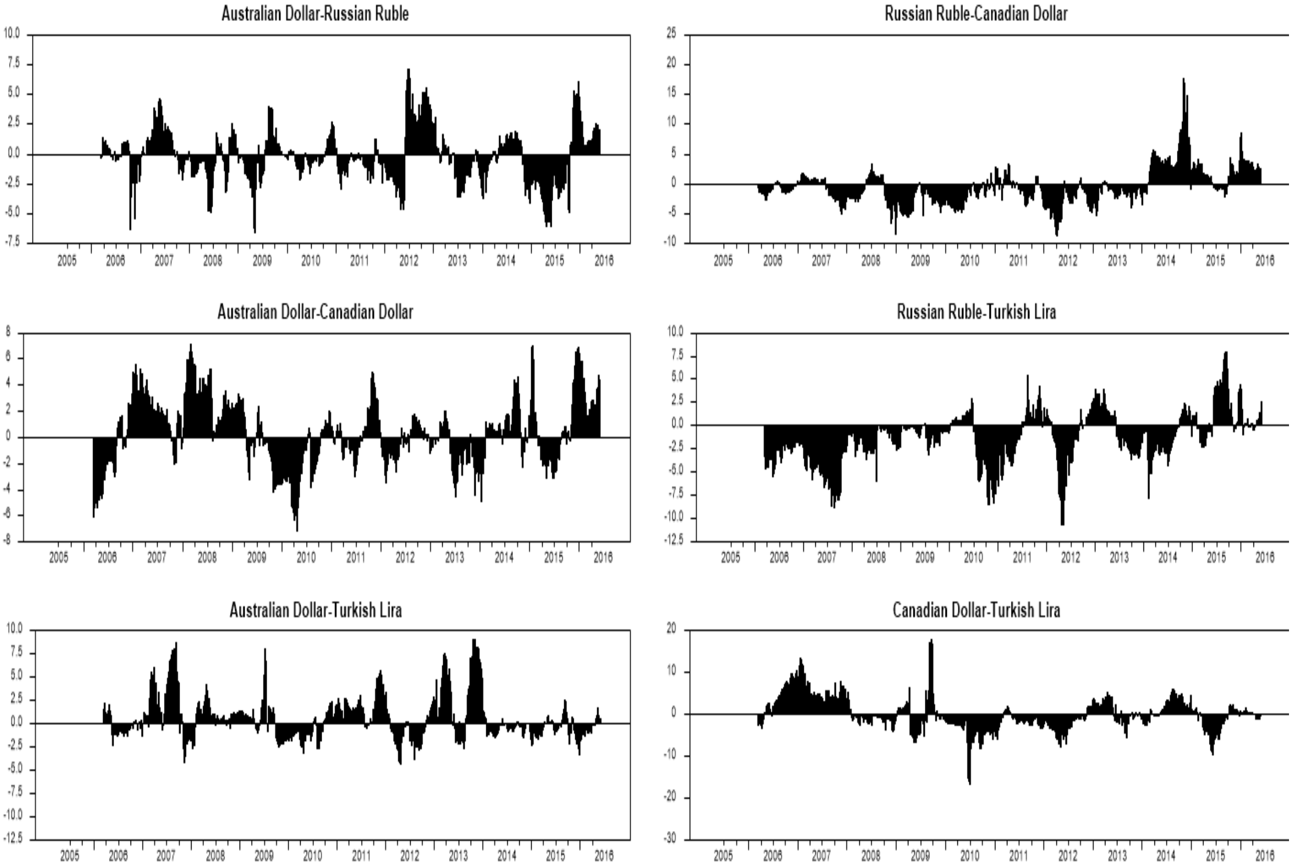
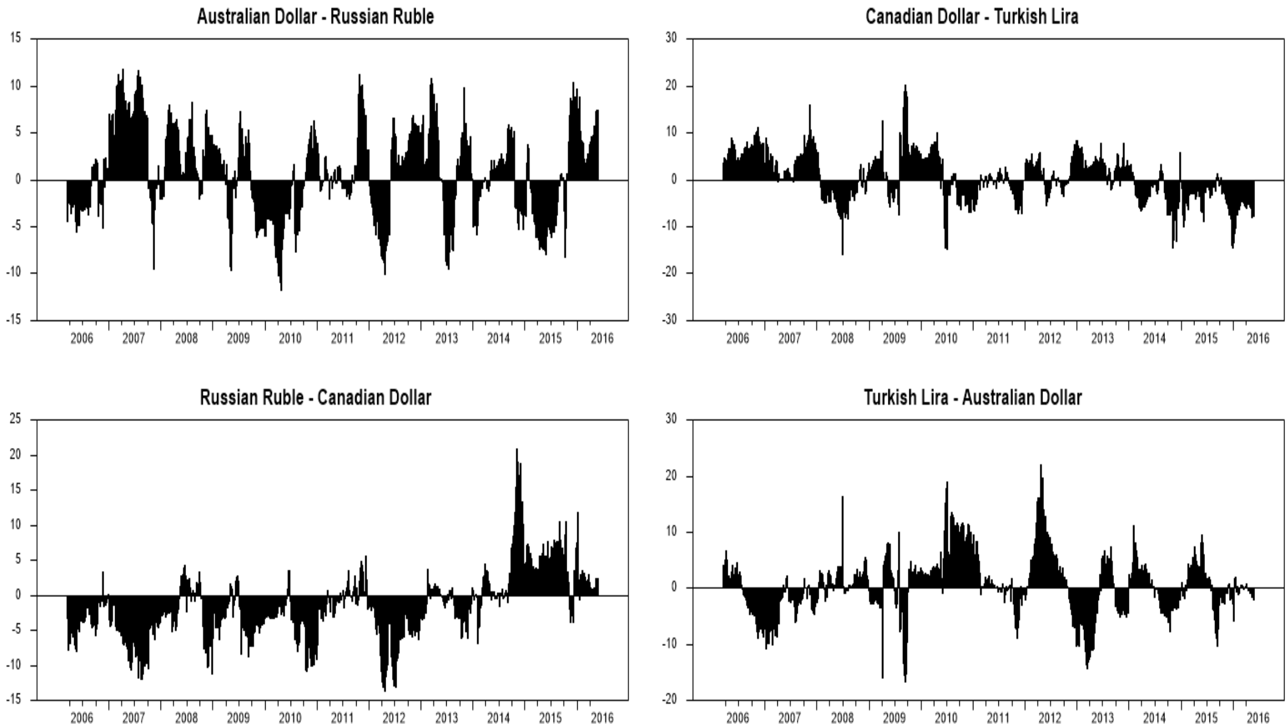


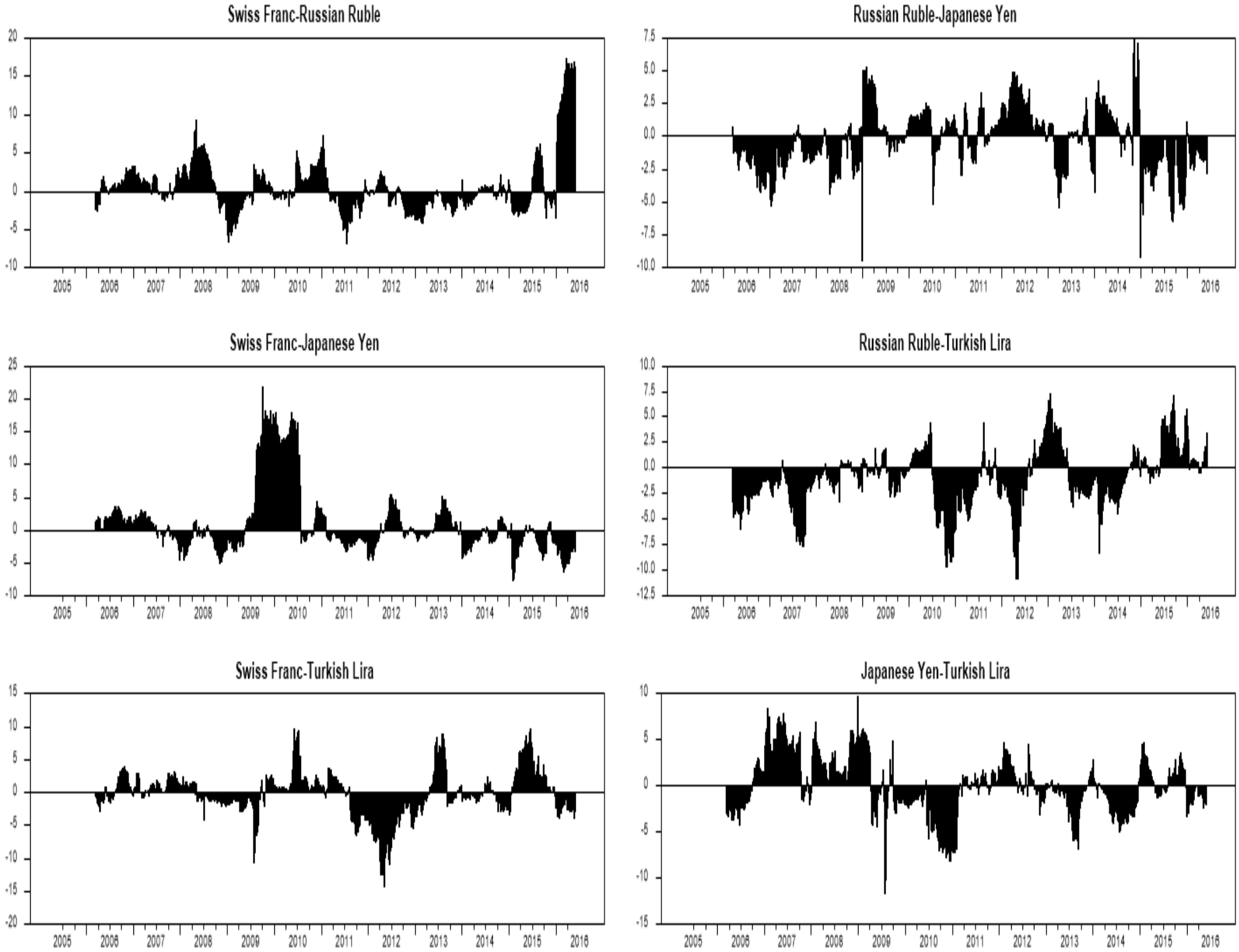
Net Pairwise Volatility Spillovers,AUD RUB CAD TRY



Net Volatility Spillovers, AUD RUB CAD TRY



Net Pairwise Volatility Spillovers,CHF RUB JPY TRY



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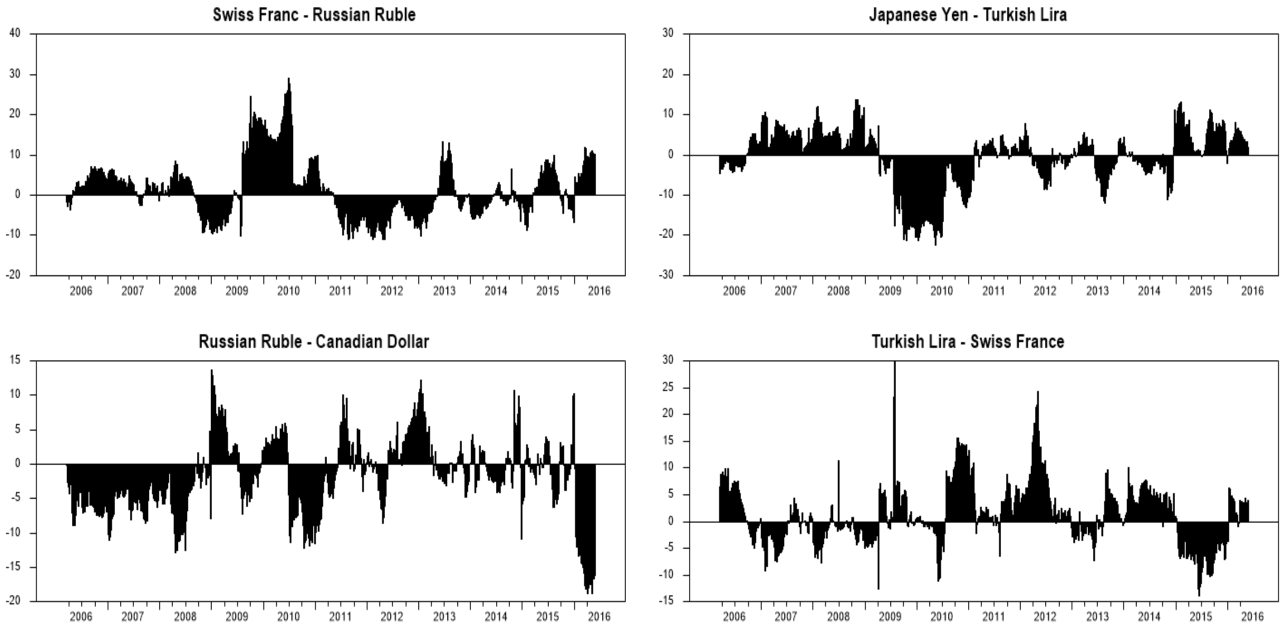
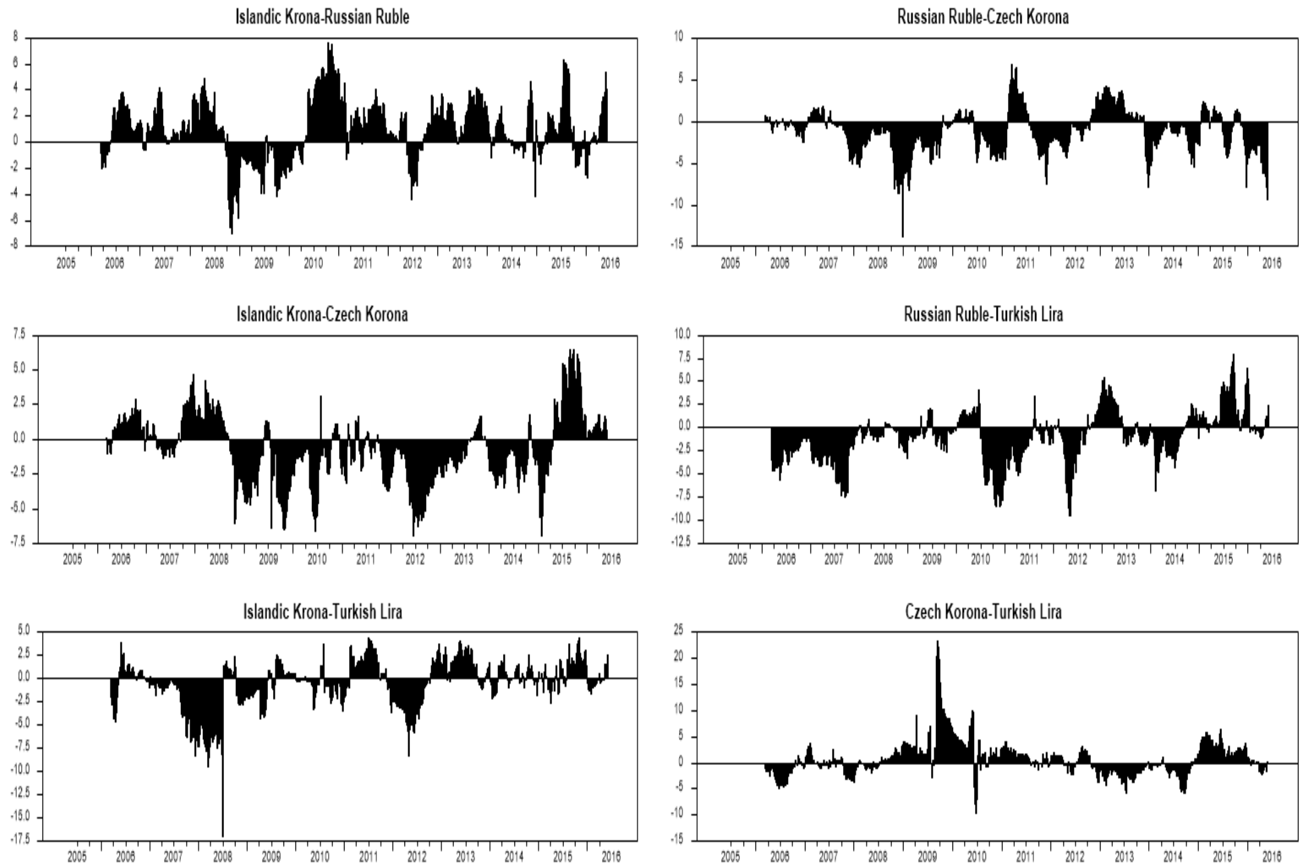
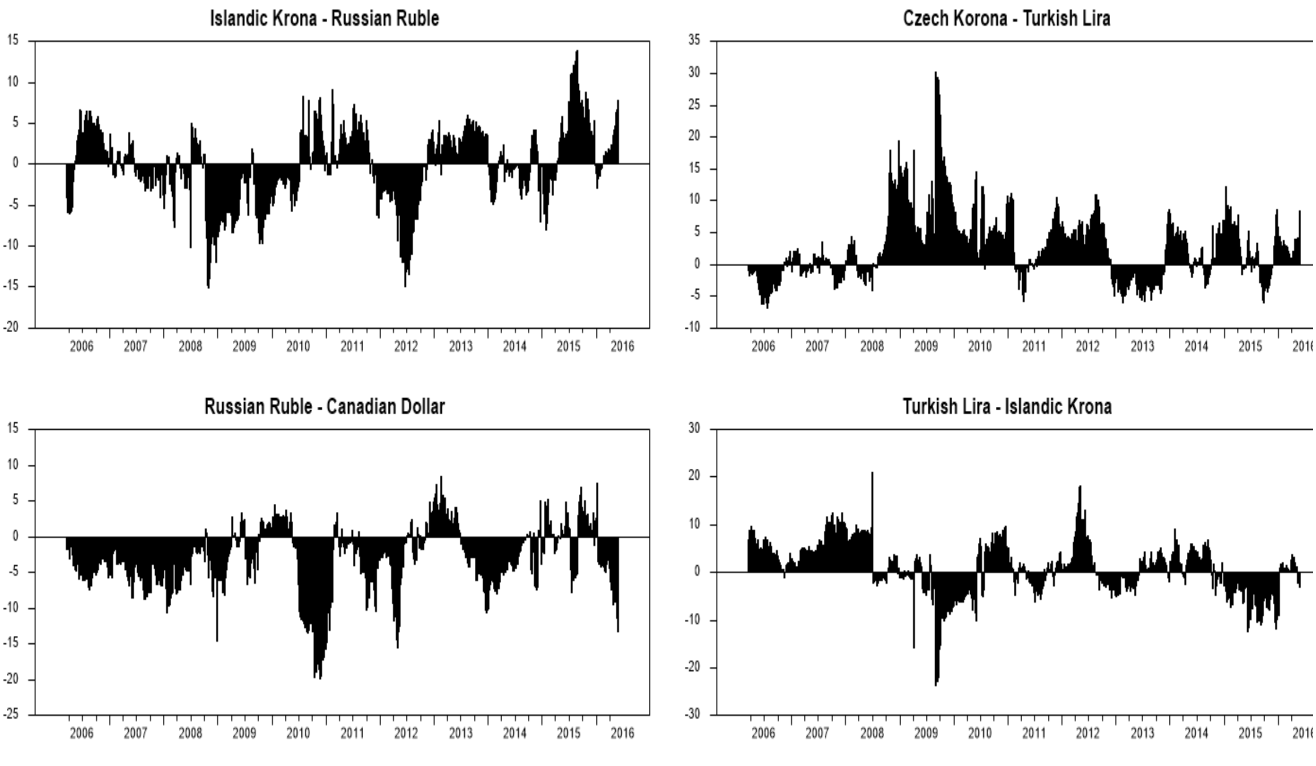


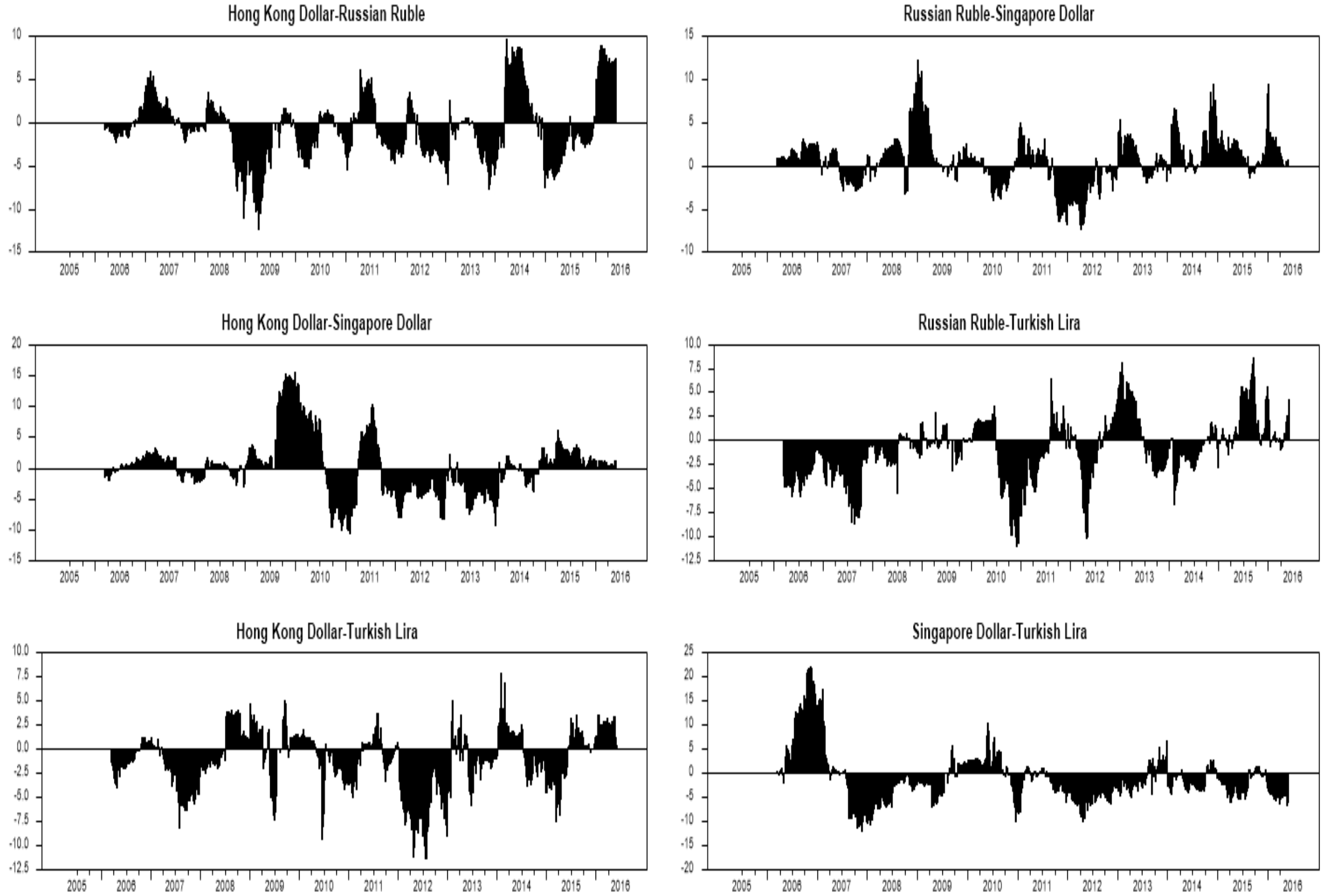
Net Pairwise Volatility Spillovers,ISK RUB CZK TRY



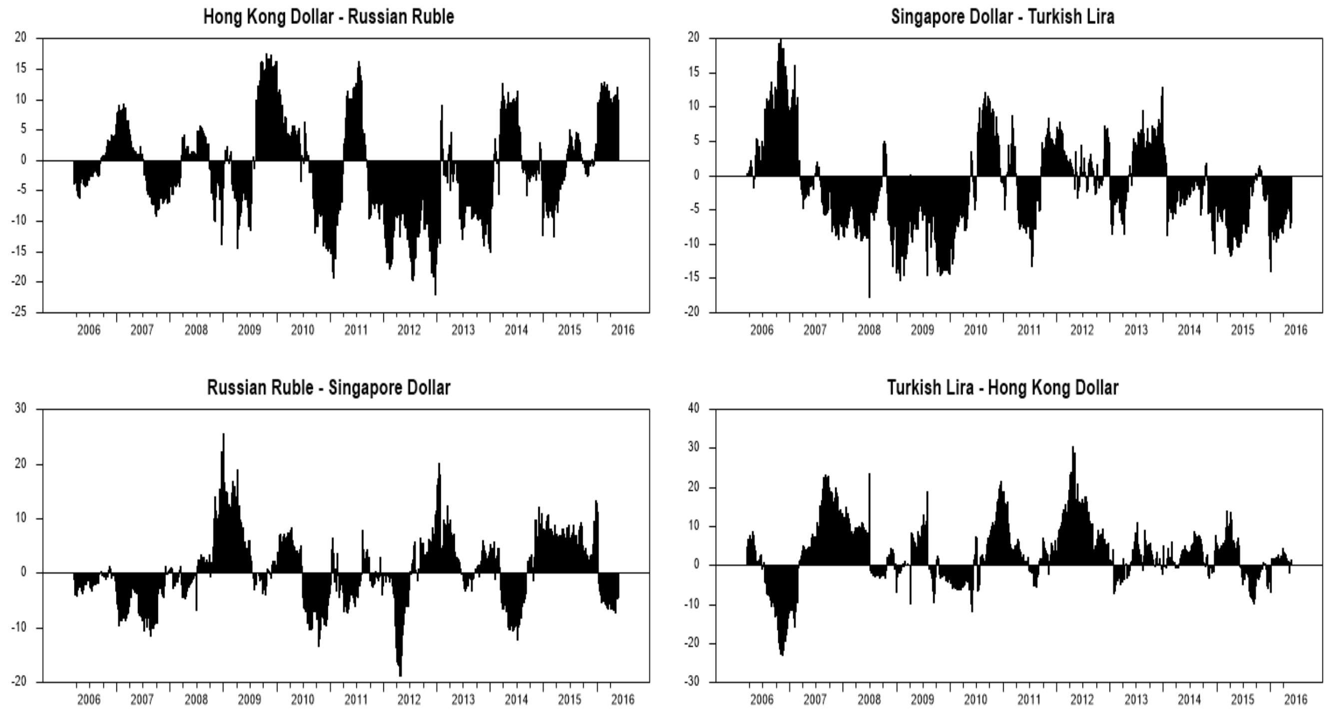
Net Volatility Spillovers, ISK RUB CZK TRY



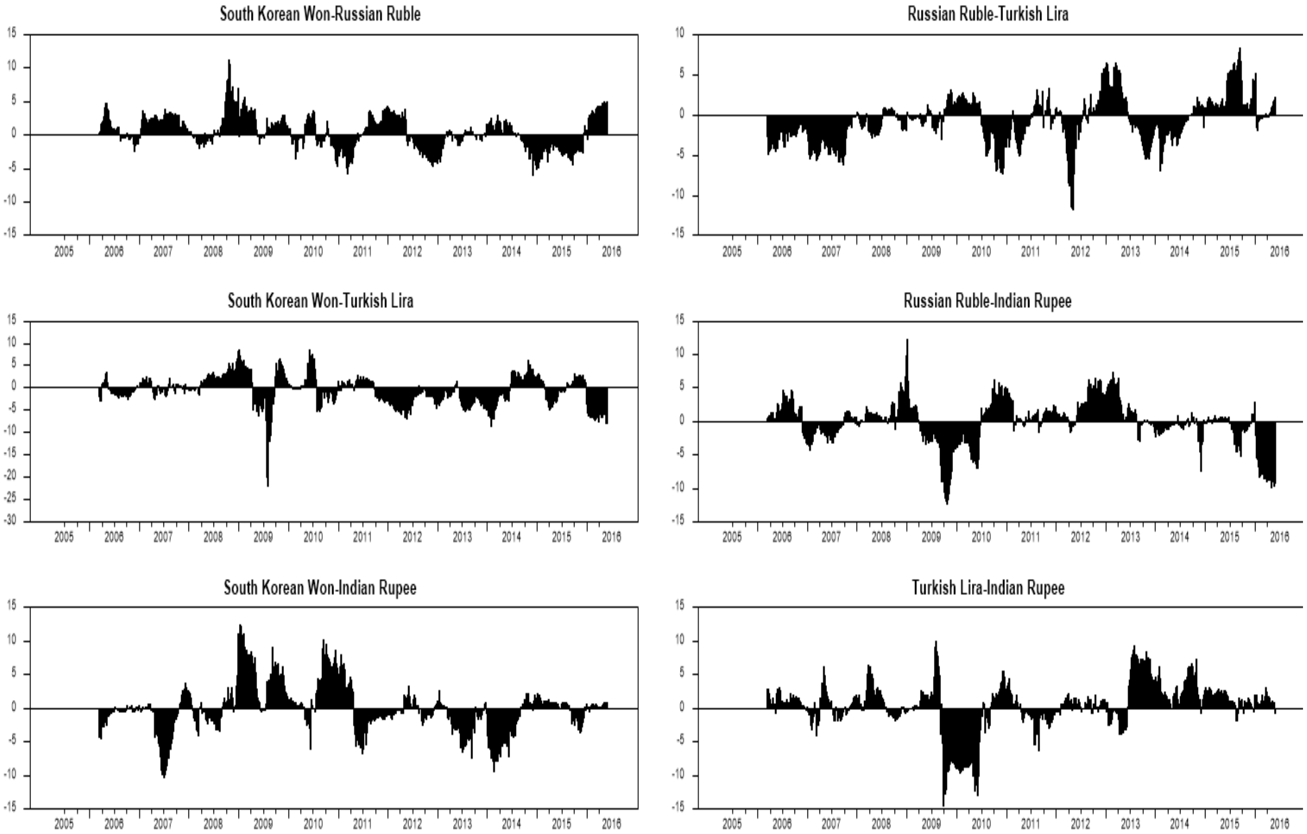
Net Pairwise Volatility Spillovers,HKD RUB SGD TRY



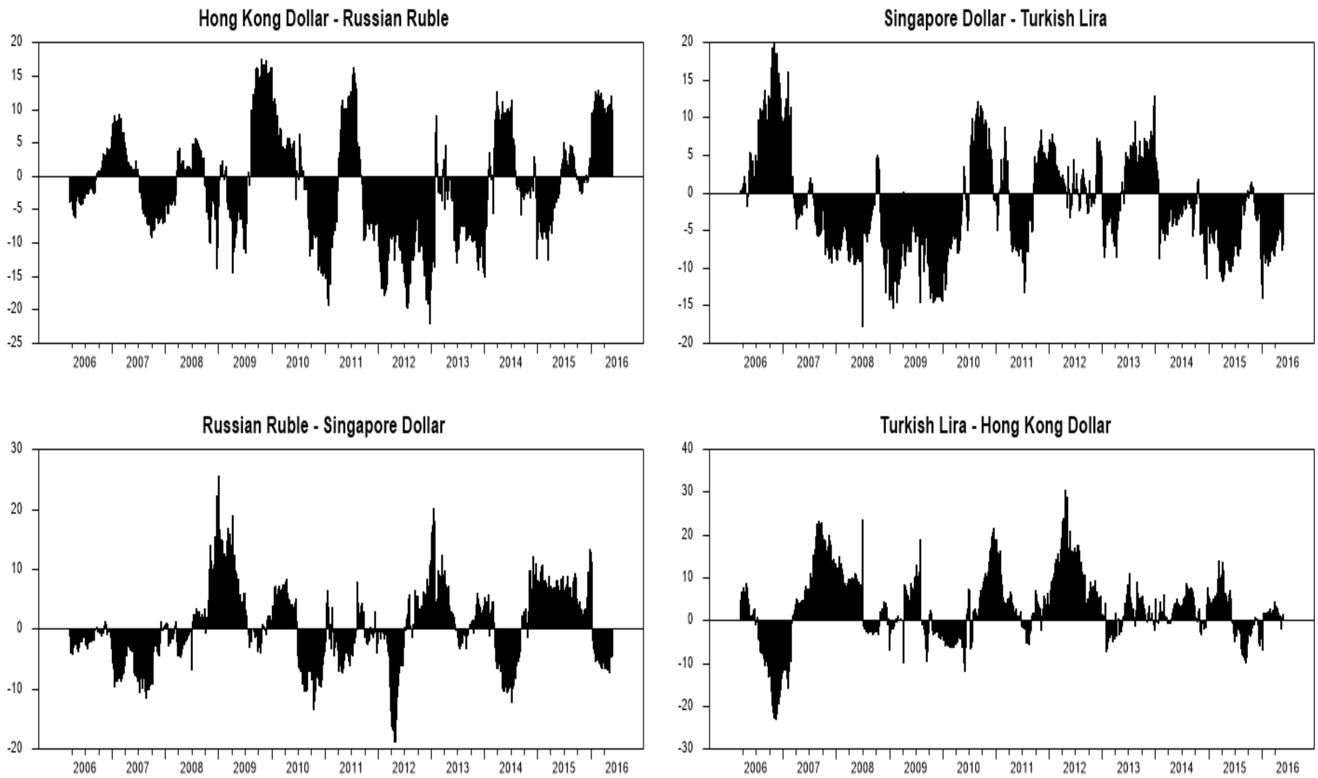
Net Volatility Spillovers, HKD RUB SGD TRY



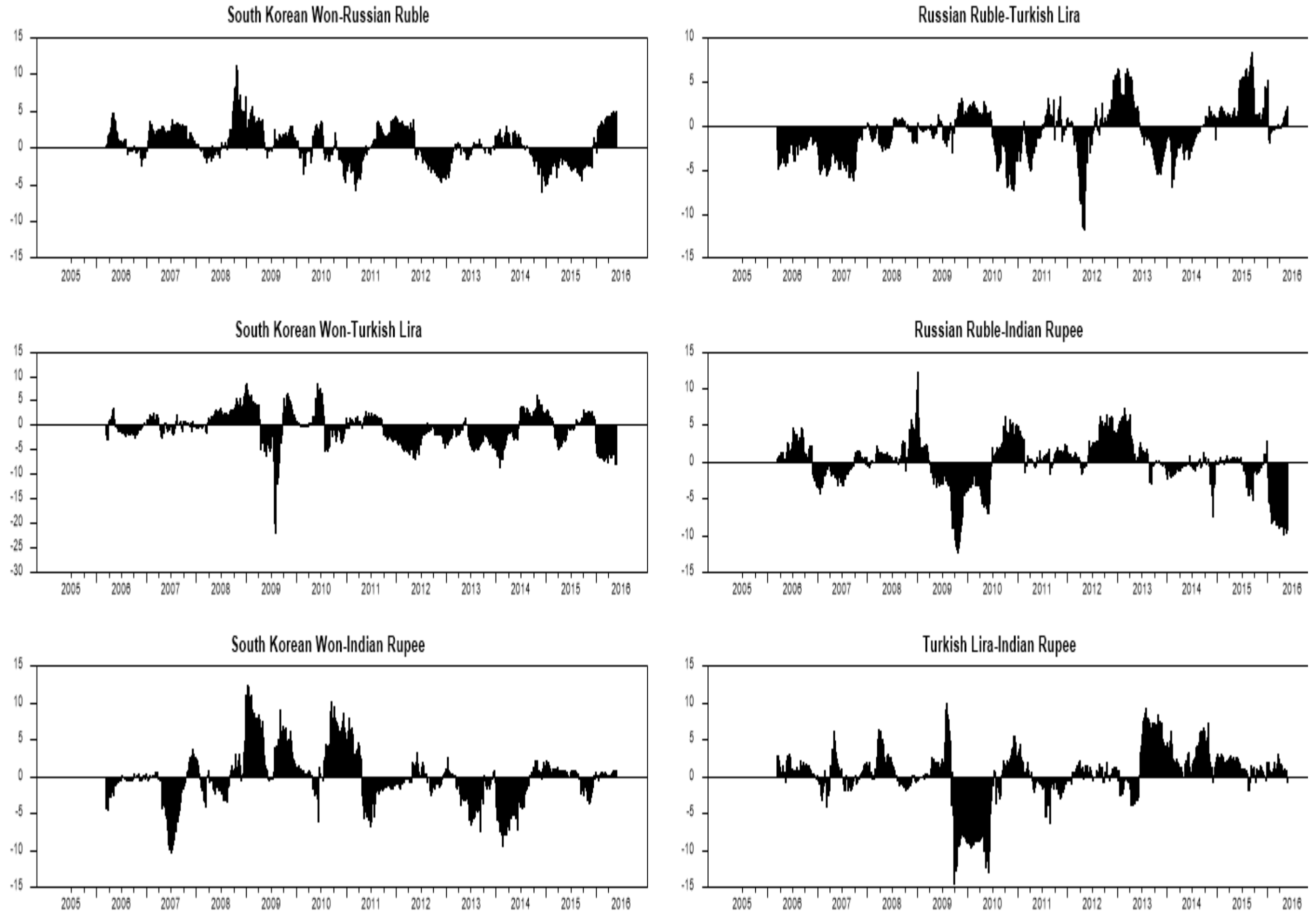
Net Pairwise Volatility Spillovers,KRW RUB TRY INR



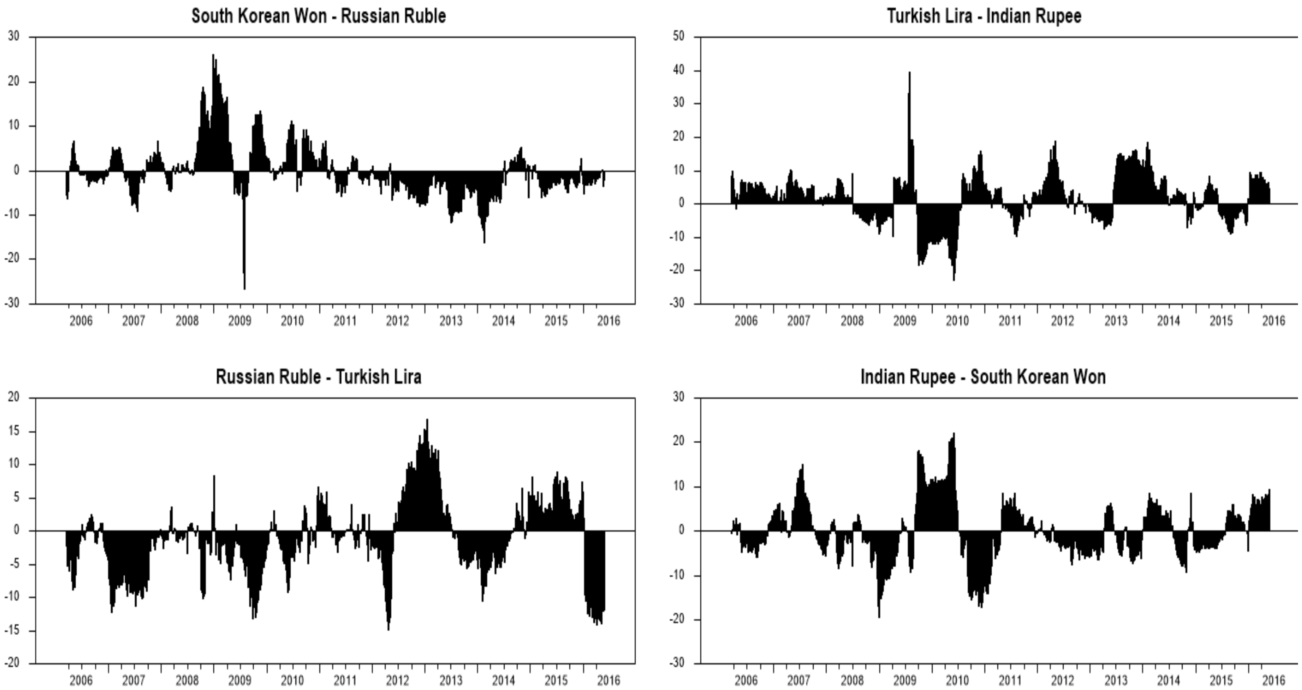
Net Volatility Spillovers, HKD RUB SGD TRY



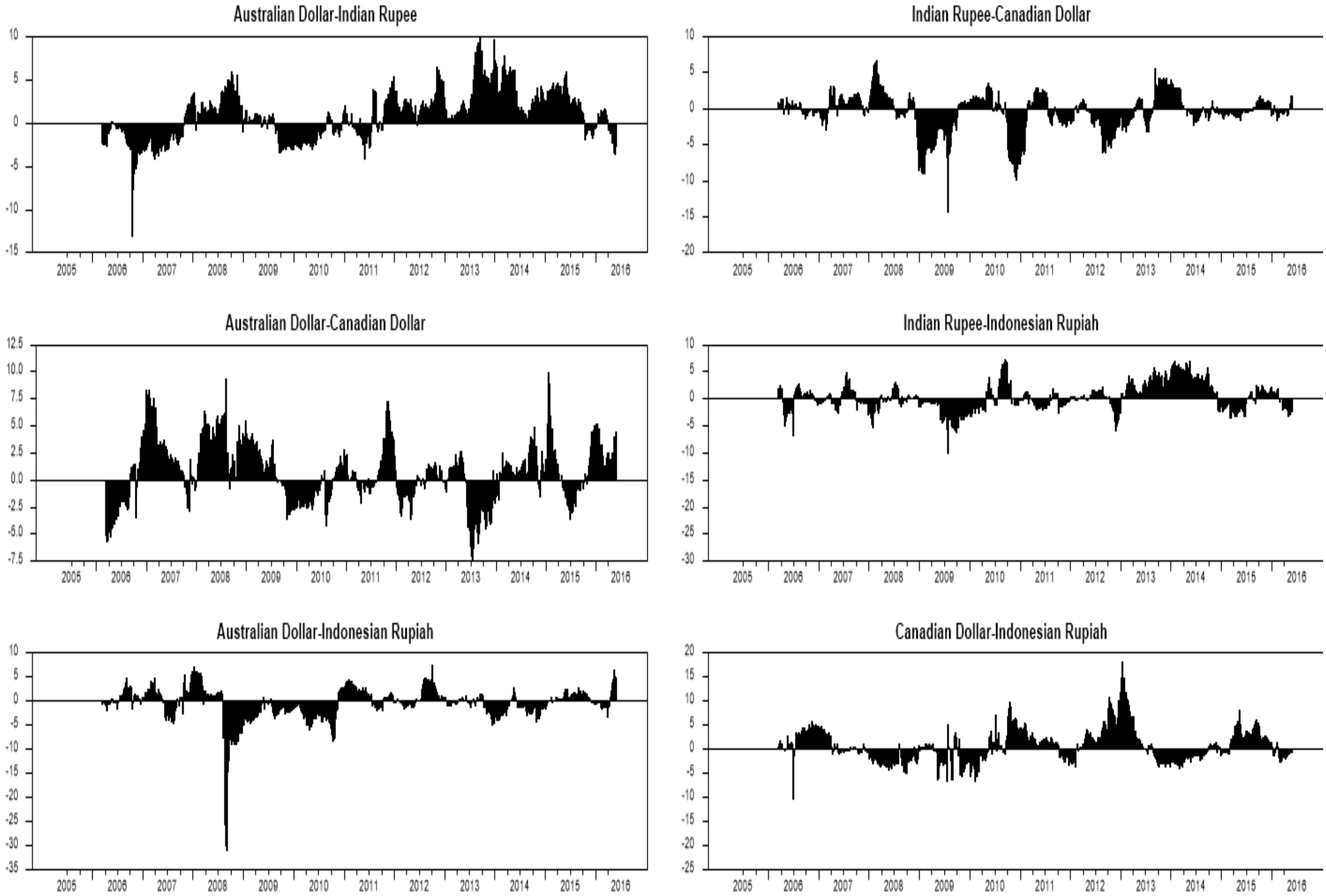
Net Pairwise Volatility Spillovers,KRW RUB TRY INR



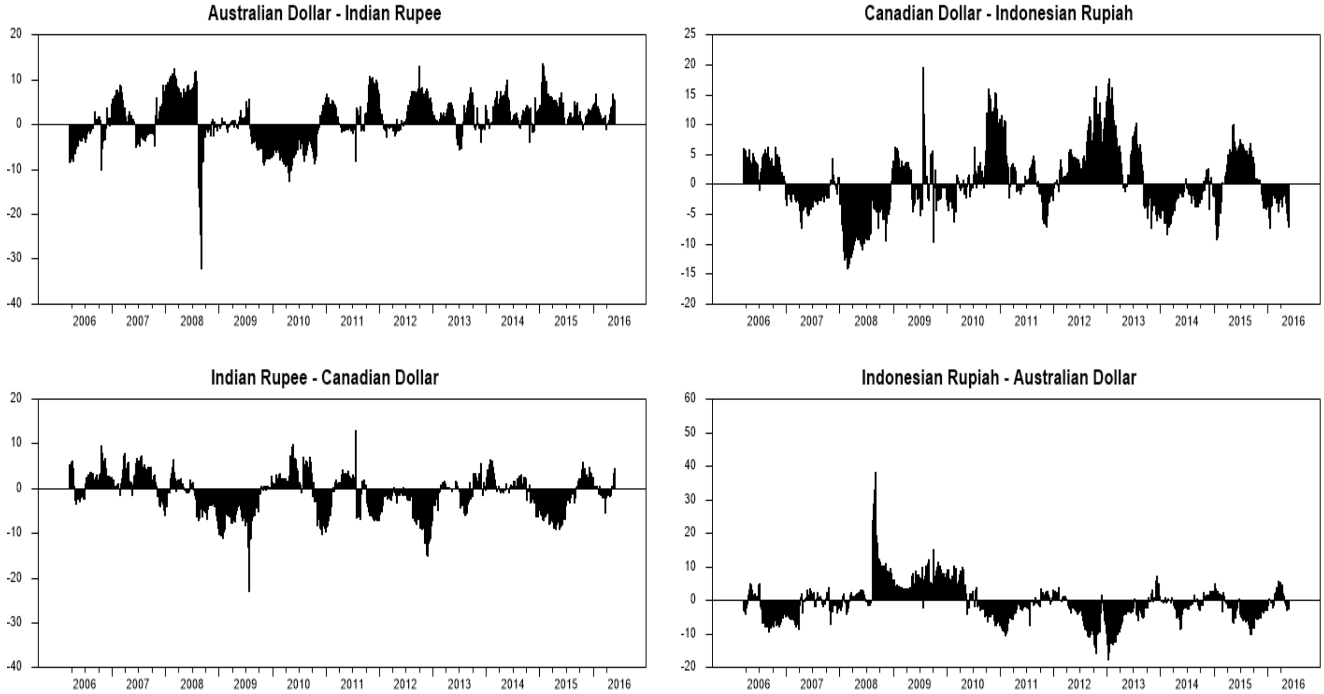
Net Volatility Spillovers, KRW RUB TRY INR



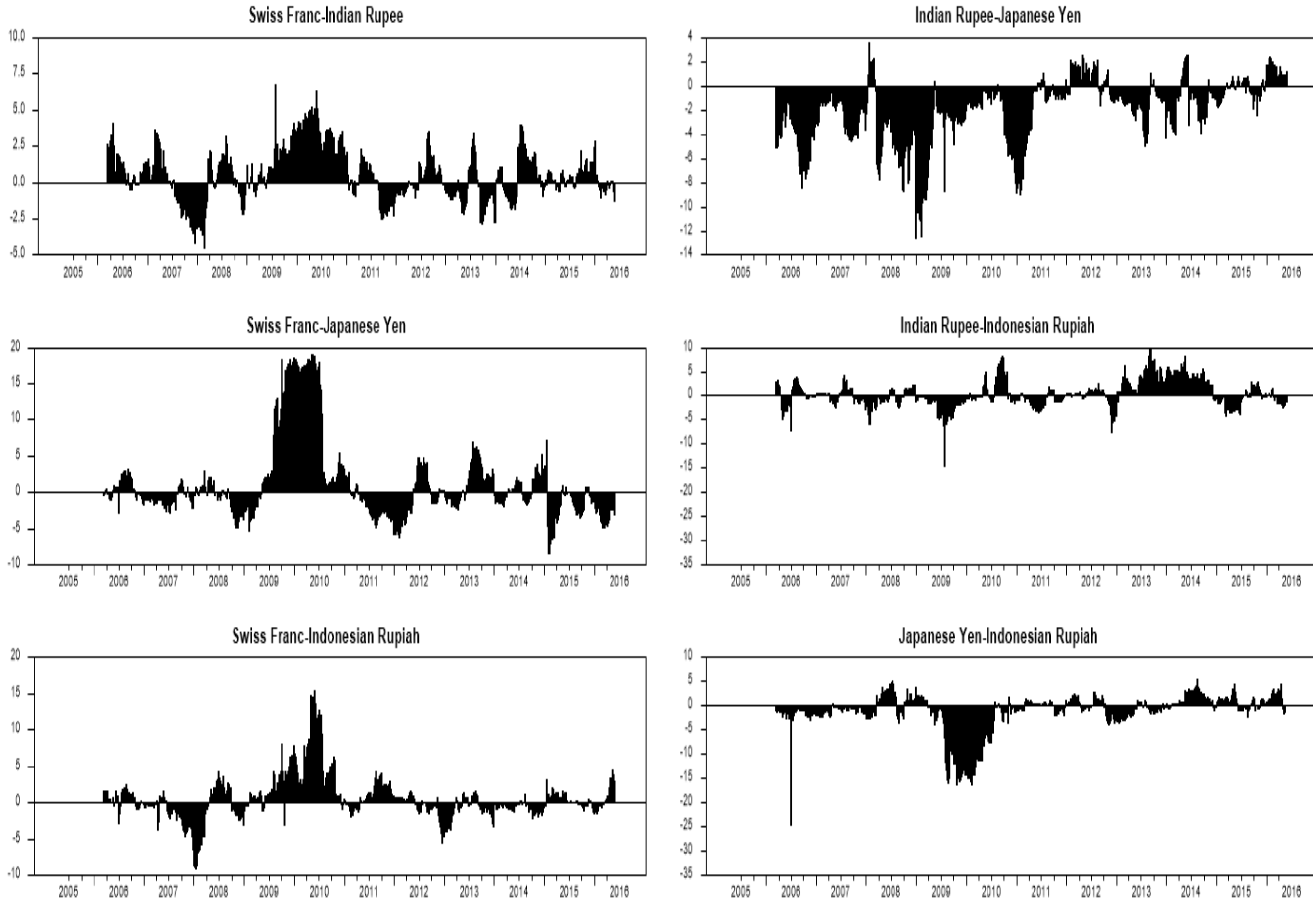
Net Pairwise Volatility Spillovers,AUD INR CAD IDR



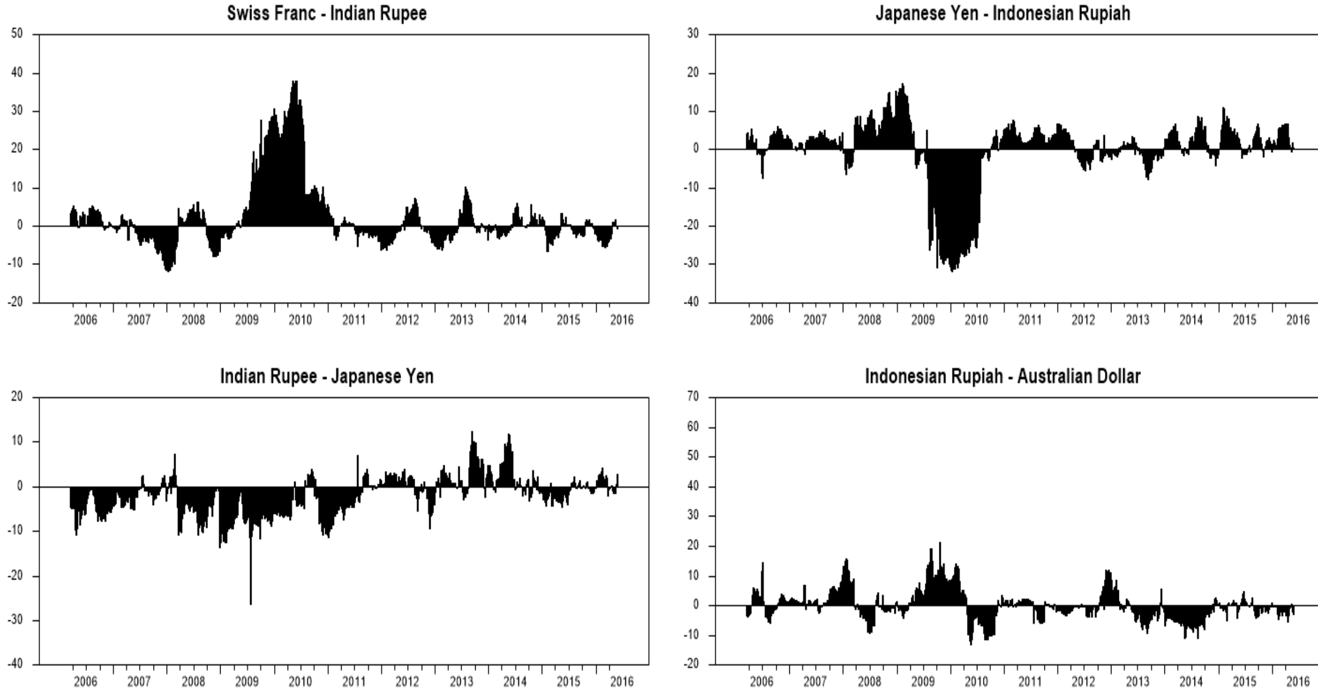
Net Volatility Spillovers, AUD INR CAD IDR



Net Pairwise Volatility Spillovers,CHF INR JPY IDR



Net Volatility Spillovers, CHF INR JPY IDR



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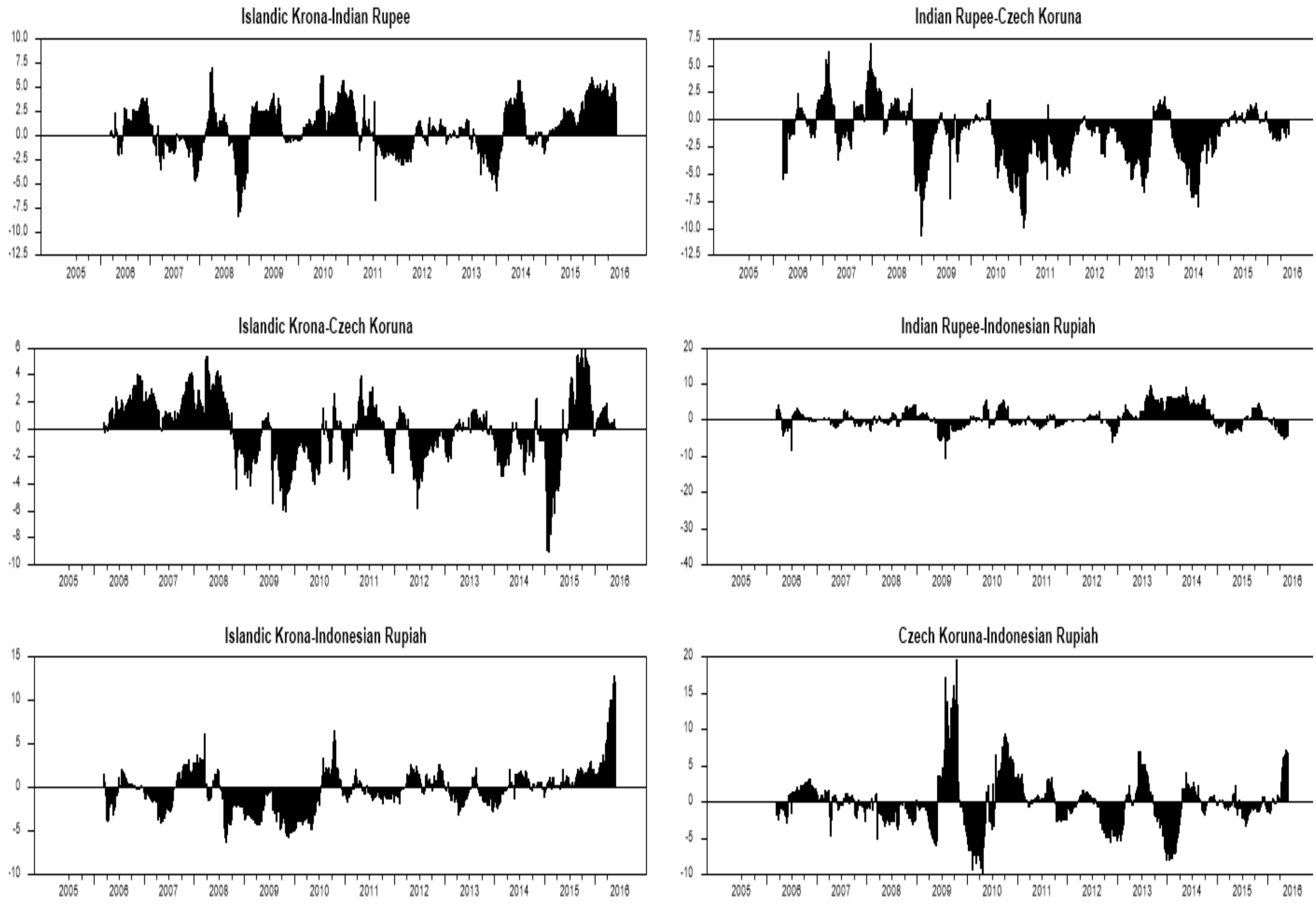

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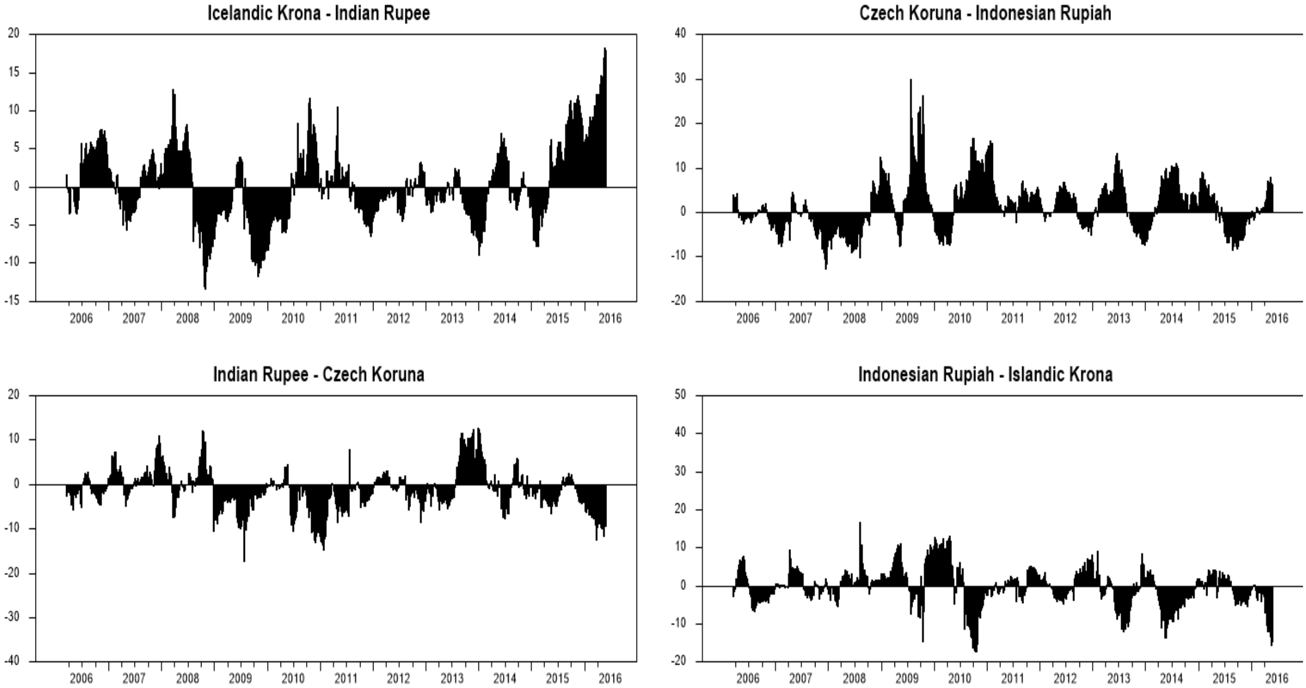
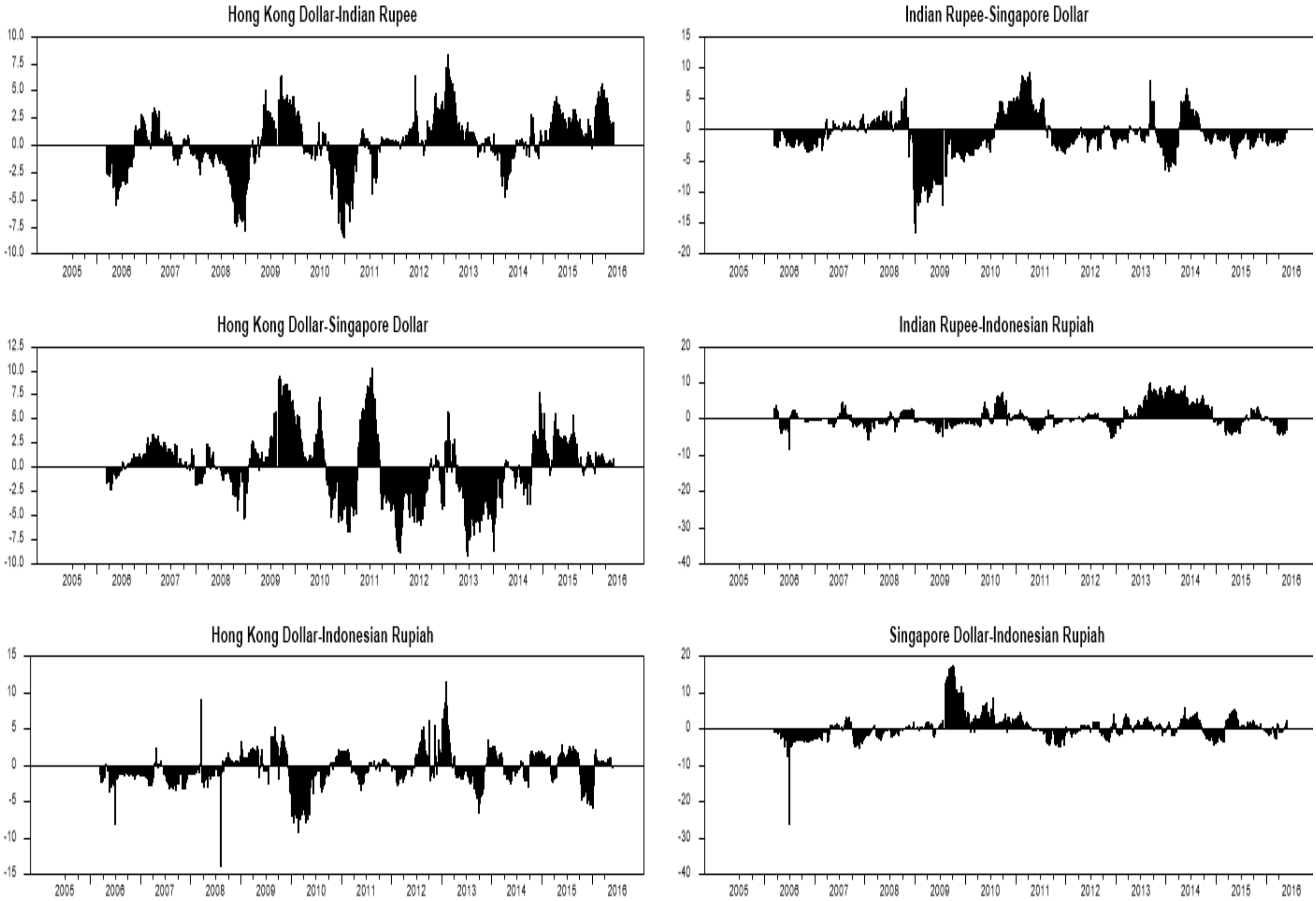
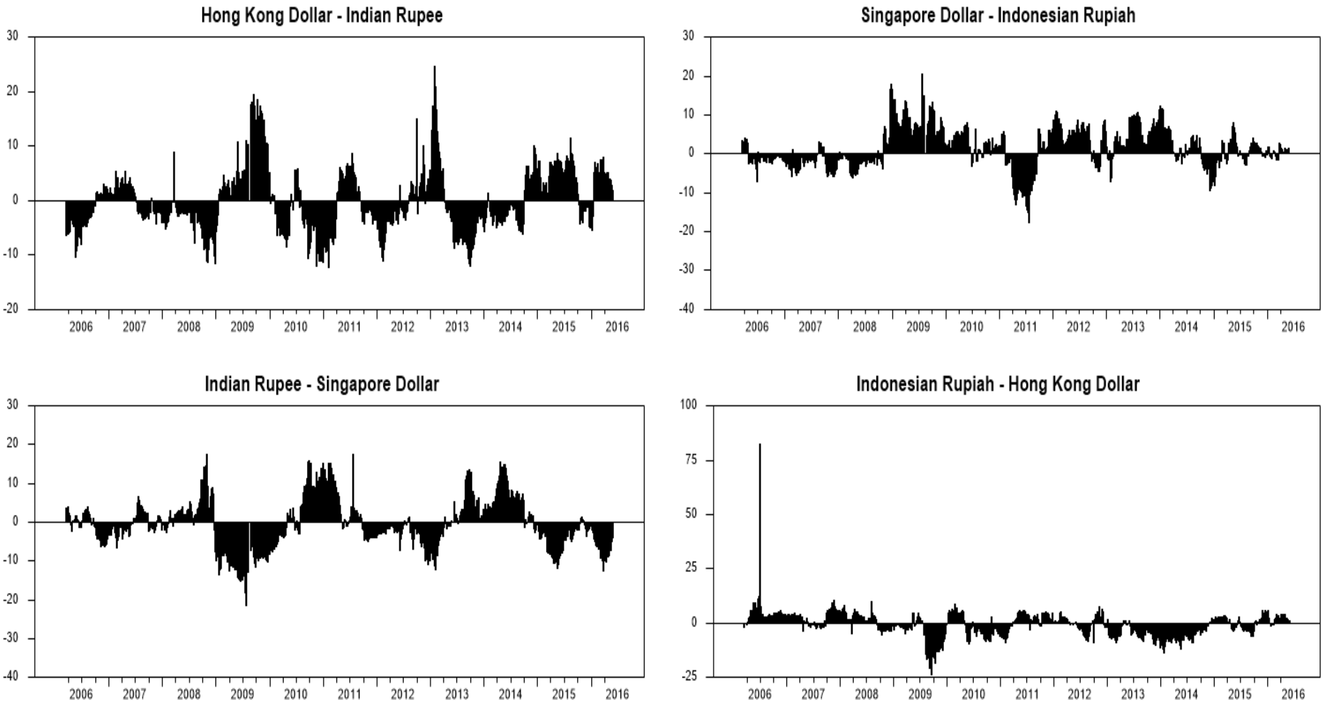


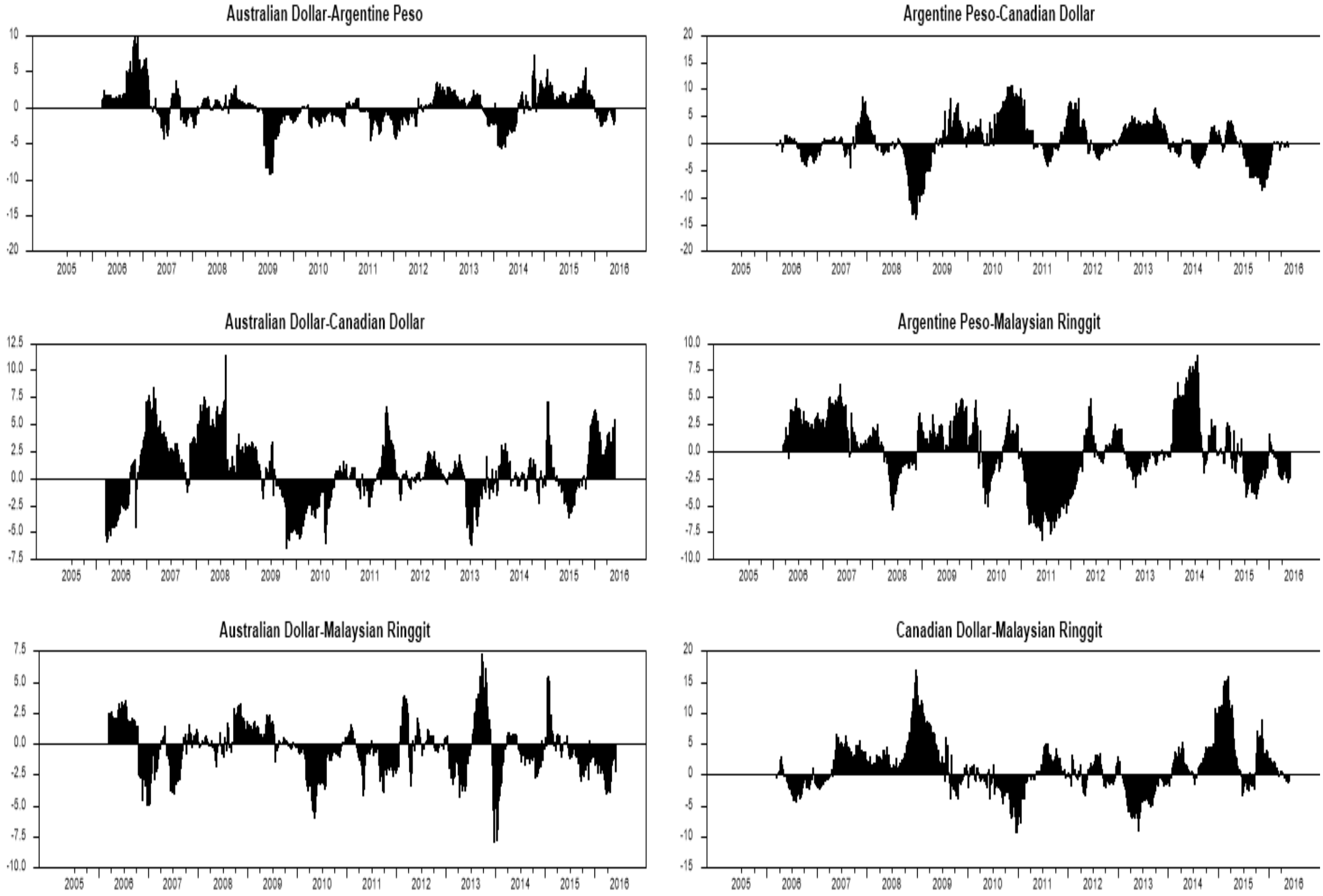
Net Pairwise Volatility Spillovers,HKD INR SGD IDR



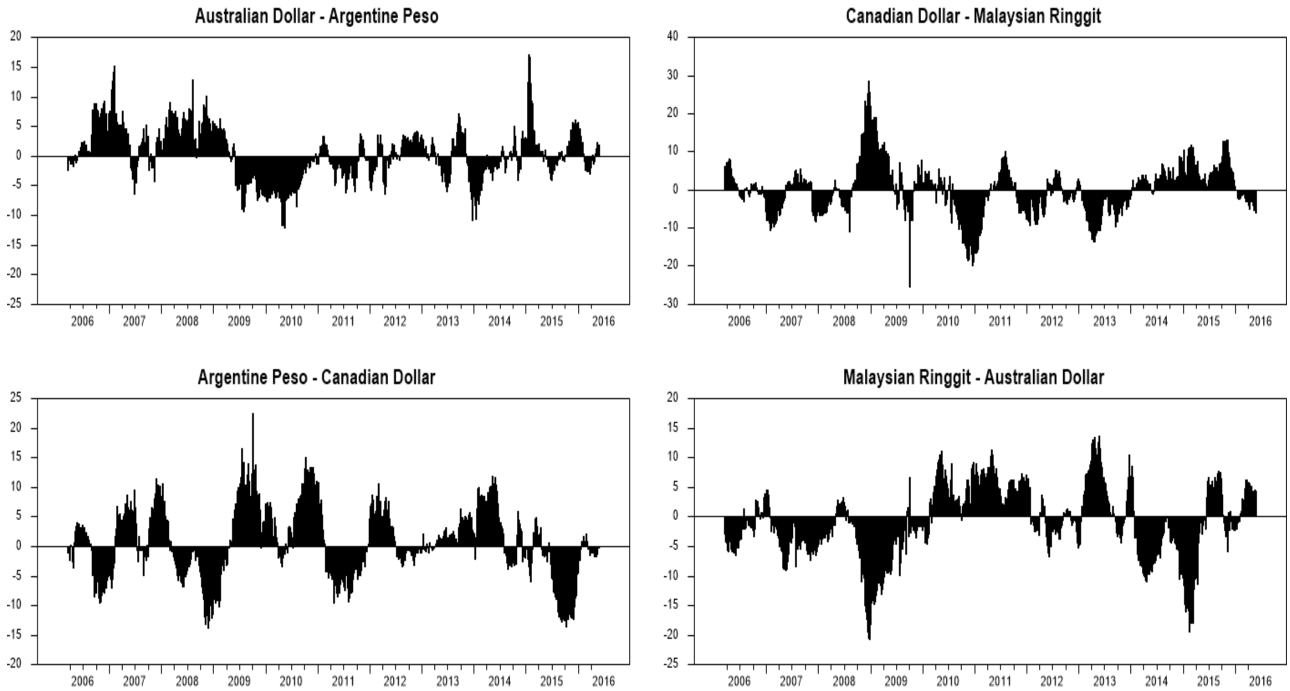
Net Volatility Spillovers, HKD INR SGD IDR



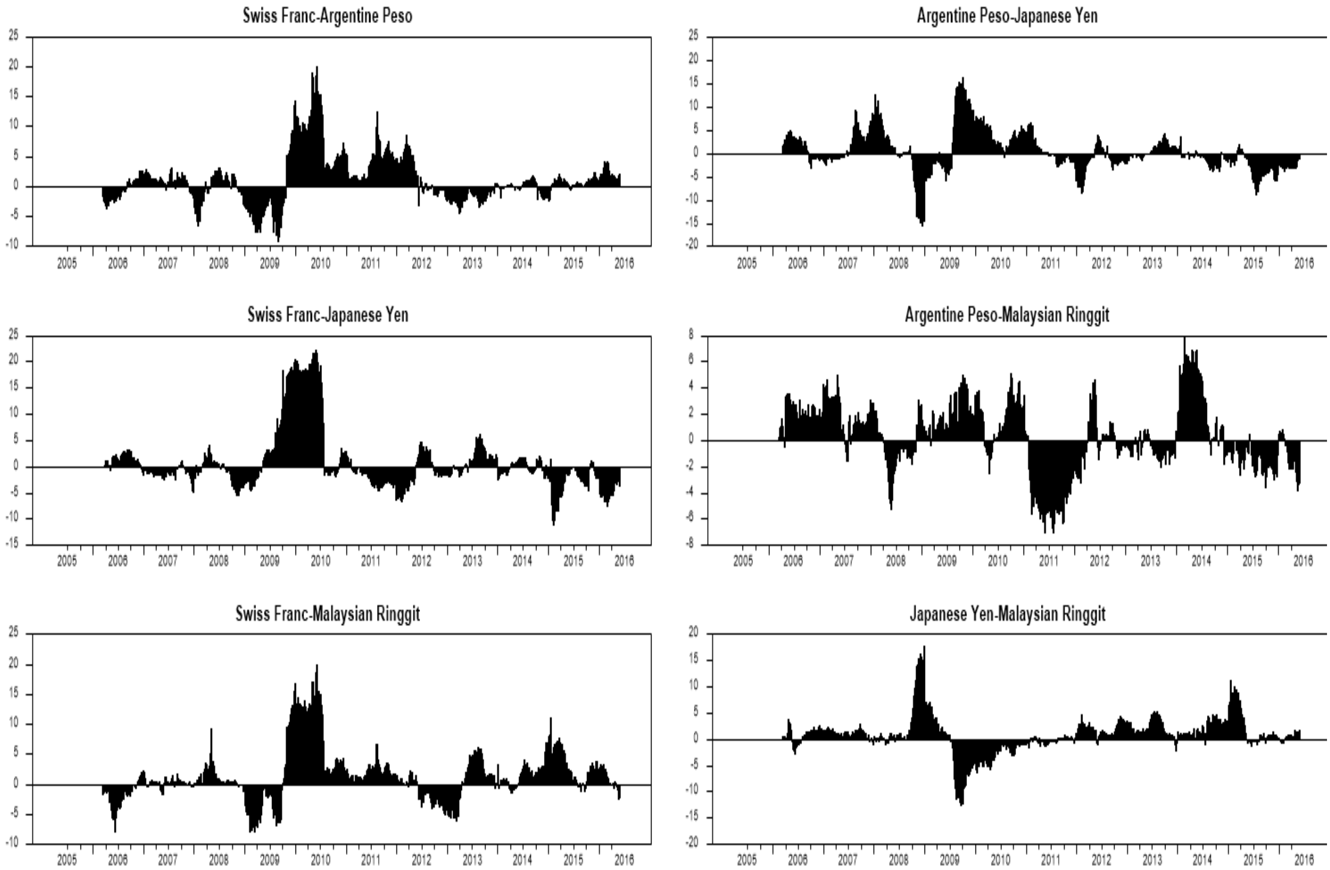
Net Pairwise Volatility Spillovers,AUD ARS CAD MYR



Net Volatility Spillovers, AUD ARS CAD MYR



Net Pairwise Volatility Spillovers,CHF ARS JPY MYR



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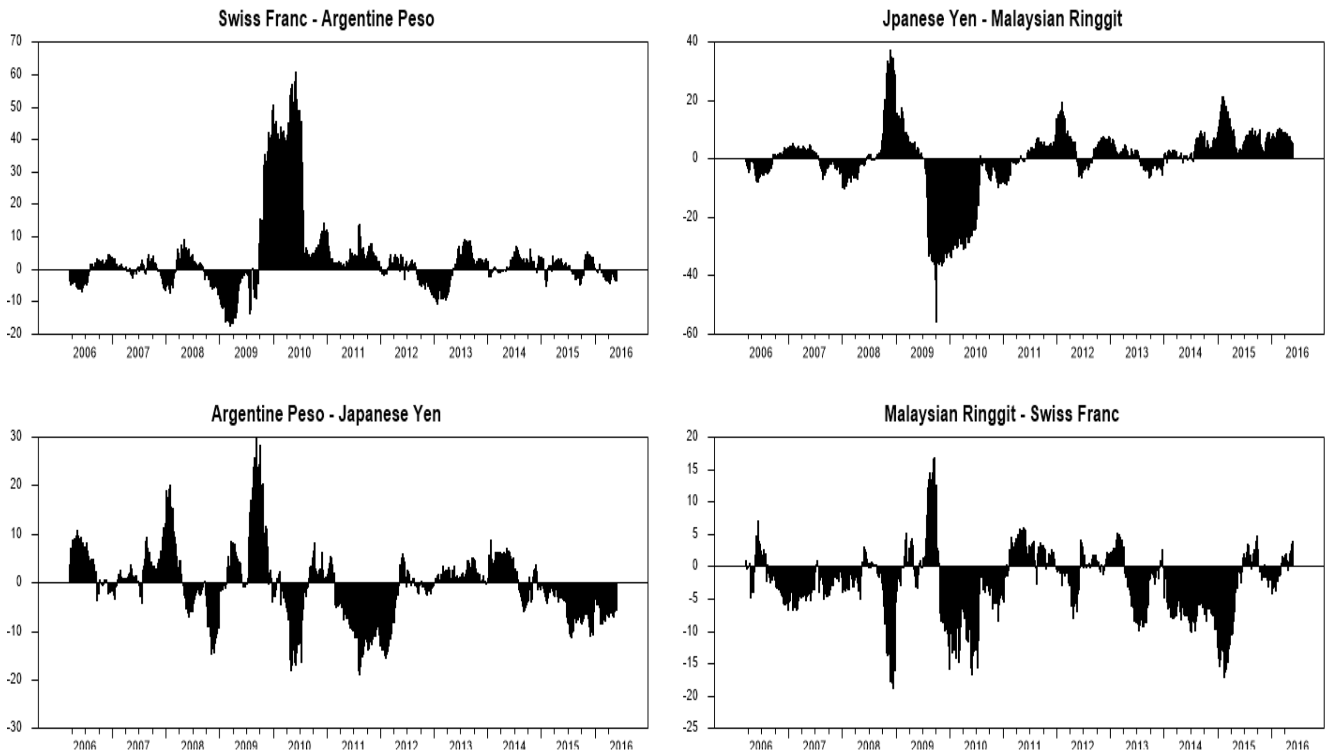
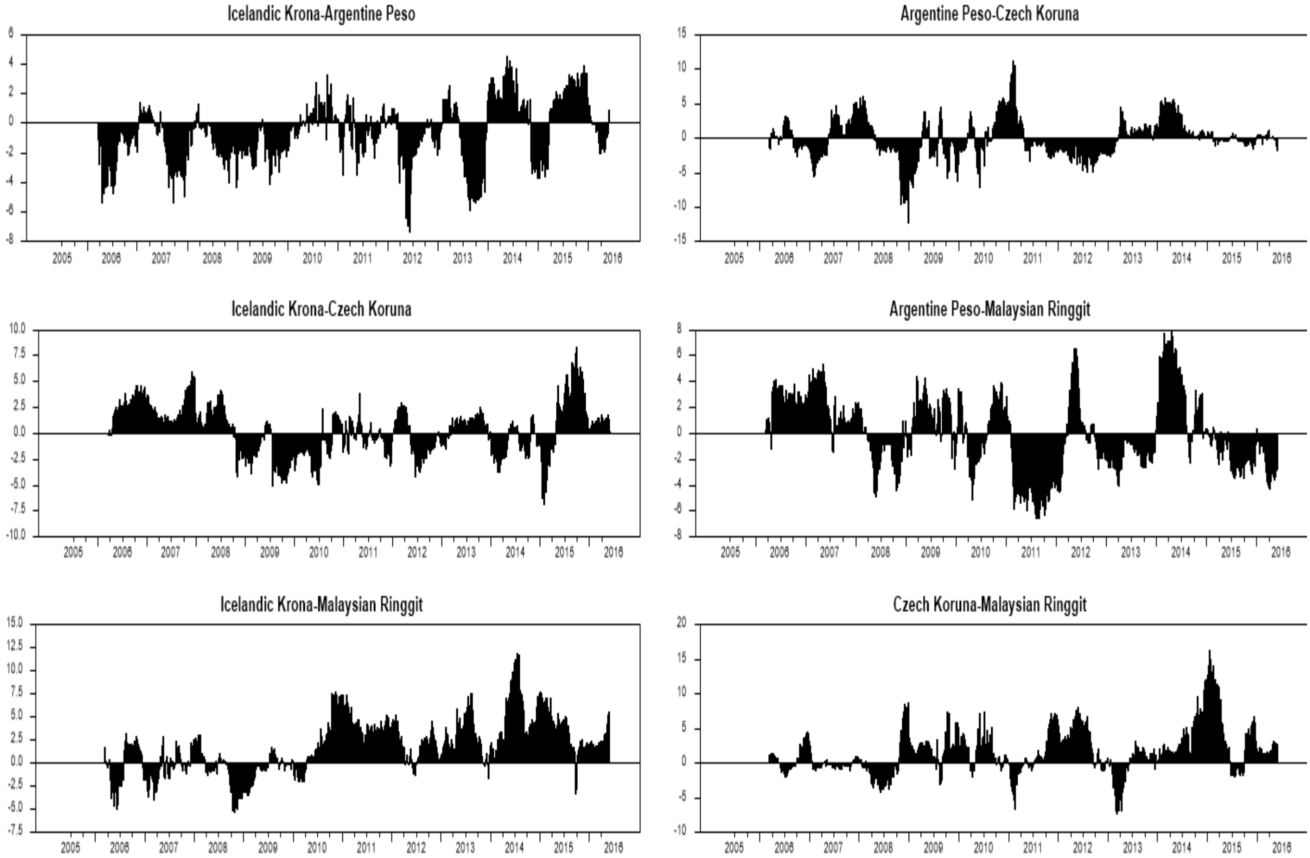
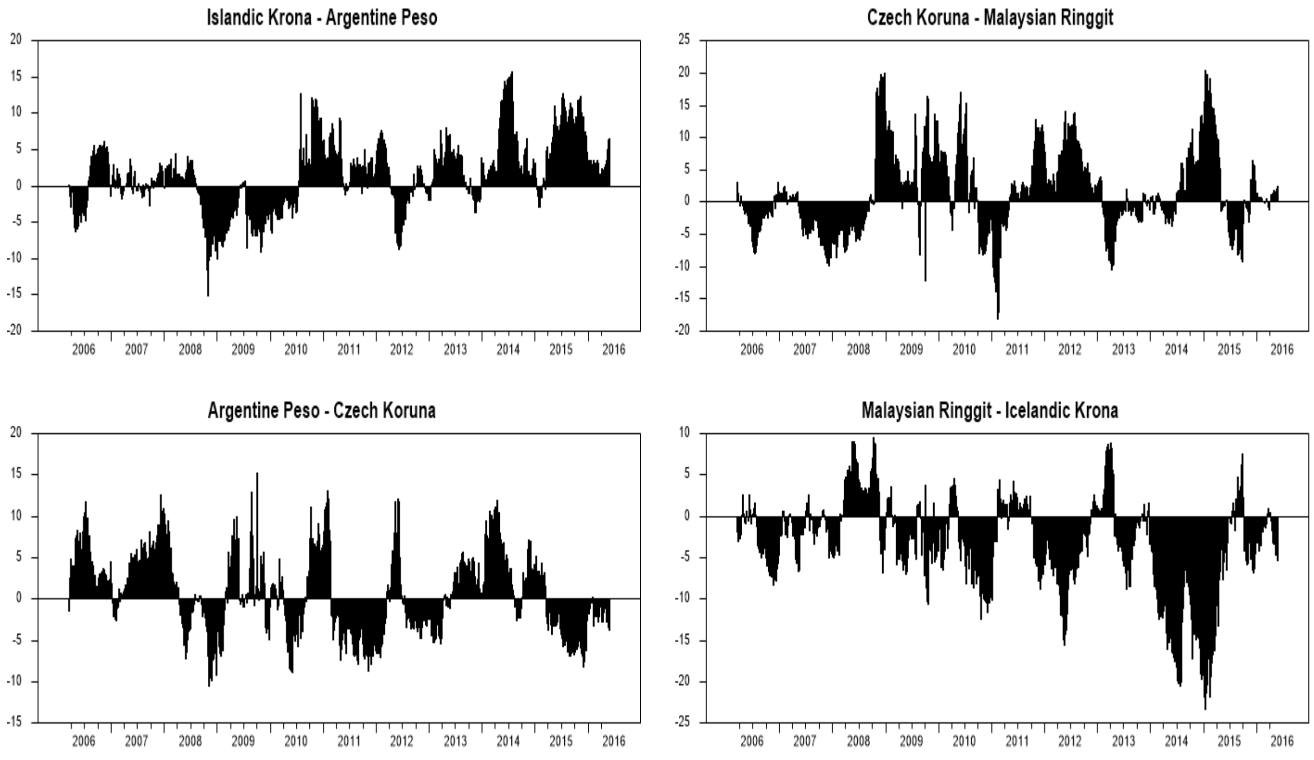


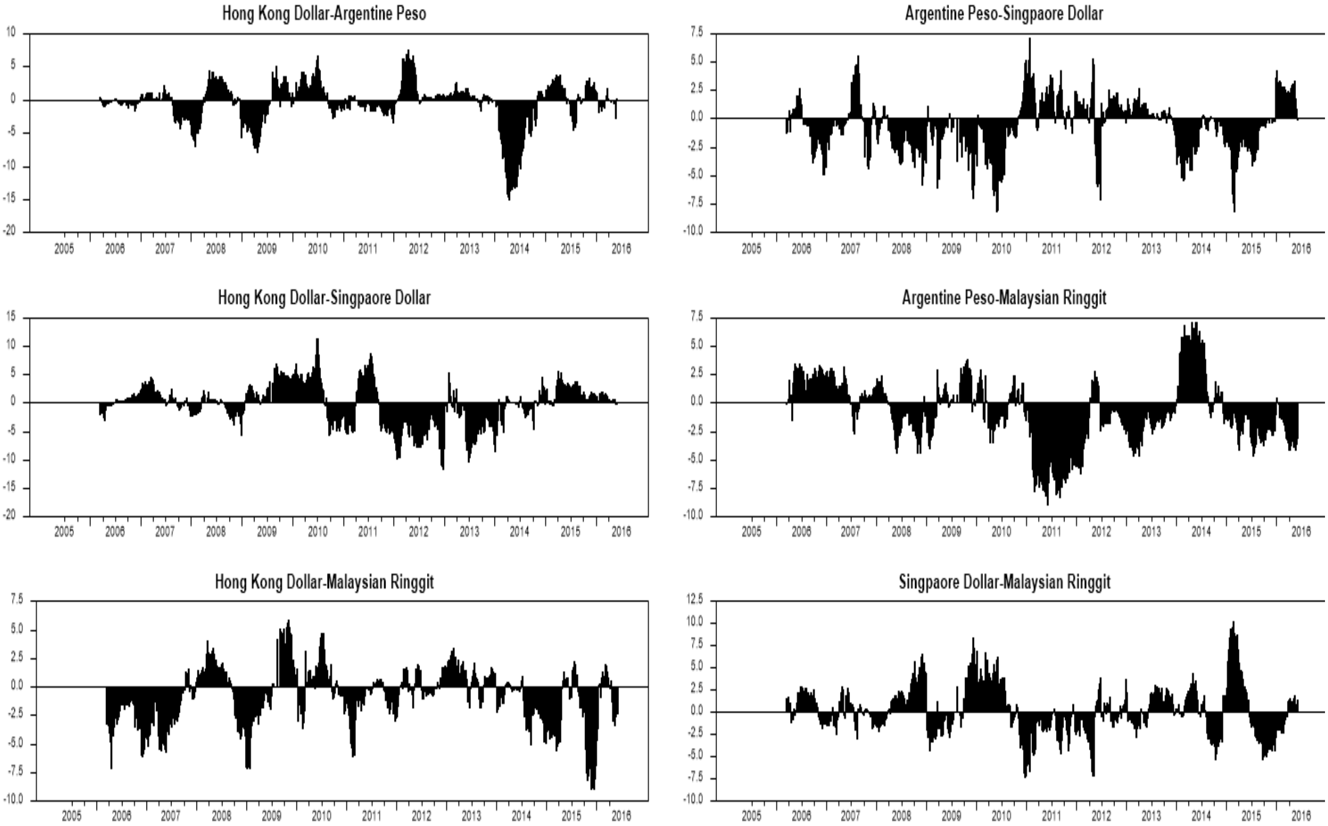
Net Pairwise Volatility Spillovers,ISK ARS CZK MYR



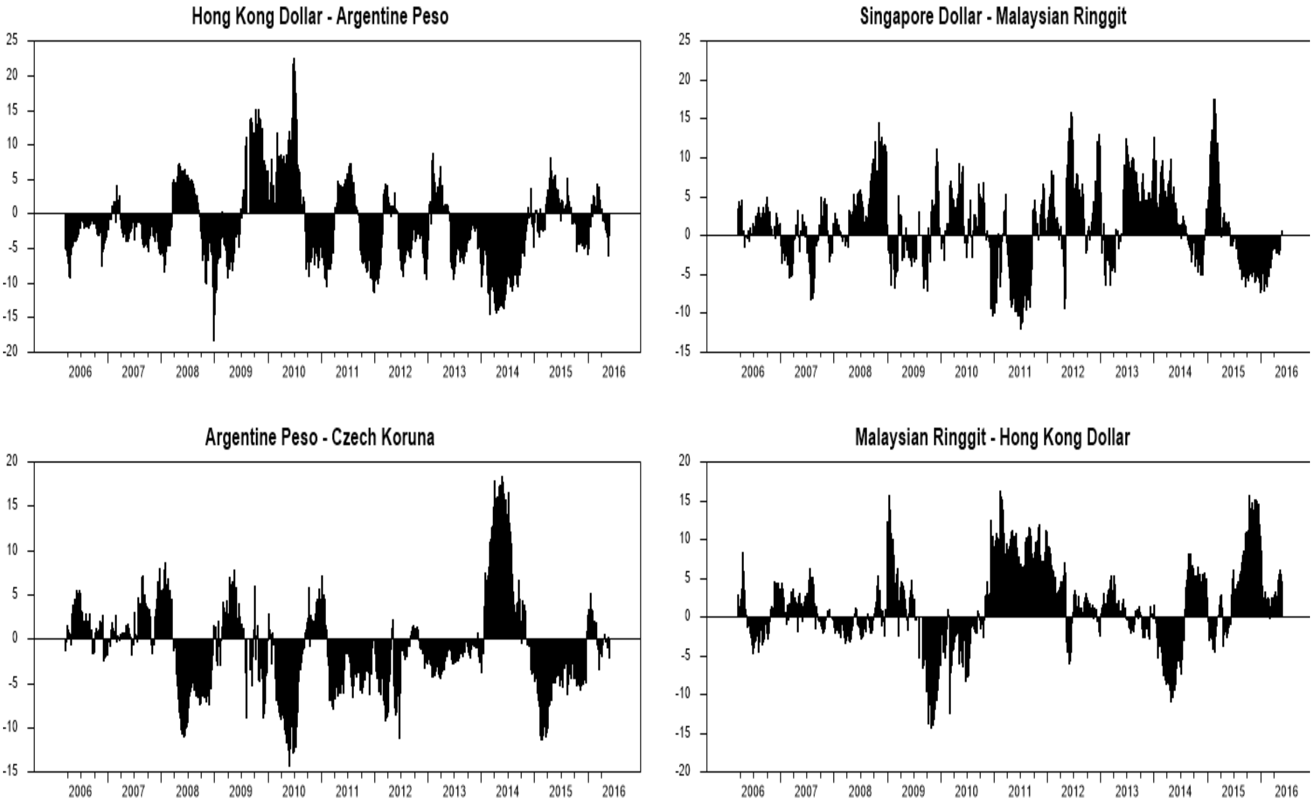
Net Volatility Spillovers, ISK ARS CZK MYR



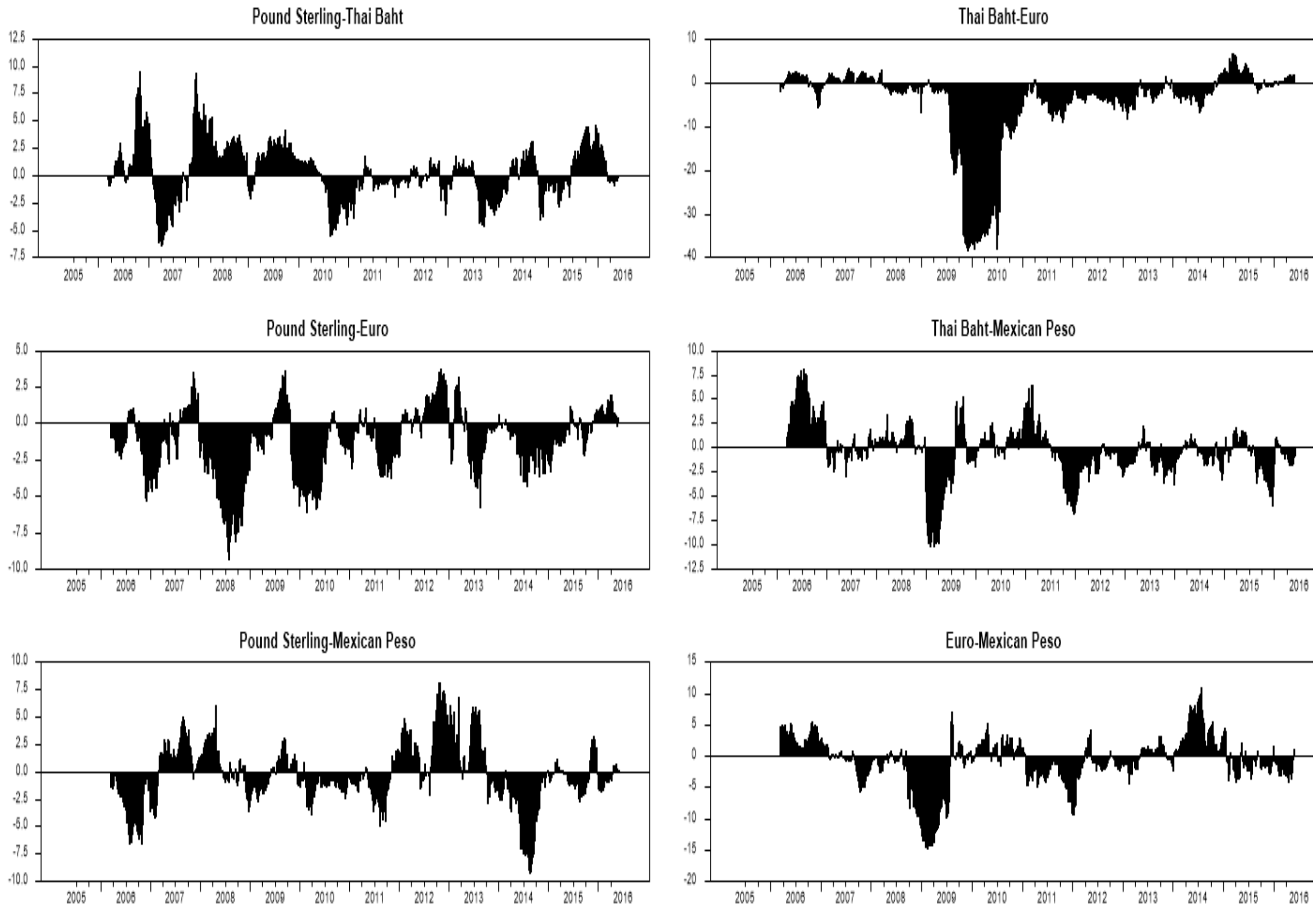
Net Pairwise Volatility Spillovers,HKD ARS SGD MYR



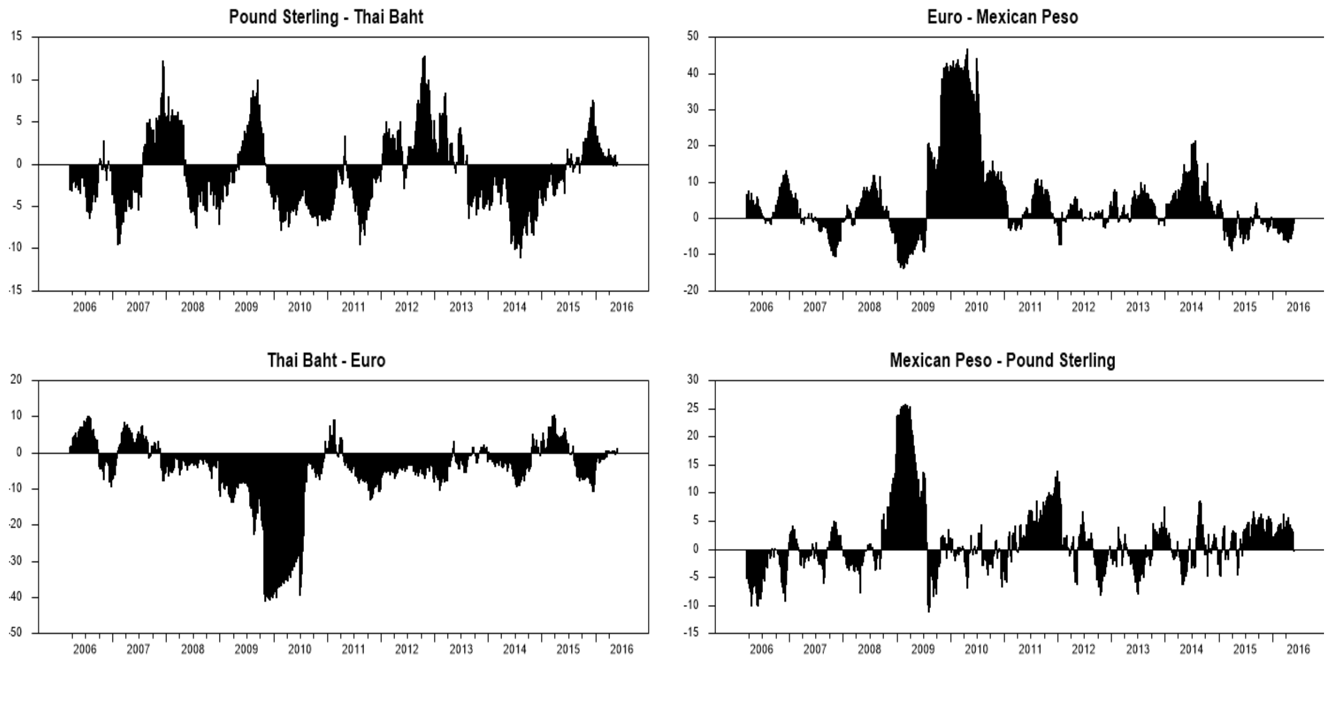
Net Volatility Spillovers, HKD ARS SGD MYR



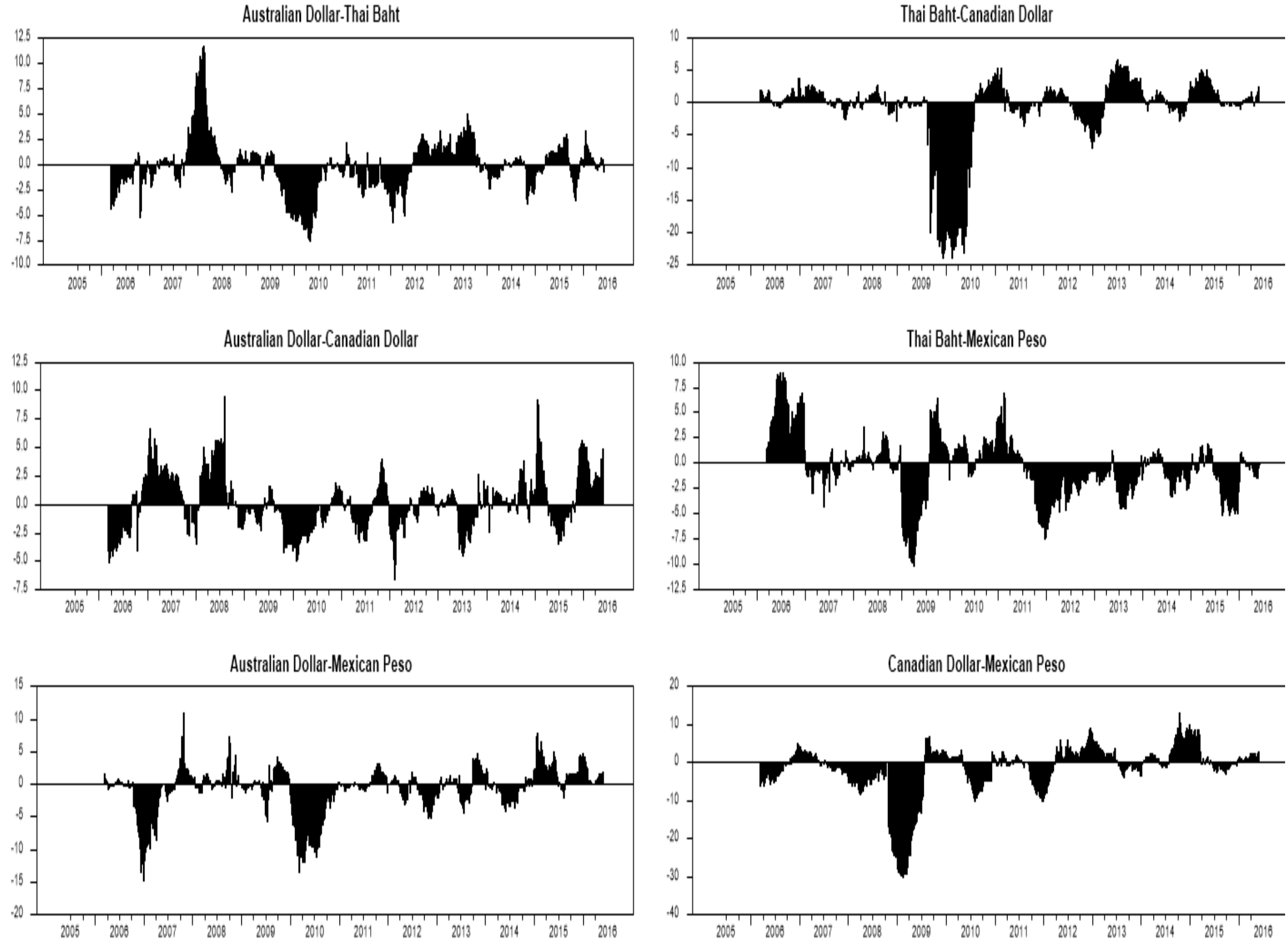
Net Pairwise Volatility Spillovers,GBP THB EUR MXN



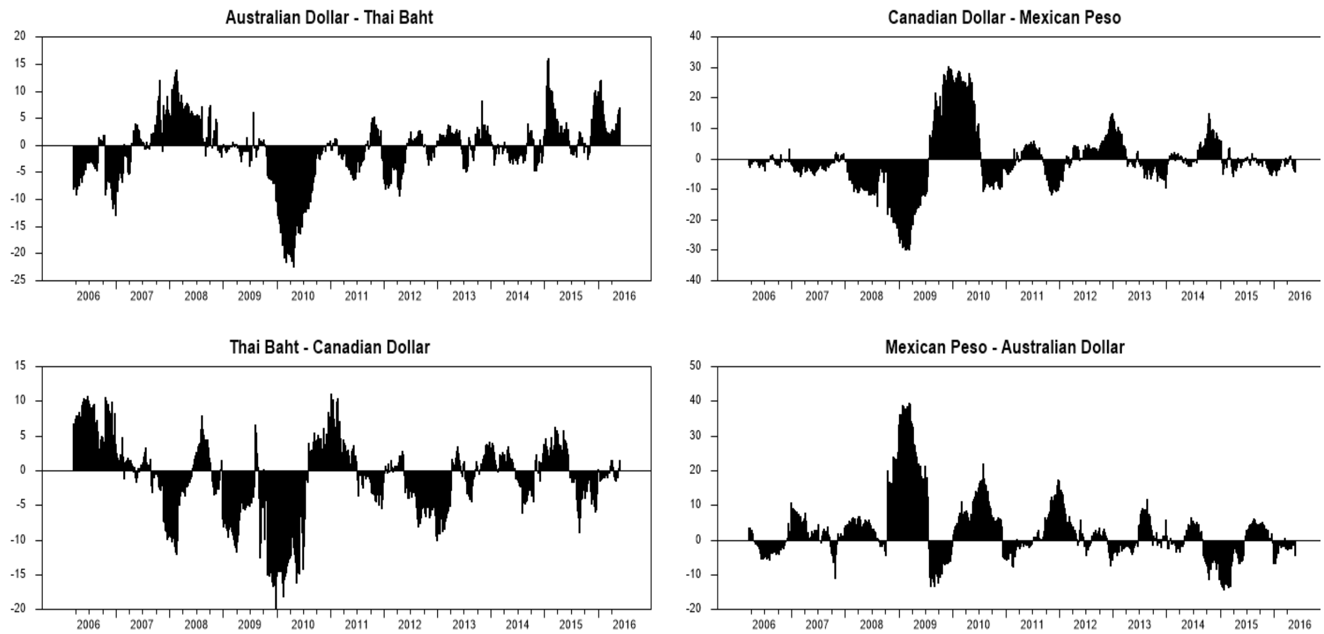
Net Volatility Spillovers, GBP THB EUR MXN



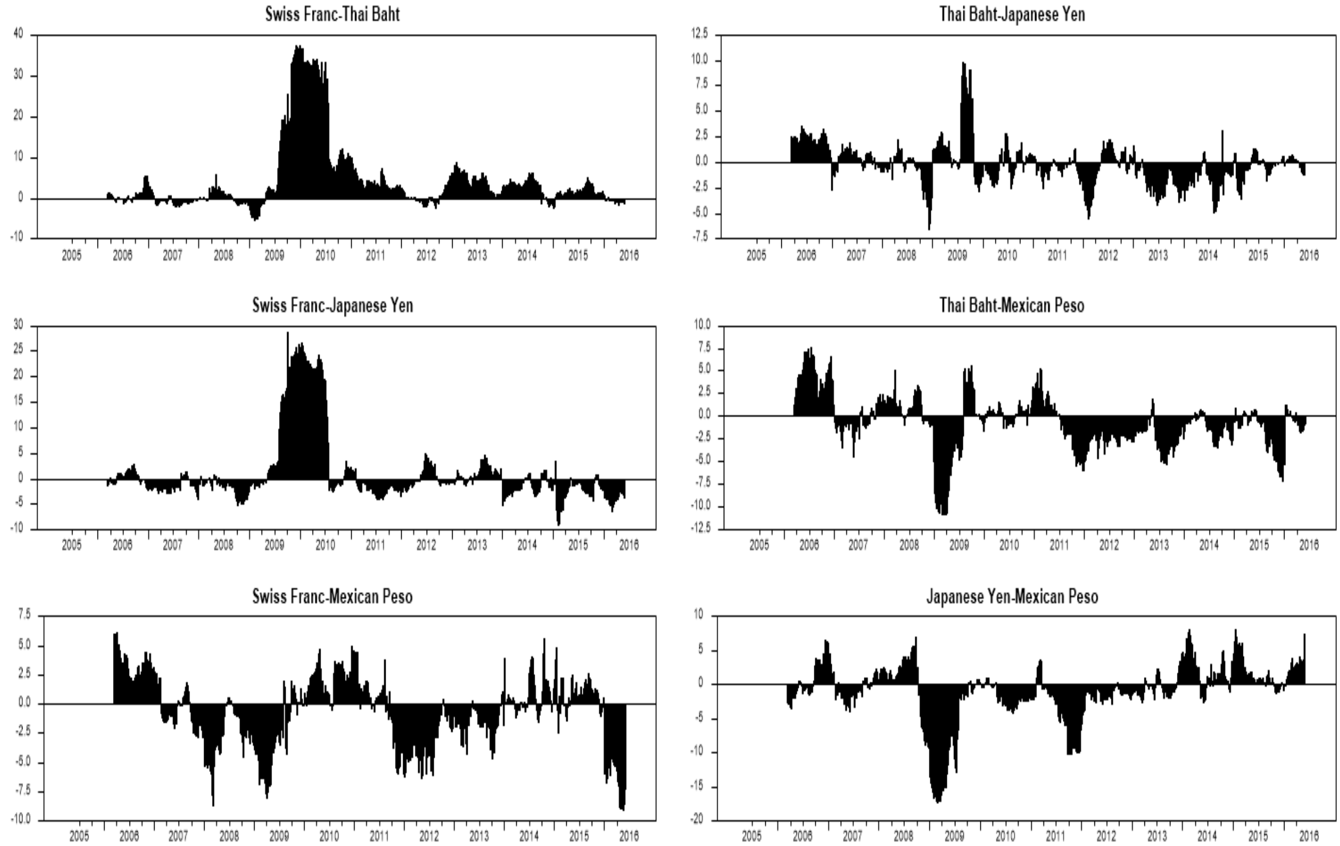
Net Pairwise Volatility Spillovers,AUD THB CAD MXN



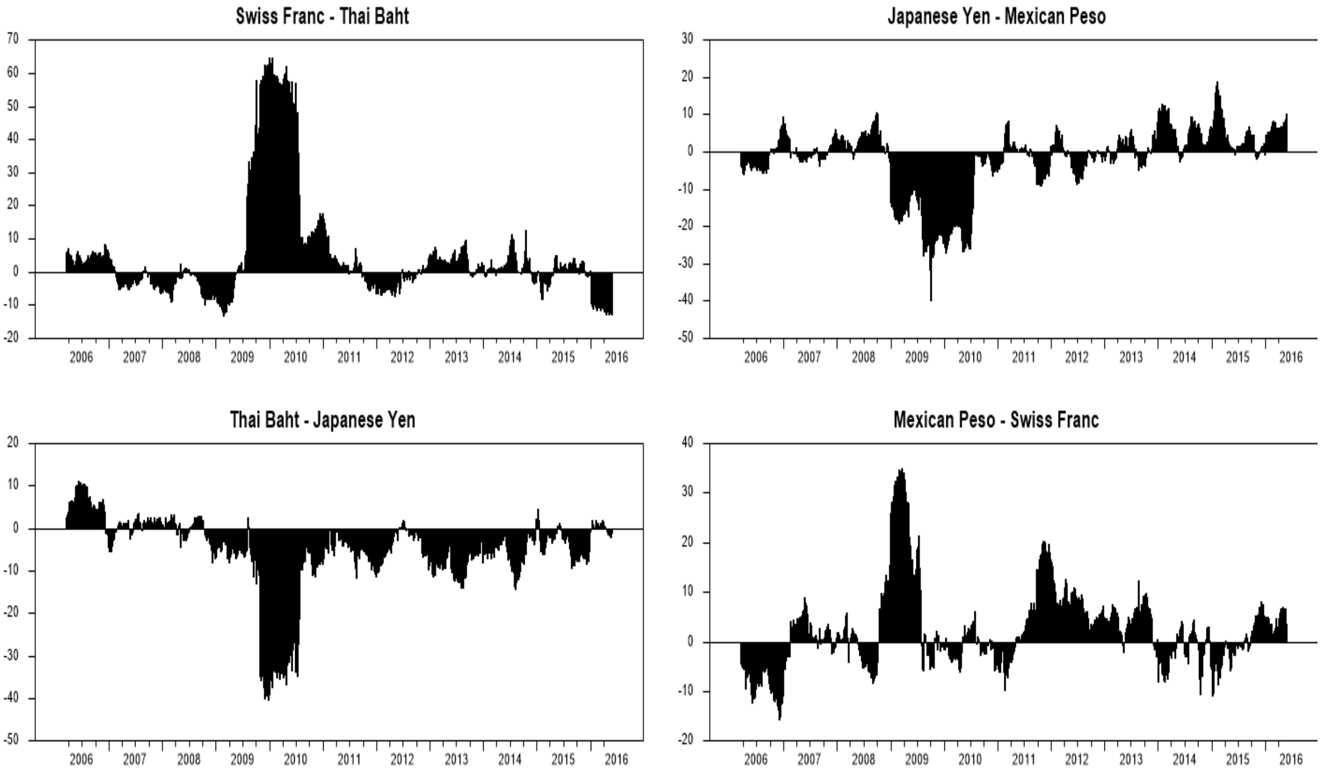
Net Volatility Spillovers, AUD THB CAD MXN



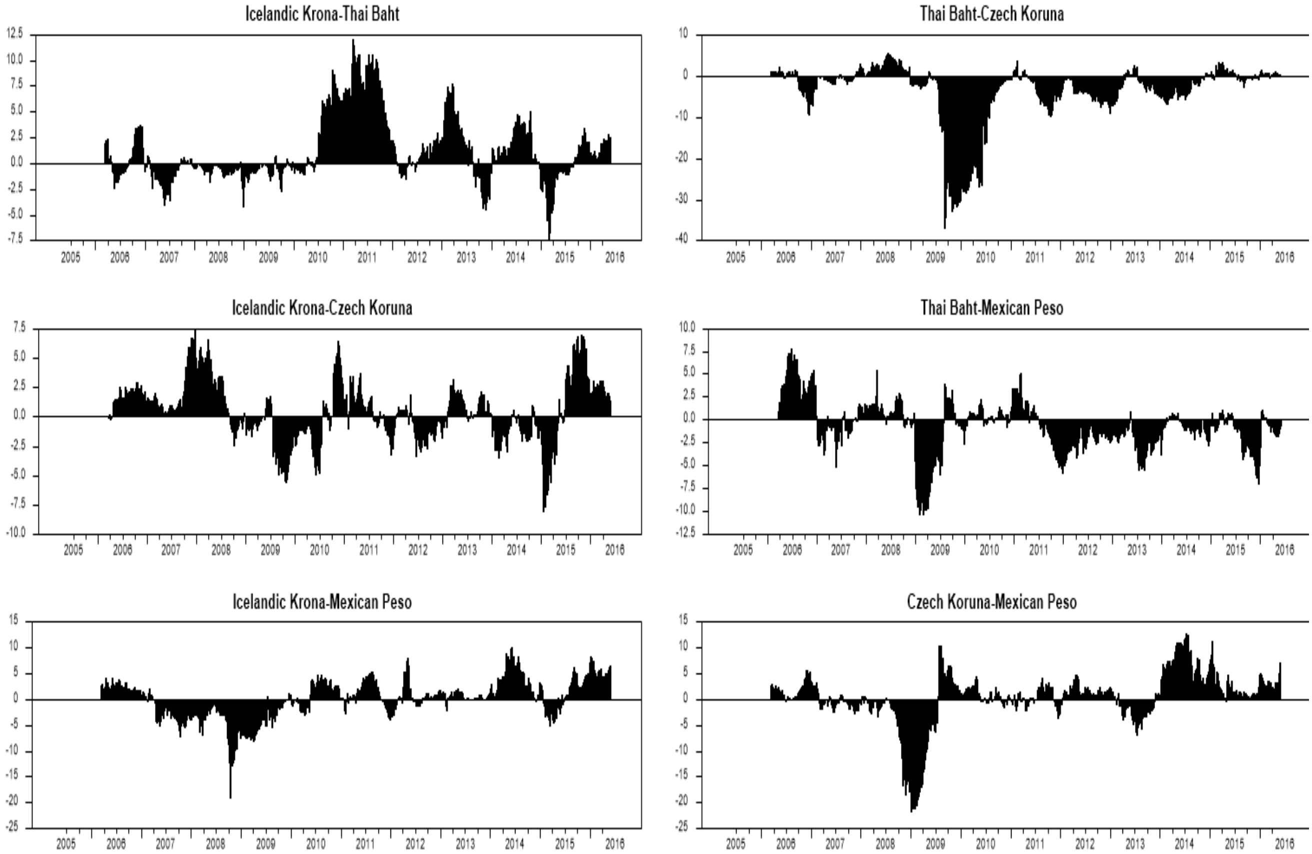
Net Pairwise Volatility Spillovers,CHF THB JPY MXN



Net Volatility Spillovers, CHF THB JPY MXN



Net Pairwise Volatility Spillovers,ISK THB CZK MXN



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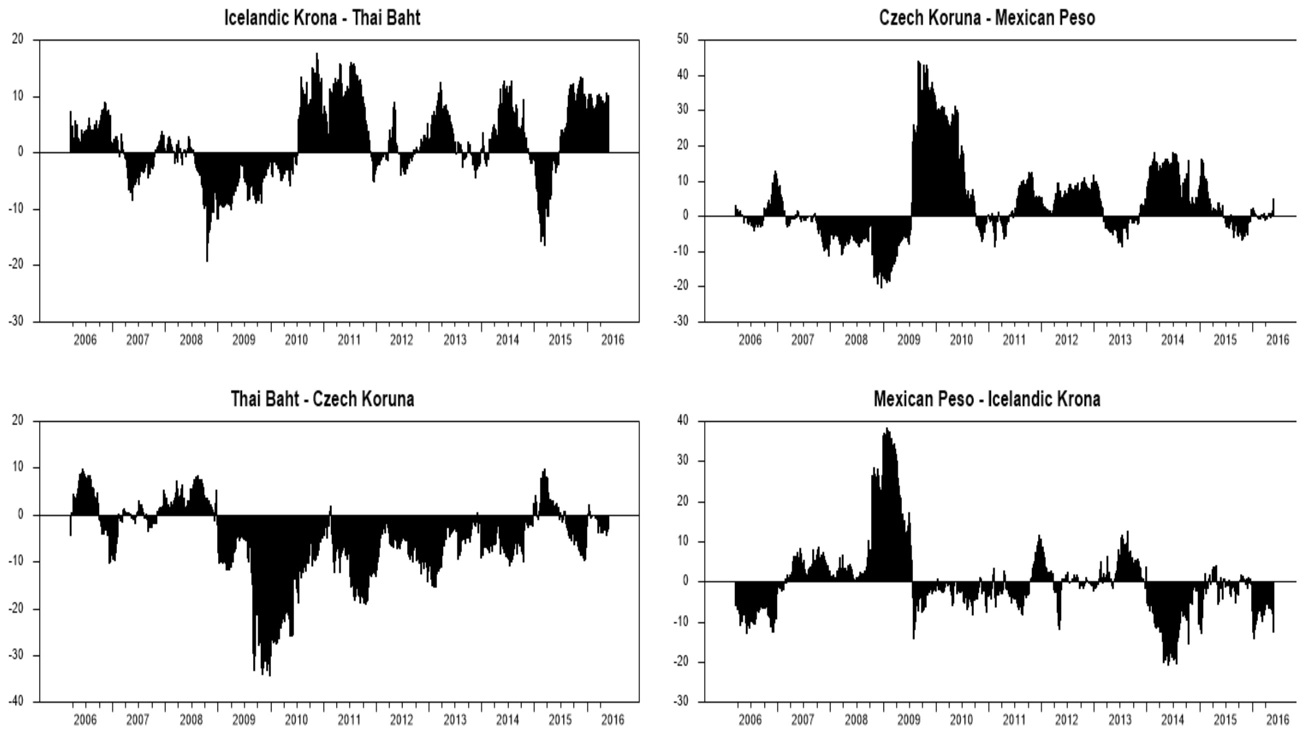
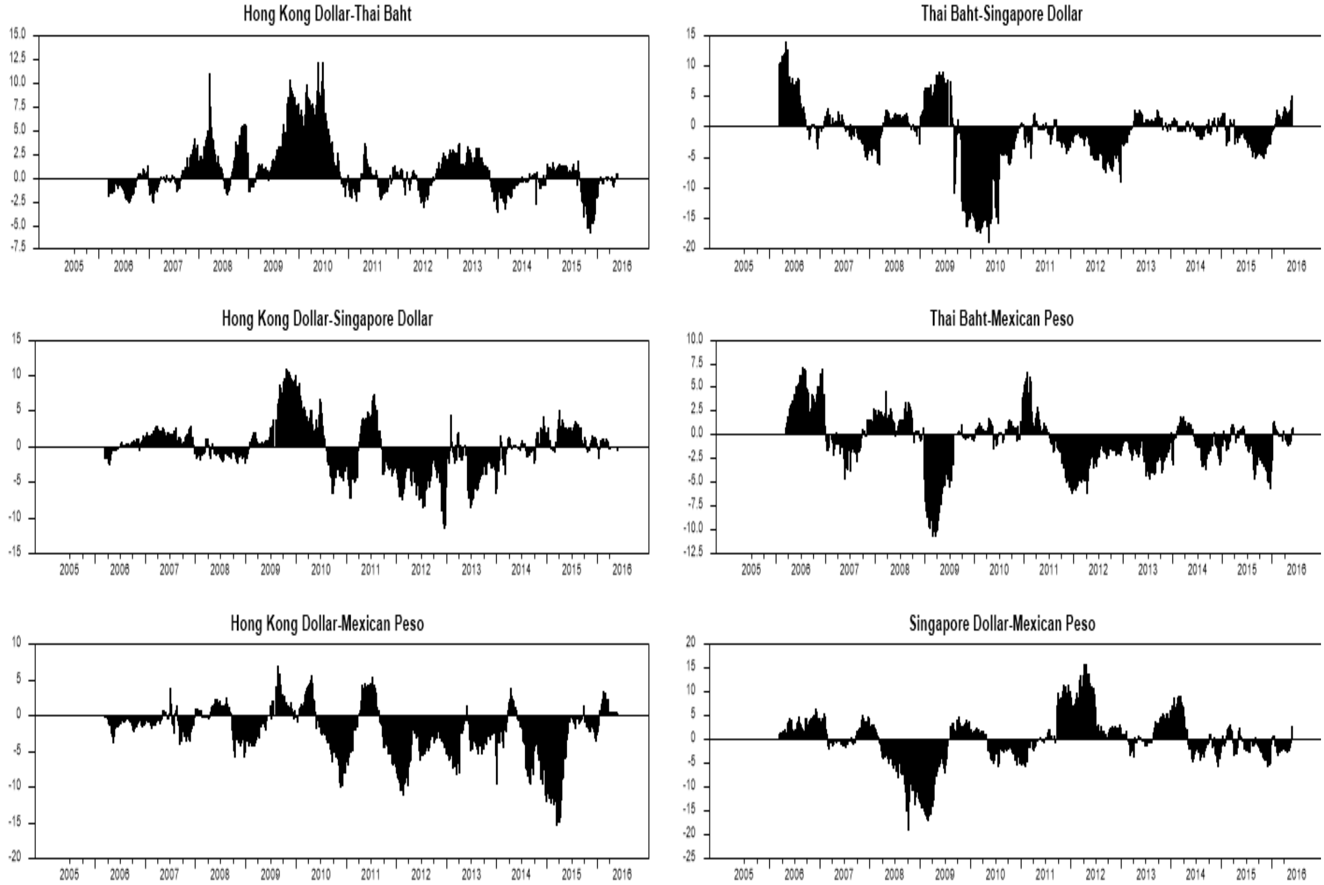
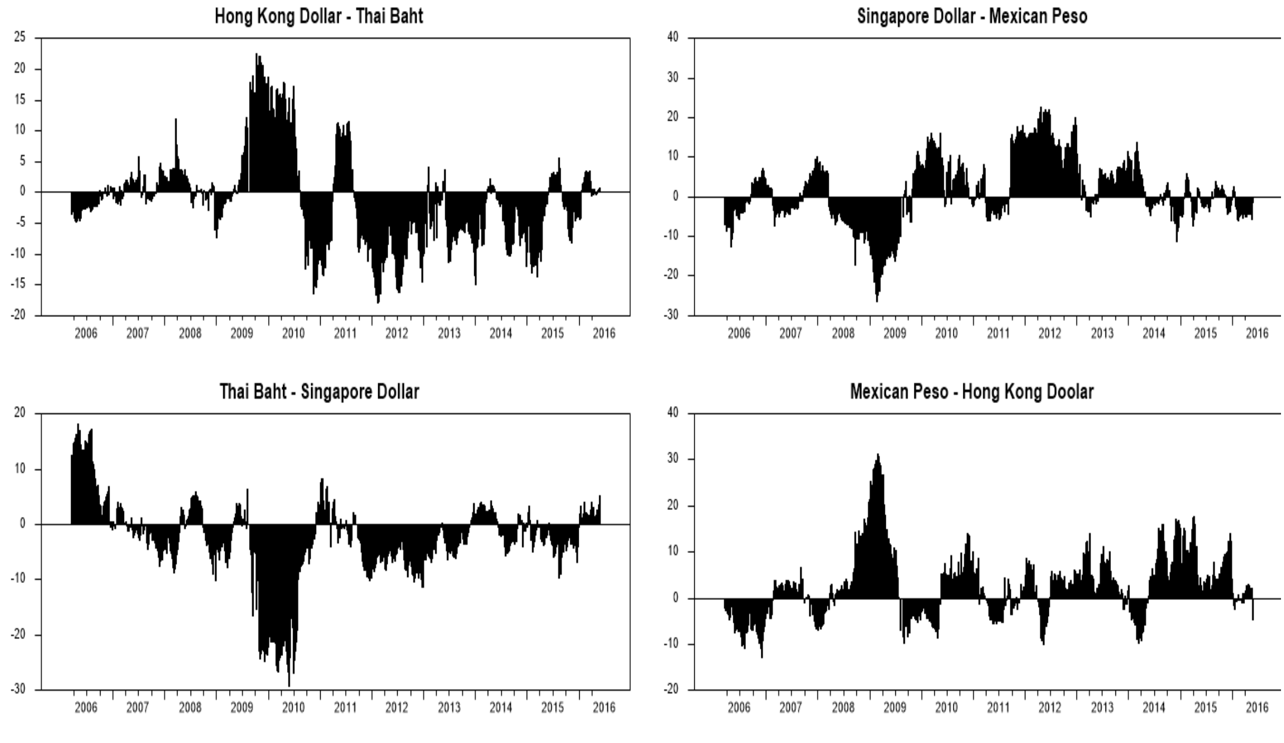


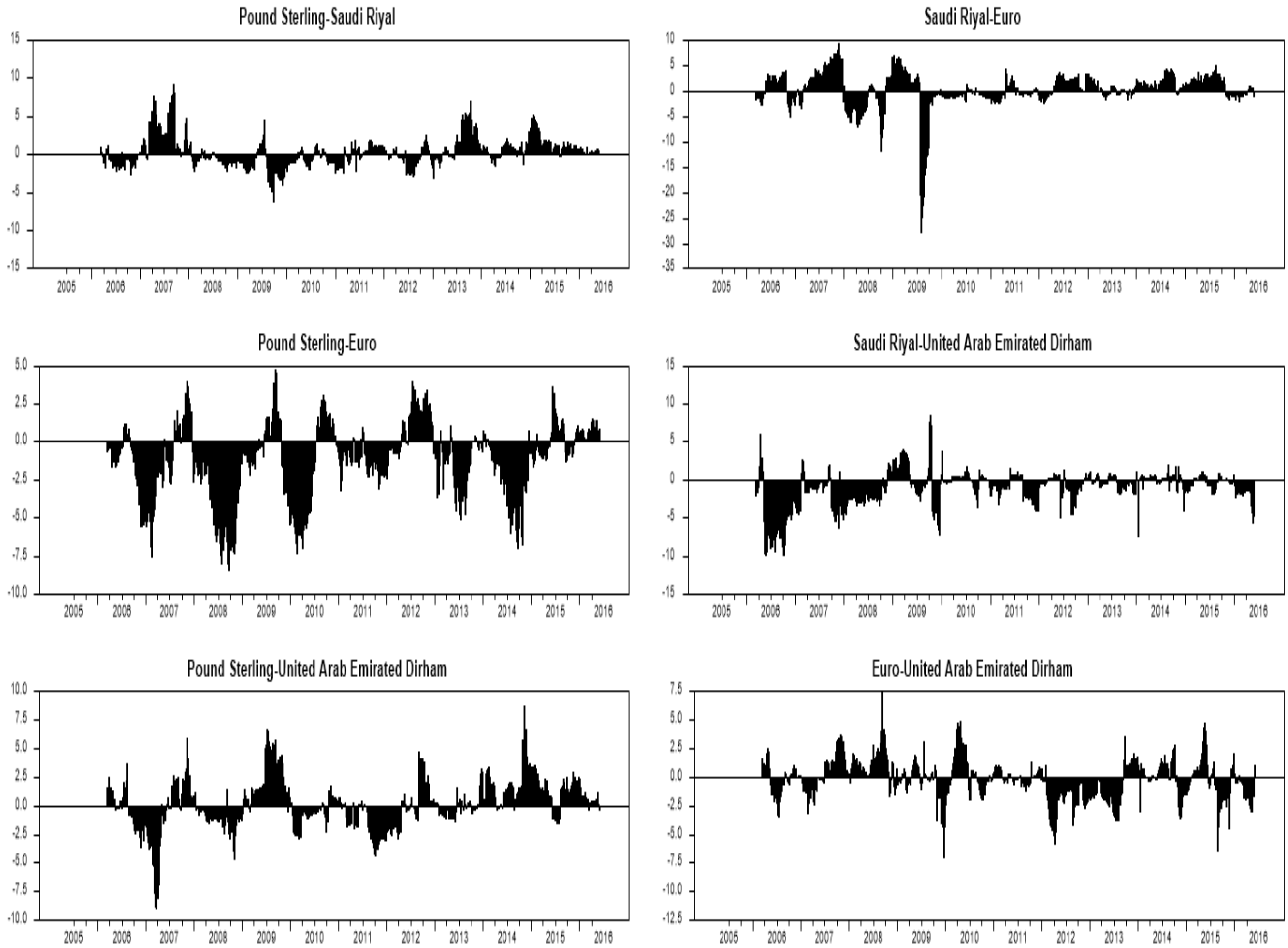
Net Pairwise Volatility Spillovers,HKD THB SGD MXN



Net Volatility Spillovers, HKD THB SGD MXN



Net Pairwise Volatility Spillovers,GBP SAR EUR AED



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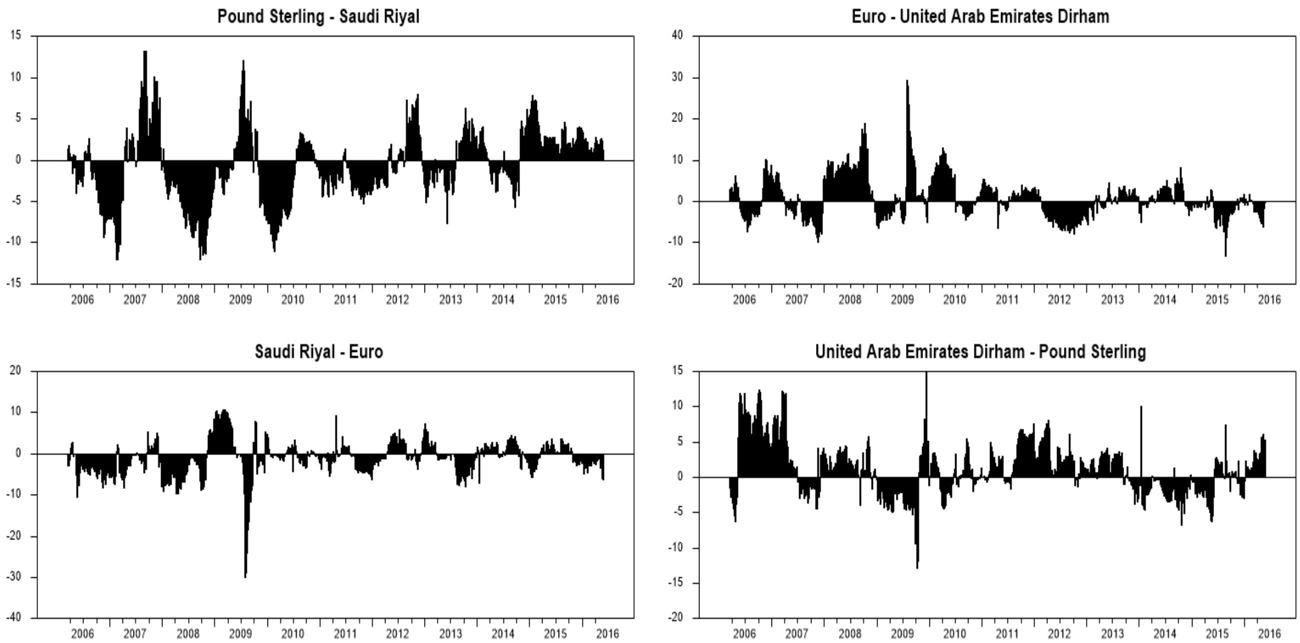
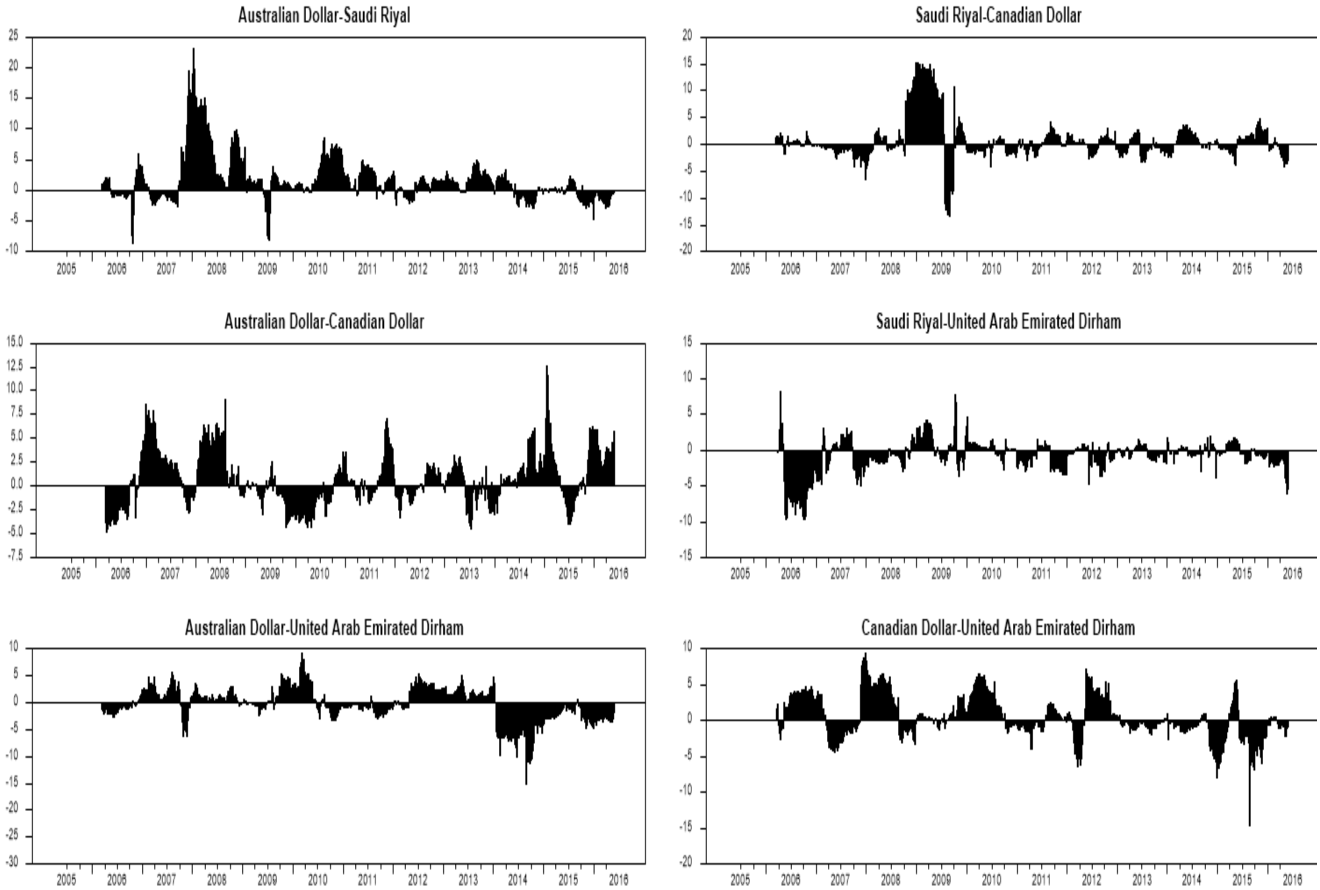


Net Pairwise Volatility Spillovers,AUD SAR CAD AED



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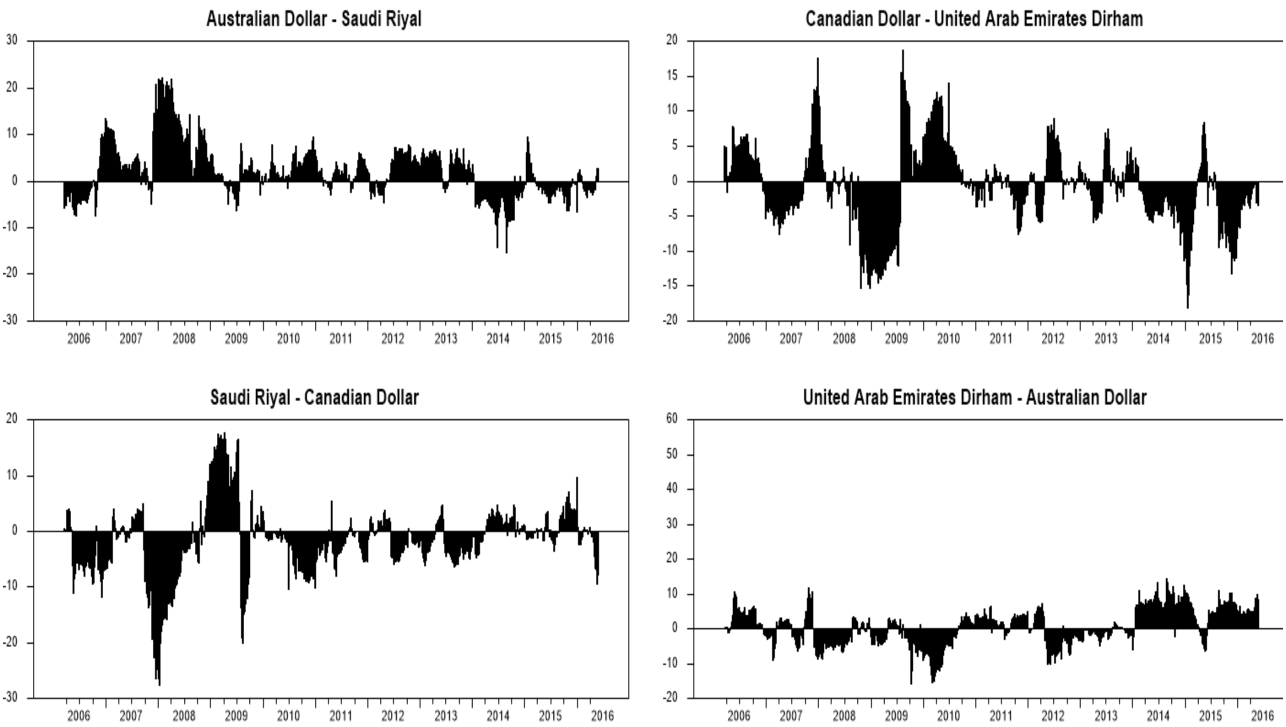
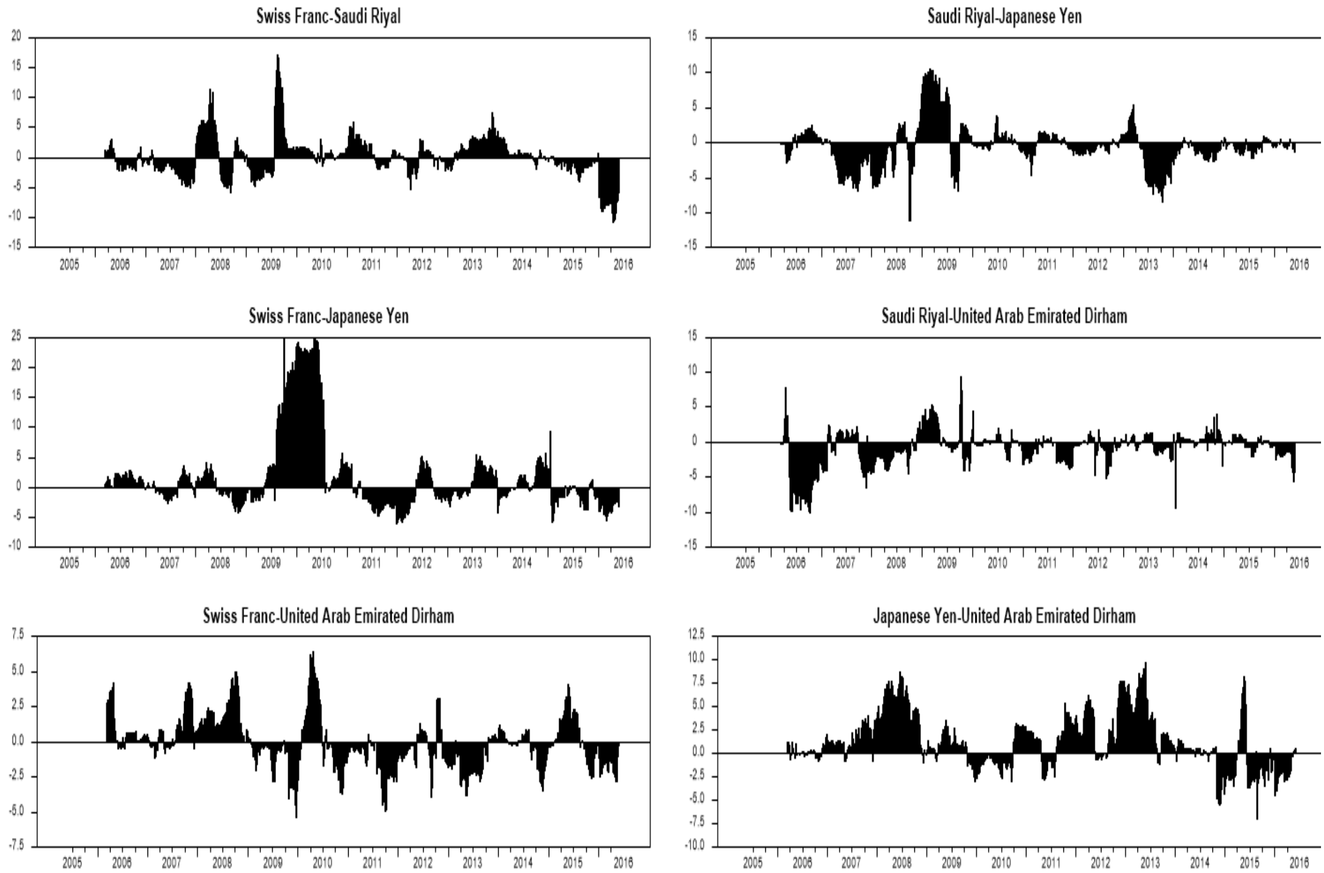


Net Pairwise Volatility Spillovers,CHF SAR JPY AED



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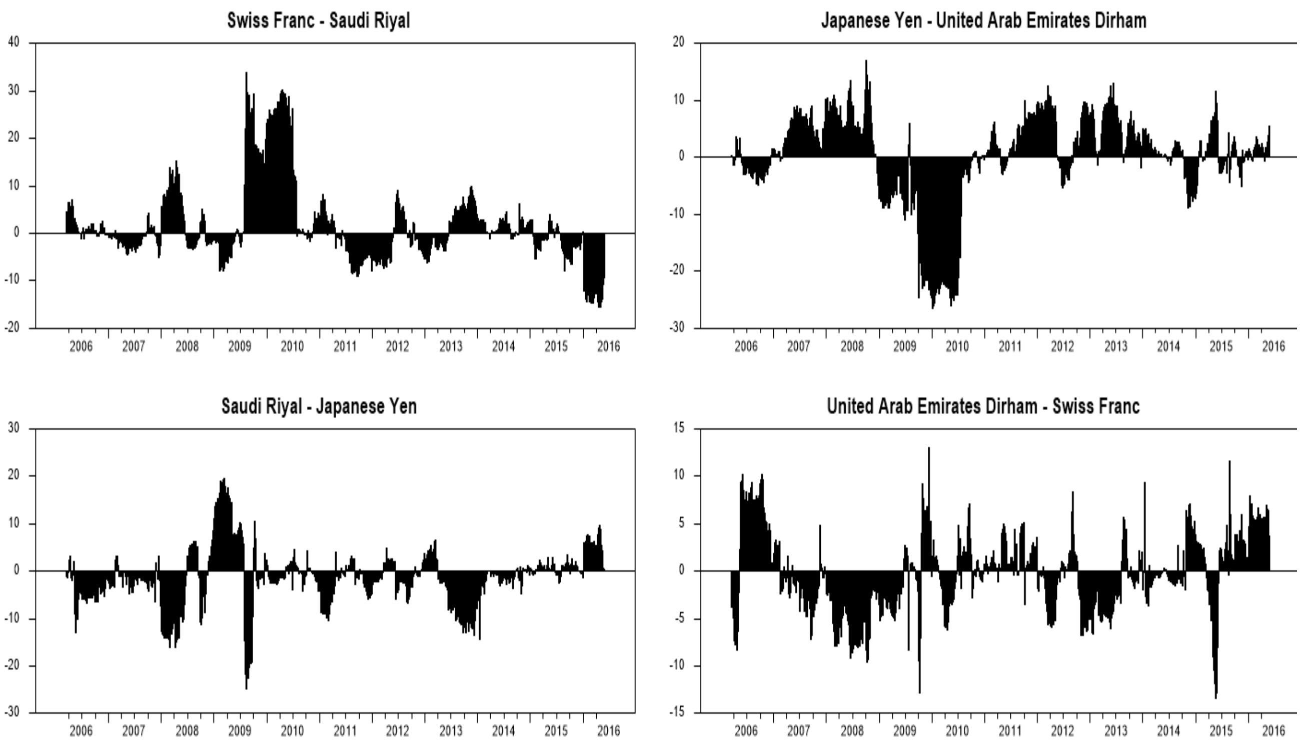
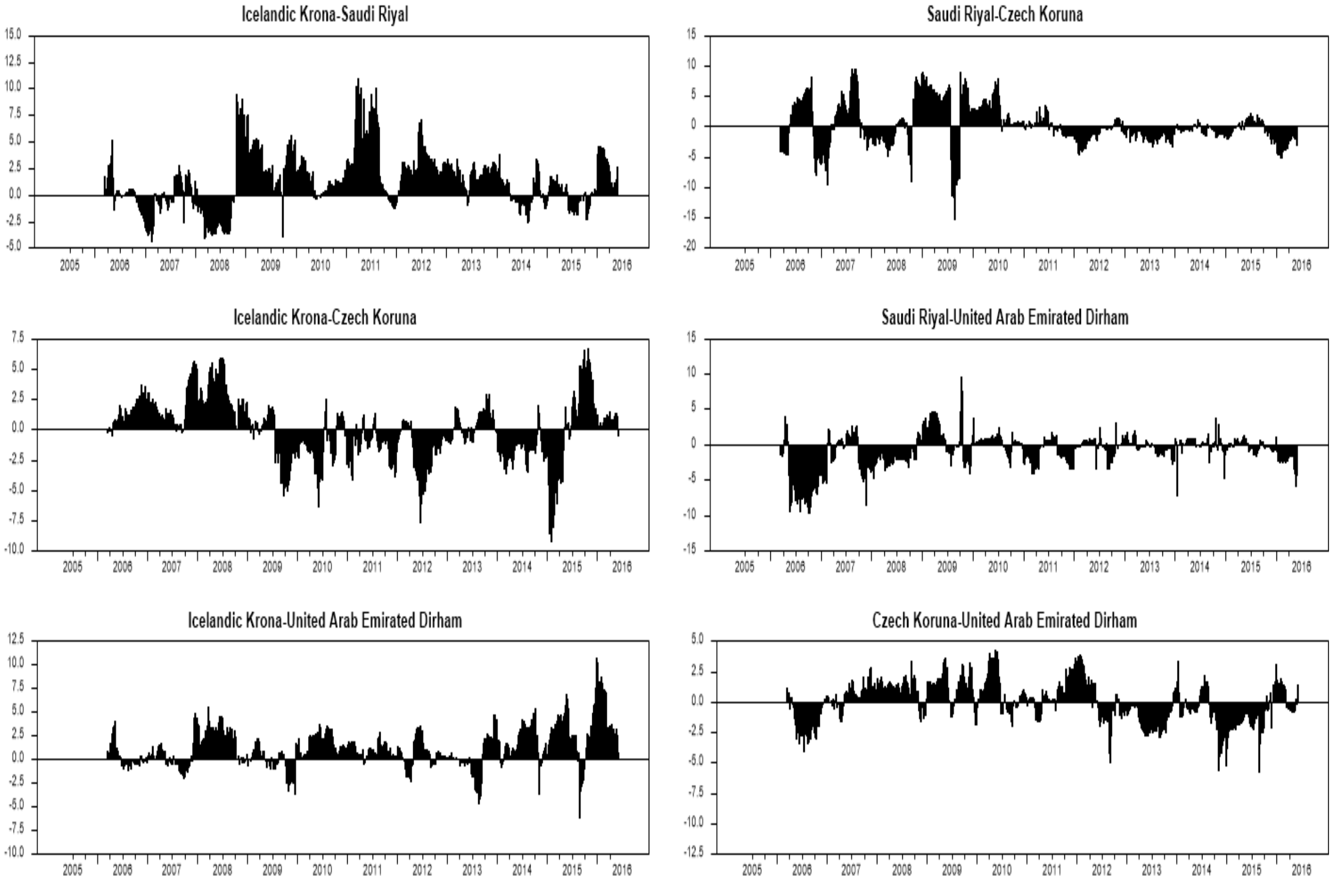


Net Pairwise Volatility Spillovers,ISK SAR CZK AED



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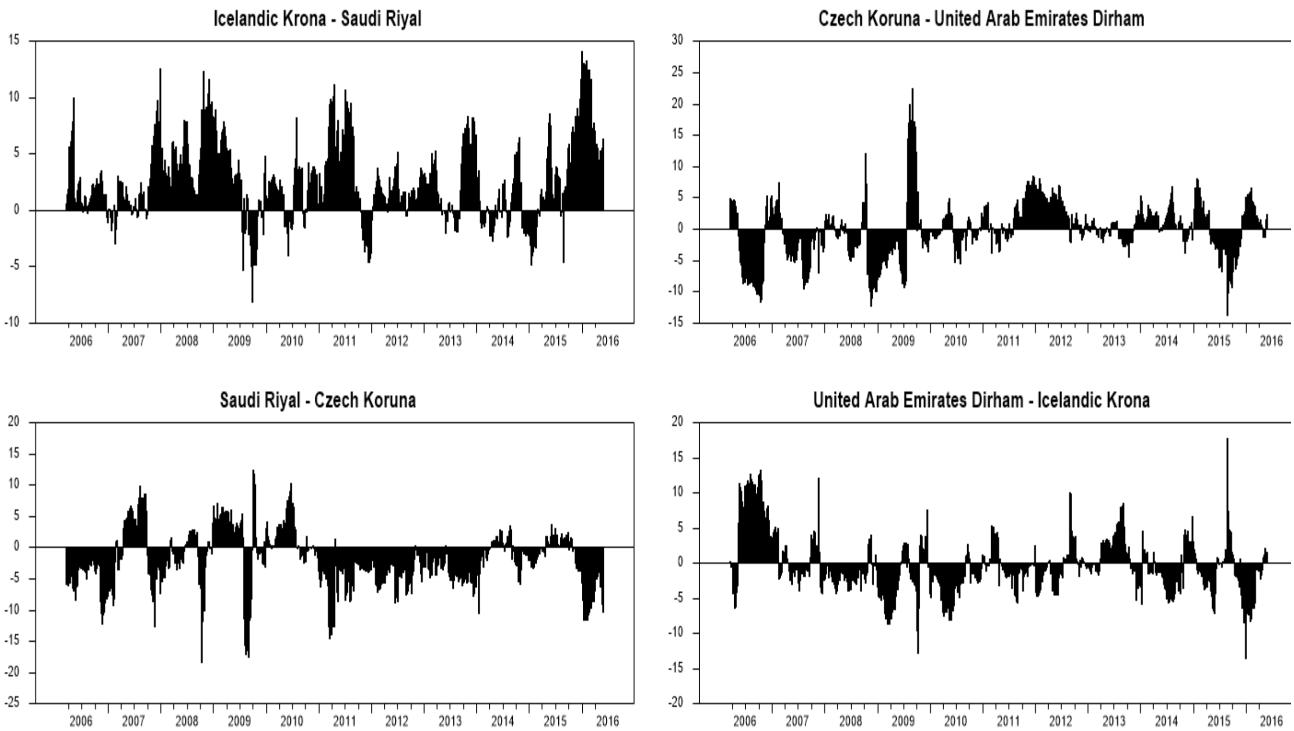

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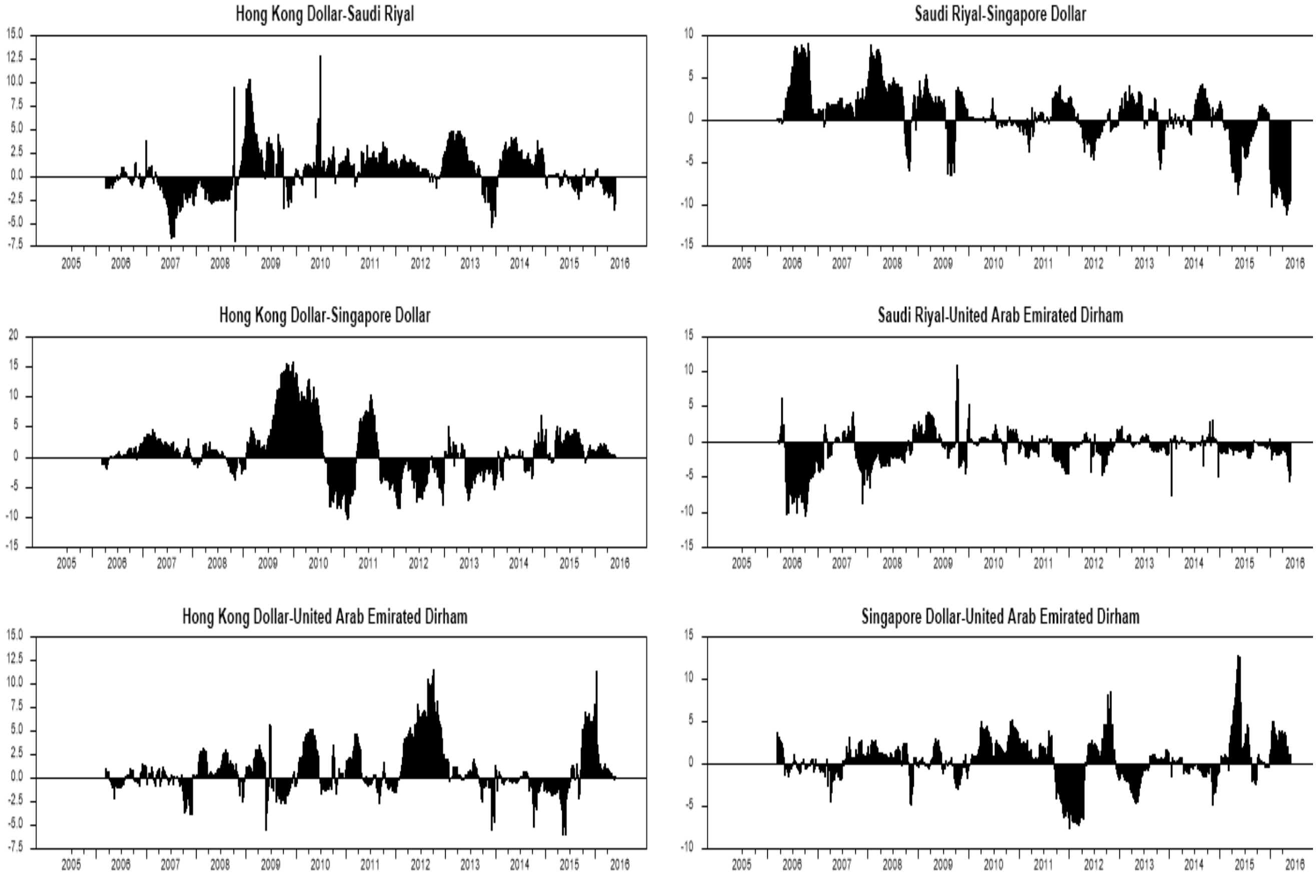
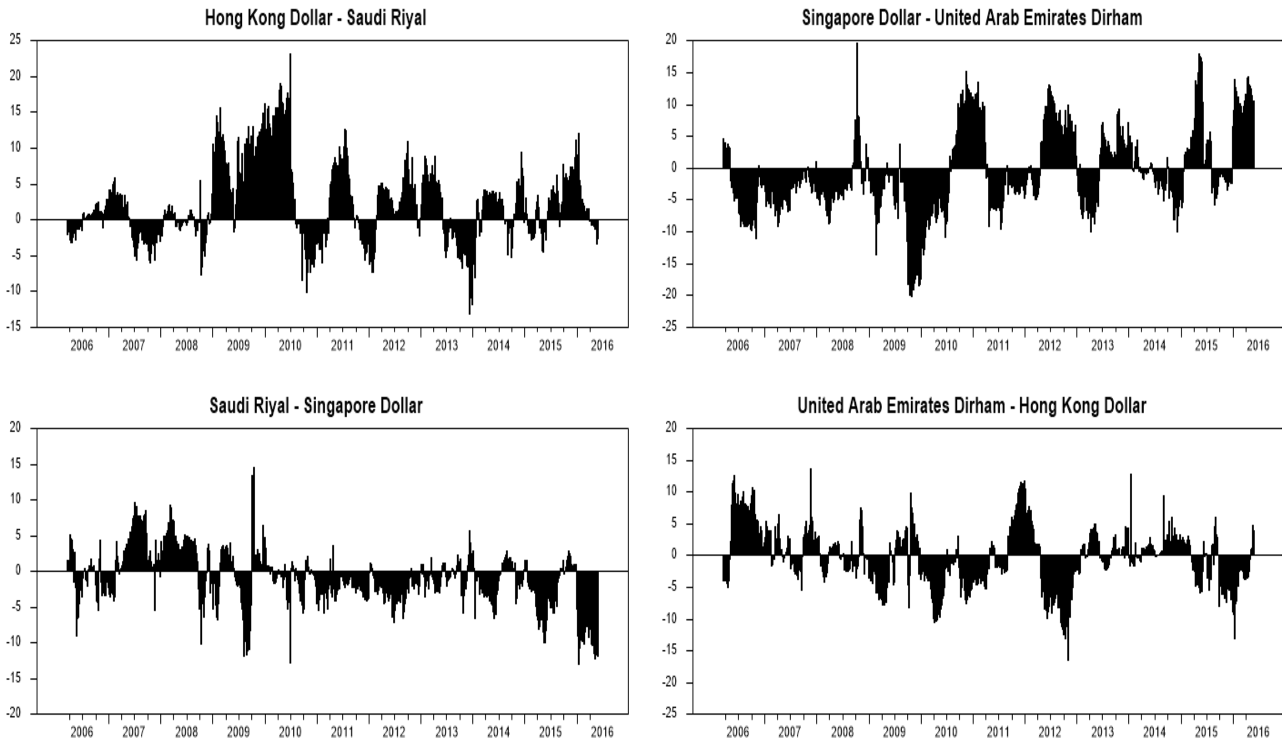
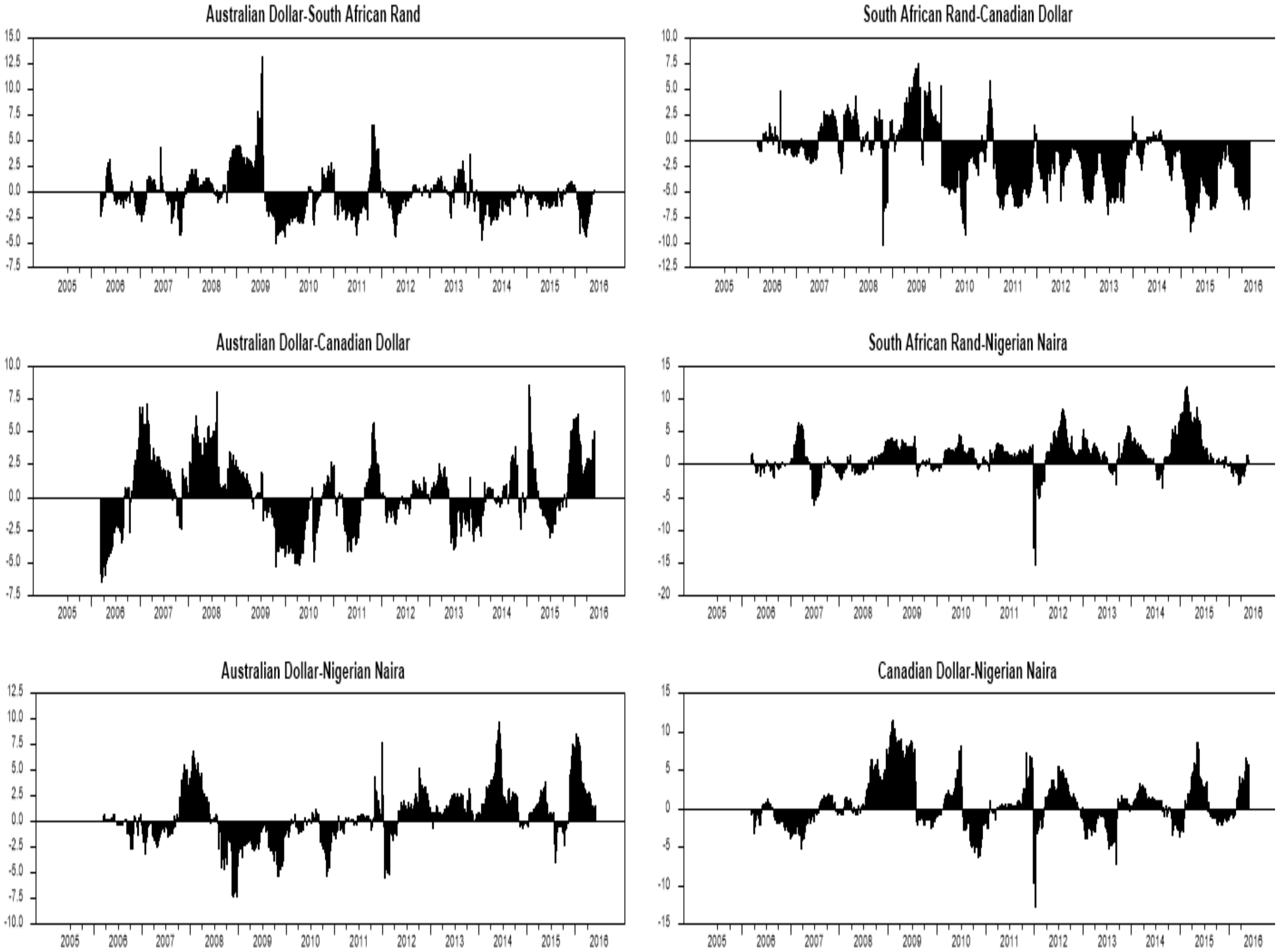


Net Volatility Spillovers, HKD SAR SGD AED



Net Pairwise Volatility Spillovers,AUD ZAR CAD NGN



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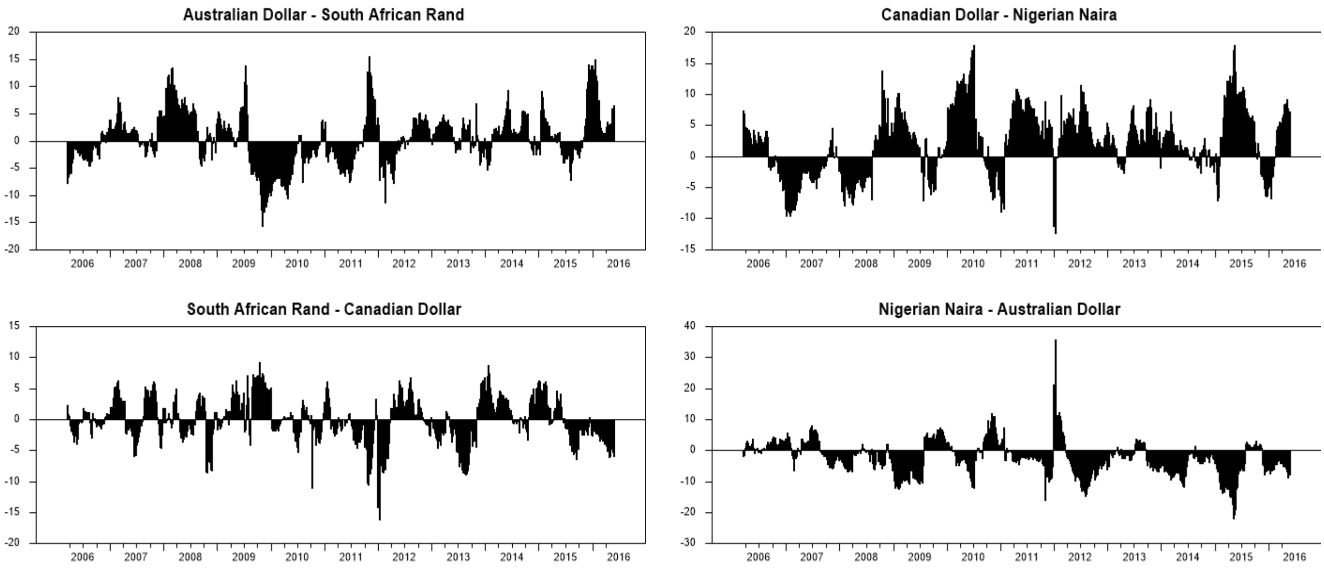

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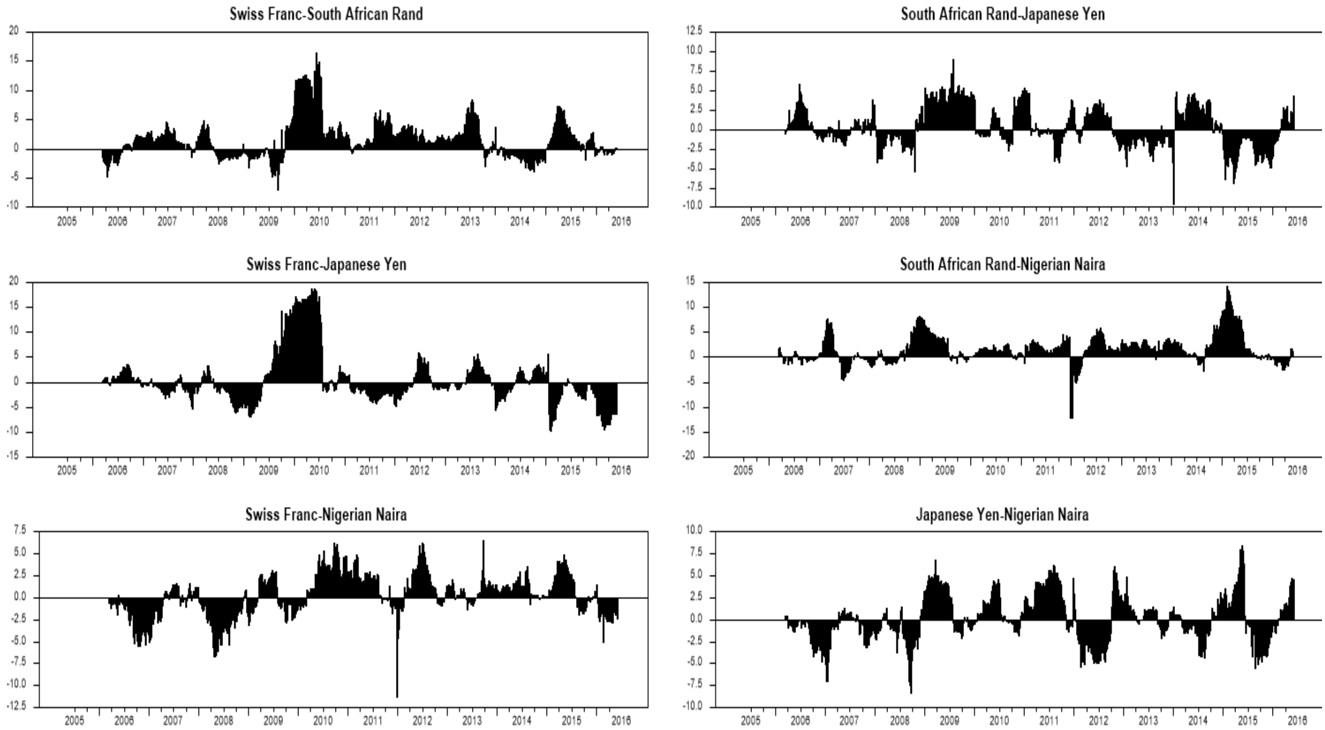

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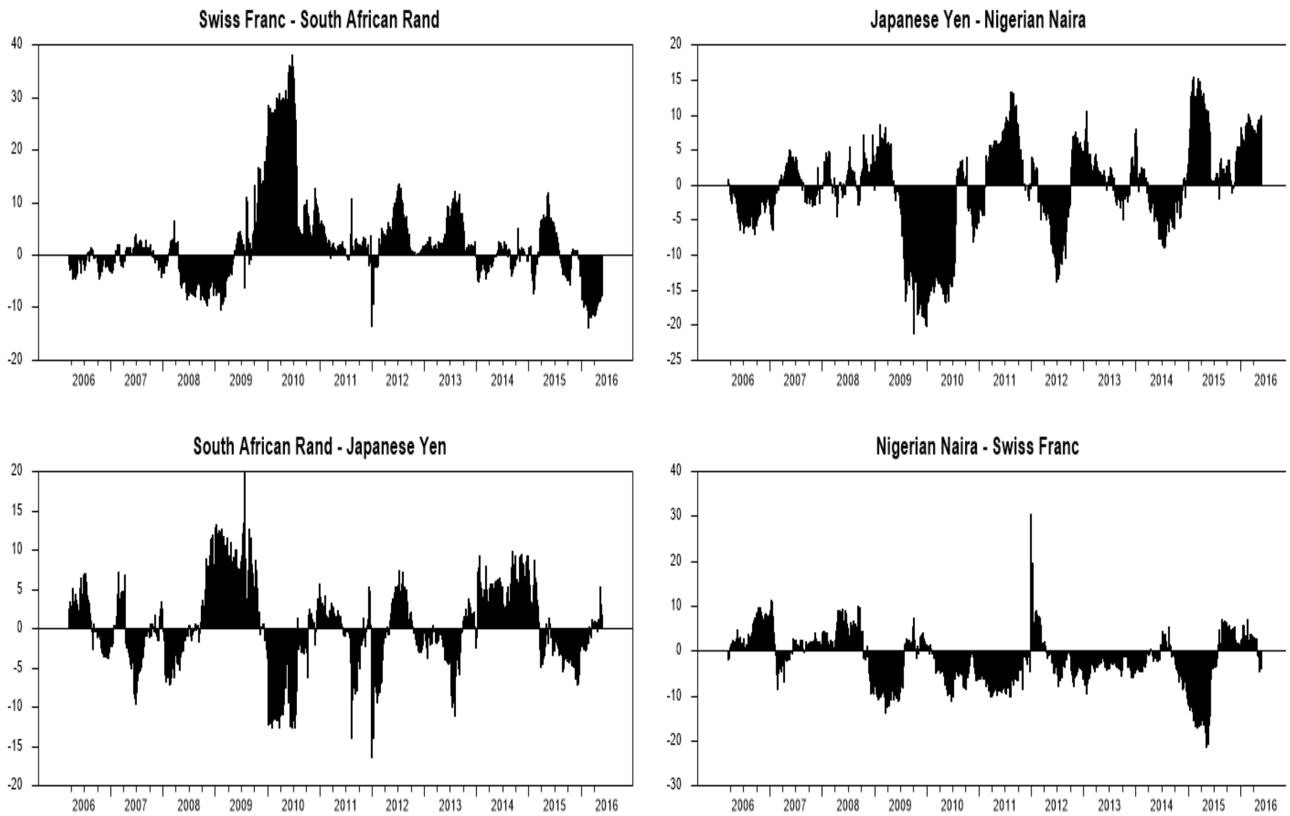

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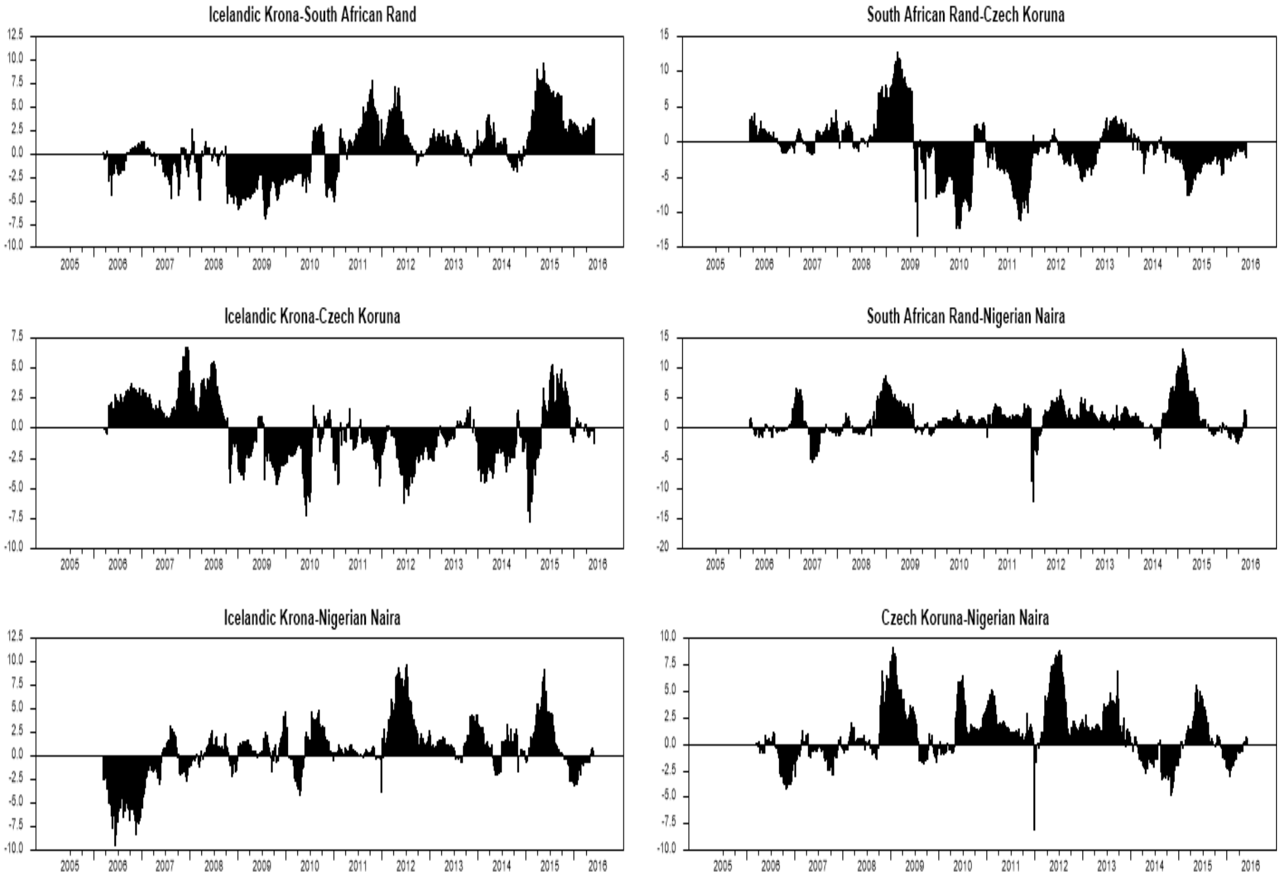

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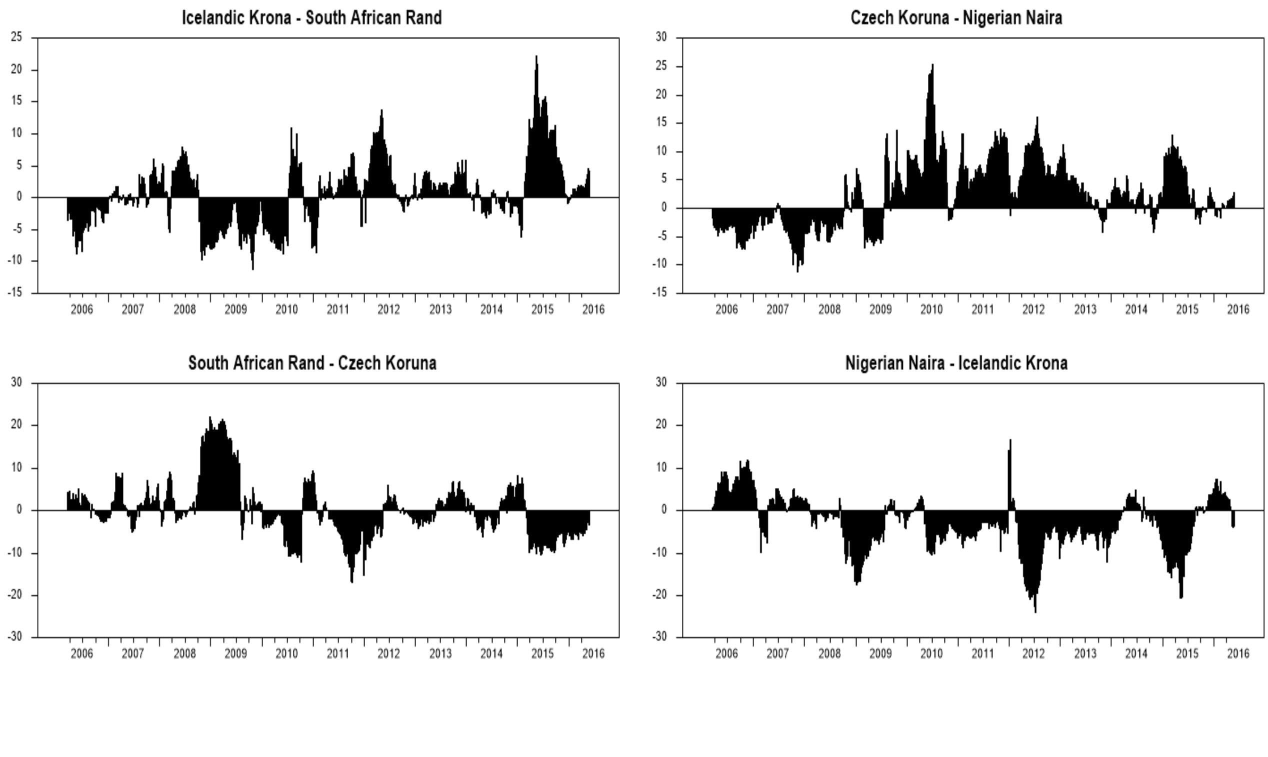
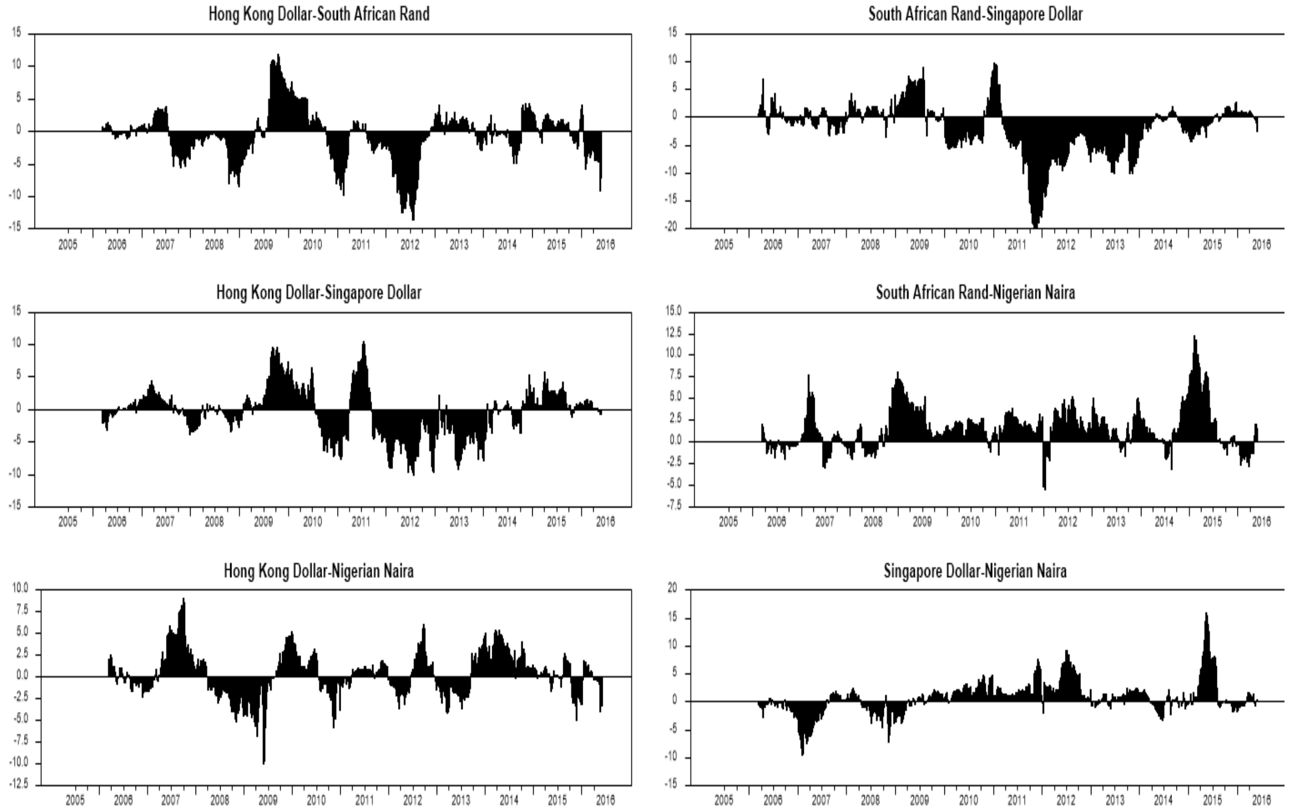
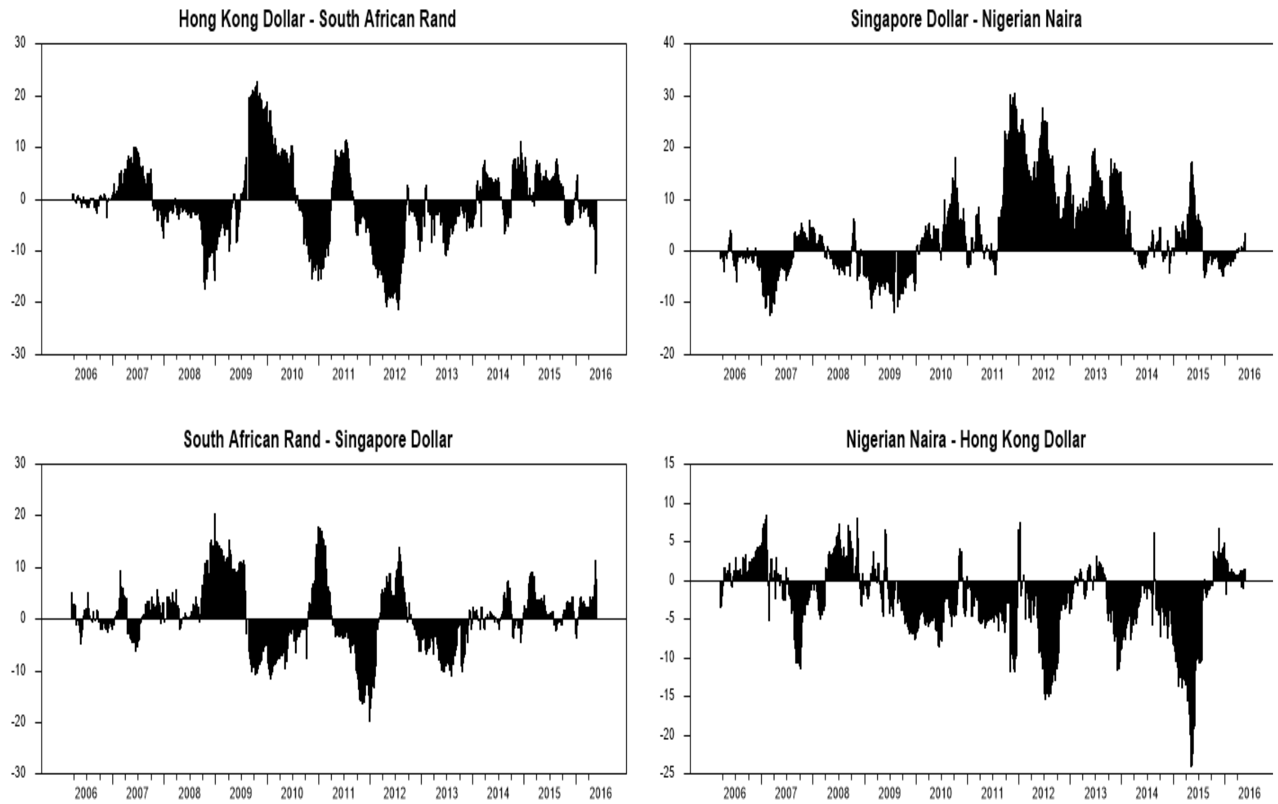


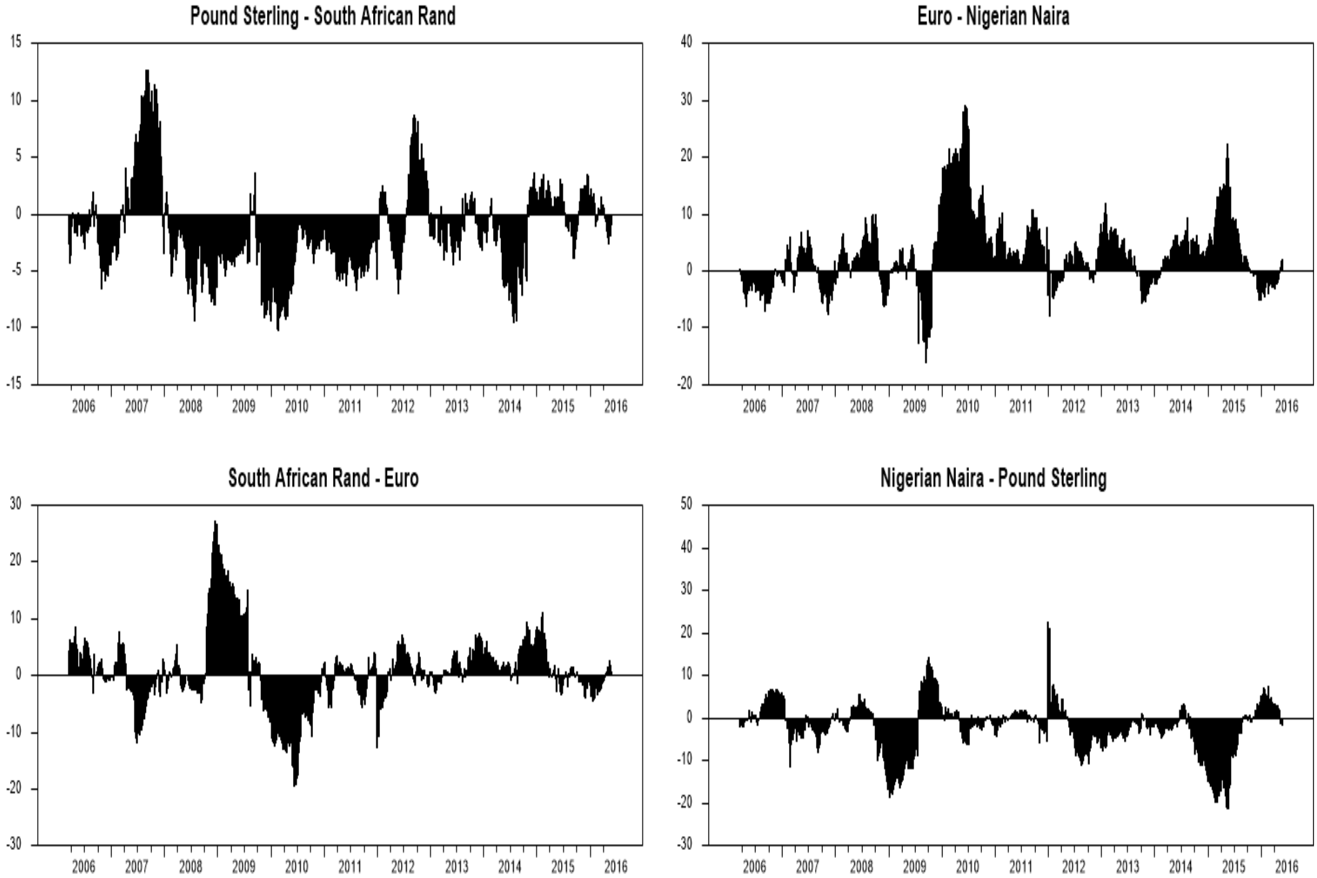
Net Pairwise Volatility Spillovers,HKD ZAR SGD NGN



Net Volatility Spillovers, HKD ZAR SGD NGN



Net Volatility Spillovers, GBP ZAR EUR NGN



Appendix B

Forecast Table for S&P 500
Model: Random walk with drift = 0.000381239

Period	*Data*	*Forecast*	*Residual*
02/01/14	7.51315		
03/01/14	7.51282	7.51353	-0.000714259
06/01/14	7.5103	7.5132	-0.00289617
07/01/14	7.51637	7.51069	0.00568211
08/01/14	7.51616	7.51675	-0.00059347
09/01/14	7.5165	7.51654	-0.0000329898
10/01/14	7.51881	7.51689	0.00192279
13/01/14	7.50615	7.51919	-0.0130372
14/01/14	7.51691	7.50653	0.0103786
15/01/14	7.52206	7.51729	0.00477165
16/01/14	7.52072	7.52245	-0.00172927
17/01/14	7.51681	7.5211	-0.00428402
21/01/14	7.51958	7.5172	0.00238867
22/01/14	7.52016	7.51997	0.000193461
23/01/14	7.51123	7.52054	-0.00931056
24/01/14	7.49013	7.51161	-0.0214777
27/01/14	7.48524	7.49051	-0.00526946
28/01/14	7.49137	7.48563	0.00574064
29/01/14	7.4811	7.49175	-0.0106429
30/01/14	7.49231	7.48149	0.0108228
31/01/14	7.48582	7.49269	-0.00686753
03/02/14	7.46273	7.4862	-0.0234778
04/02/14	7.47034	7.46311	0.0072308
05/02/14	7.46831	7.47072	-0.00241152
06/02/14	7.48067	7.46869	0.0119818
07/02/14	7.49389	7.48105	0.012833
10/02/14	7.49545	7.49427	0.00118677
11/02/14	7.50645	7.49583	0.0106201
12/02/14	7.50619	7.50684	-0.000650537
13/02/14	7.51198	7.50657	0.00541197
14/02/14	7.51678	7.51236	0.00441645
18/02/14	7.51793	7.51716	0.000776565
19/02/14	7.51139	7.51832	-0.0069271
20/02/14	7.5174	7.51177	0.0056321
21/02/14	7.51548	7.51778	-0.00230181
24/02/14	7.52165	7.51586	0.00578622
25/02/14	7.5203	7.52203	-0.00172983
26/02/14	7.52032	7.52068	-0.000359539
27/02/14	7.52526	7.5207	0.00455464
28/02/14	7.52804	7.52564	0.00239759
03/03/14	7.52063	7.52842	-0.0077871
04/03/14	7.53578	7.52101	0.0147711
05/03/14	7.53573	7.53616	-0.000434591
06/03/14	7.53745	7.53611	0.00133569
07/03/14	7.53798	7.53783	0.000156706
10/03/14	7.53752	7.53837	-0.000844592
11/03/14	7.53243	7.5379	-0.00547634
12/03/14	7.53273	7.53281	-0.0000761143
13/03/14	7.52096	7.53311	-0.0121513
14/03/14	7.51813	7.52134	-0.003207
17/03/14	7.5277	7.51852	0.00918648
18/03/14	7.5349	7.52808	0.00681244
19/03/14	7.52875	7.53528	-0.00653176
20/03/14	7.53477	7.52913	0.0056411

21/03/14	7.53183	7.53515	-0.00331822
24/03/14	7.52695	7.53221	-0.00525782
25/03/14	7.53135	7.52734	0.00401303
26/03/14	7.52432	7.53173	-0.00740618
27/03/14	7.52242	7.52471	-0.00228313
28/03/14	7.52705	7.5228	0.00424825
31/03/14	7.53494	7.52743	0.00751163
01/04/14	7.54196	7.53533	0.00663345
02/04/14	7.54481	7.54234	0.00246802
03/04/14	7.54368	7.54519	-0.00150832
04/04/14	7.53106	7.54406	-0.0129978
07/04/14	7.52026	7.53145	-0.0111896
08/04/14	7.524	7.52064	0.0033623
09/04/14	7.53486	7.52438	0.0104778
10/04/14	7.51375	7.53524	-0.0214872
11/04/14	7.50422	7.51413	-0.0099133
14/04/14	7.5124	7.5046	0.00780247
15/04/14	7.51914	7.51279	0.00635334
16/04/14	7.52957	7.51952	0.0100526
17/04/14	7.53094	7.52995	0.000981685
21/04/14	7.5347	7.53132	0.00338678
22/04/14	7.53879	7.53509	0.00370255
23/04/14	7.53657	7.53917	-0.00259701
24/04/14	7.53829	7.53695	0.00133425
25/04/14	7.53016	7.53867	-0.00851058
28/04/14	7.53339	7.53054	0.00284957
29/04/14	7.53814	7.53377	0.00436822
30/04/14	7.54113	7.53852	0.00260631
01/05/14	7.54098	7.54151	-0.00052451
02/05/14	7.53963	7.54136	-0.00173059
05/05/14	7.5415	7.54001	0.00148823
06/05/14	7.53247	7.54188	-0.00941027
07/05/14	7.53807	7.53285	0.00521952
08/05/14	7.5367	7.53846	-0.00175581
09/05/14	7.53822	7.53708	0.00113708
12/05/14	7.54784	7.5386	0.00924502
13/05/14	7.54827	7.54823	0.0000404304
14/05/14	7.54355	7.54865	-0.00509333
15/05/14	7.53415	7.54394	-0.00978714
16/05/14	7.53789	7.53453	0.00335872
19/05/14	7.54173	7.53827	0.00345618
20/05/14	7.53521	7.54211	-0.00690084
21/05/14	7.54329	7.53559	0.0077021
22/05/14	7.54565	7.54367	0.00197821
23/05/14	7.54989	7.54603	0.00385815
27/05/14	7.55586	7.55027	0.00558871
28/05/14	7.55474	7.55624	-0.00149593
29/05/14	7.5601	7.55512	0.00497152
30/05/14	7.56194	7.56048	0.00146074
02/06/14	7.56267	7.56232	0.000346323
03/06/14	7.56229	7.56305	-0.000760527
04/06/14	7.56418	7.56267	0.00150864
05/06/14	7.57068	7.56456	0.00612284
06/06/14	7.5753	7.57106	0.00423584
09/06/14	7.57624	7.57568	0.000557093
10/06/14	7.57599	7.57662	-0.000627253
11/06/14	7.57245	7.57637	-0.00392455
12/06/14	7.56533	7.57283	-0.00749538
13/06/14	7.56846	7.56571	0.00274842
16/06/14	7.5693	7.56884	0.000455117
17/06/14	7.57147	7.56968	0.00178897
18/06/14	7.57916	7.57185	0.007308

19/06/14	7.58043	7.57954	0.000895425
20/06/14	7.58216	7.58082	0.00134733
23/06/14	7.58203	7.58254	-0.000513711
24/06/14	7.57557	7.58241	-0.00683735
25/06/14	7.58046	7.57596	0.00450432
26/06/14	7.57928	7.58084	-0.00156082
27/06/14	7.58119	7.57966	0.00152781
30/06/14	7.58082	7.58157	-0.000753565
01/07/14	7.58747	7.5812	0.00627433
02/07/14	7.58813	7.58785	0.000277358
03/07/14	7.5936	7.58851	0.00508331
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08/07/14	7.58259	7.59005	-0.007455
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13/08/14	7.5739	7.5676	0.00630353
14/08/14	7.57824	7.57428	0.00395516
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18/08/14	7.58667	7.57856	0.00811424
19/08/14	7.59166	7.58705	0.00460695
20/08/14	7.59413	7.59204	0.00209351
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14/11/14	7.62062	7.62076	-0.000140997
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18/11/14	7.62647	7.62173	0.00473961
19/11/14	7.62497	7.62685	-0.00188353
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26/11/14	7.63667	7.63425	0.00242081
28/11/14	7.63412	7.63705	-0.0029269
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03/12/14	7.63739	7.63402	0.00337644
04/12/14	7.63623	7.63777	-0.00154381
05/12/14	7.63789	7.63661	0.00128259
08/12/14	7.63061	7.63828	-0.00766426
09/12/14	7.63037	7.63099	-0.000619091
10/12/14	7.61389	7.63076	-0.0168674
11/12/14	7.61841	7.61427	0.0041442
12/12/14	7.60207	7.61879	-0.0167277

15/12/14	7.5957	7.60245	-0.00674402
16/12/14	7.58718	7.59609	-0.0089065
17/12/14	7.60733	7.58756	0.0197668
18/12/14	7.63106	7.60771	0.0233501
19/12/14	7.63562	7.63144	0.0041784
22/12/14	7.63942	7.636	0.00342198
23/12/14	7.64117	7.6398	0.0013636
24/12/14	7.64103	7.64155	-0.000520545
26/12/14	7.64433	7.64141	0.00292287
29/12/14	7.64519	7.64471	0.000480165
30/12/14	7.64029	7.64557	-0.00528183
31/12/14	7.62993	7.64067	-0.0107456
02/01/15	7.62959	7.63031	-0.00072126
05/01/15	7.61114	7.62997	-0.0188285
06/01/15	7.60221	7.61152	-0.00931449
07/01/15	7.61377	7.60259	0.0111815
08/01/15	7.6315	7.61415	0.0173489
09/01/15	7.62306	7.63188	-0.00882056
12/01/15	7.61493	7.62344	-0.00850786
13/01/15	7.61235	7.61531	-0.00296312
14/01/15	7.60652	7.61273	-0.00621127
15/01/15	7.59723	7.6069	-0.00967214
16/01/15	7.61057	7.59761	0.0129537
20/01/15	7.61211	7.61095	0.00116751
21/01/15	7.61683	7.6125	0.00433923
22/01/15	7.63199	7.61722	0.0147731
23/01/15	7.62648	7.63237	-0.00588789
26/01/15	7.62905	7.62686	0.00218393
27/01/15	7.61557	7.62943	-0.0138595
28/01/15	7.60198	7.61595	-0.0139687
29/01/15	7.61147	7.60236	0.00910828
30/01/15	7.59839	7.61185	-0.0134583
02/02/15	7.61127	7.59878	0.0124979
03/02/15	7.62561	7.61165	0.013955
04/02/15	7.62145	7.62599	-0.00454594
05/02/15	7.63168	7.62183	0.00985757
06/02/15	7.62826	7.63207	-0.00380527
09/02/15	7.624	7.62864	-0.00463748
10/02/15	7.63462	7.62438	0.0102377
11/02/15	7.63459	7.635	-0.000410273
12/02/15	7.64419	7.63497	0.00921706
13/02/15	7.64826	7.64457	0.00368522
17/02/15	7.64985	7.64864	0.00121506
18/02/15	7.64954	7.65024	-0.000695597
19/02/15	7.64848	7.64992	-0.00144386
20/02/15	7.65459	7.64886	0.0057266
23/02/15	7.65428	7.65497	-0.000684624
24/02/15	7.65704	7.65466	0.00237373
25/02/15	7.65627	7.65742	-0.00114726
26/02/15	7.65479	7.65665	-0.00185836
27/02/15	7.65183	7.65518	-0.00334192
02/03/15	7.65794	7.65221	0.005725
03/03/15	7.65339	7.65832	-0.00493011
04/03/15	7.64899	7.65377	-0.0047794
05/03/15	7.65019	7.64937	0.000814127
06/03/15	7.63591	7.65057	-0.0146566
09/03/15	7.63985	7.63629	0.00355542
10/03/15	7.62274	7.64023	-0.0174881
11/03/15	7.62082	7.62312	-0.00230076
12/03/15	7.63335	7.6212	0.0121415
13/03/15	7.62725	7.63373	-0.00647448
16/03/15	7.6407	7.62763	0.0130617

17/03/15	7.63737	7.64108	-0.00370694
18/03/15	7.64945	7.63775	0.0117039
19/03/15	7.64457	7.64984	-0.00526573
20/03/15	7.65354	7.64495	0.00859114
23/03/15	7.6518	7.65392	-0.0021285
24/03/15	7.64564	7.65218	-0.00653958
25/03/15	7.63097	7.64602	-0.0150472
26/03/15	7.62859	7.63135	-0.00276157
27/03/15	7.63096	7.62897	0.00198452
30/03/15	7.64312	7.63134	0.0117811
31/03/15	7.63428	7.6435	-0.00921592
01/04/15	7.63031	7.63467	-0.00435449
02/04/15	7.63383	7.63069	0.00314221
06/04/15	7.64042	7.63422	0.00620583
07/04/15	7.63836	7.6408	-0.00244527
08/04/15	7.64104	7.63874	0.0022977
09/04/15	7.64548	7.64142	0.00406634
10/04/15	7.65067	7.64586	0.00480814
13/04/15	7.64608	7.65105	-0.00497305
14/04/15	7.64771	7.64646	0.00124719
15/04/15	7.65284	7.64809	0.00475375
16/04/15	7.65207	7.65323	-0.00115999
17/04/15	7.64069	7.65245	-0.0117569
20/04/15	7.64988	7.64107	0.00881151
21/04/15	7.6484	7.65026	-0.00186294
22/04/15	7.65348	7.64878	0.00469334
23/04/15	7.65583	7.65386	0.0019737
24/04/15	7.65808	7.65621	0.00186903
27/04/15	7.65393	7.65846	-0.00453115
28/04/15	7.6567	7.65431	0.00238417
29/04/15	7.65295	7.65708	-0.00412859
30/04/15	7.64277	7.65333	-0.0105618
01/05/15	7.65363	7.64315	0.0104825
04/05/15	7.65657	7.65401	0.00255519
05/05/15	7.64466	7.65695	-0.0122892
06/05/15	7.6402	7.64504	-0.00484692
07/05/15	7.64396	7.64058	0.00338547
08/05/15	7.65733	7.64434	0.0129869
11/05/15	7.65223	7.65771	-0.0054838
12/05/15	7.64927	7.65261	-0.00333523
13/05/15	7.64897	7.64965	-0.00068624
14/05/15	7.65969	7.64935	0.0103404
15/05/15	7.66046	7.66007	0.00038688
18/05/15	7.6635	7.66084	0.00266207
19/05/15	7.66286	7.66388	-0.00102482
20/05/15	7.66193	7.66324	-0.00131219
21/05/15	7.66426	7.66231	0.00195391
22/05/15	7.66203	7.66464	-0.00261762
26/05/15	7.65169	7.66241	-0.0107164
27/05/15	7.66081	7.65207	0.00873968
28/05/15	7.65954	7.66119	-0.0016488
29/05/15	7.65321	7.65993	-0.00671975
01/06/15	7.65526	7.65359	0.0016761
02/06/15	7.65425	7.65564	-0.00139034
03/06/15	7.65637	7.65463	0.00173539
04/06/15	7.64771	7.65675	-0.0090418
05/06/15	7.64627	7.64809	-0.00181845
08/06/15	7.63978	7.64665	-0.0068768
09/06/15	7.6402	7.64016	0.000037027
10/06/15	7.65217	7.64058	0.0115893
11/06/15	7.6539	7.65255	0.00135588
12/06/15	7.64688	7.65428	-0.00740011

15/06/15	7.64225	7.64727	-0.00501453
16/06/15	7.64792	7.64263	0.00529249
17/06/15	7.6499	7.64831	0.00159645
18/06/15	7.65976	7.65028	0.00947276
19/06/15	7.65444	7.66014	-0.00569885
22/06/15	7.66051	7.65482	0.00569513
23/06/15	7.66115	7.6609	0.000254428
24/06/15	7.65377	7.66153	-0.0077617
25/06/15	7.65079	7.65415	-0.00335924
26/06/15	7.6504	7.65117	-0.000771395
29/06/15	7.62931	7.65078	-0.0214682
30/06/15	7.63197	7.6297	0.00227372
01/07/15	7.63888	7.63235	0.00653086
02/07/15	7.63857	7.63926	-0.000689309
06/07/15	7.6347	7.63896	-0.00425047
07/07/15	7.64077	7.63509	0.00568132
08/07/15	7.62397	7.64115	-0.0171742
09/07/15	7.62623	7.62436	0.00187841
10/07/15	7.6385	7.62662	0.0118817
13/07/15	7.6495	7.63888	0.010624
14/07/15	7.65395	7.64988	0.00406203
15/07/15	7.65321	7.65433	-0.00111649
16/07/15	7.66119	7.65359	0.0076015
17/07/15	7.6623	7.66157	0.000724333
20/07/15	7.66307	7.66268	0.000389698
21/07/15	7.6588	7.66345	-0.00465203
22/07/15	7.65641	7.65918	-0.0027718
23/07/15	7.65072	7.65679	-0.00607345
24/07/15	7.63995	7.6511	-0.0111423
27/07/15	7.63416	7.64034	-0.00617299
28/07/15	7.64647	7.63454	0.0119288
29/07/15	7.65377	7.64685	0.0069109
30/07/15	7.65379	7.65415	-0.000352871
31/07/15	7.65152	7.65417	-0.00265534
03/08/15	7.64876	7.6519	-0.00314193
04/08/15	7.64651	7.64914	-0.00263348
05/08/15	7.64962	7.64689	0.0027286
06/08/15	7.64183	7.65	-0.00816443
07/08/15	7.63895	7.64221	-0.00326026
10/08/15	7.65168	7.63934	0.0123456
11/08/15	7.64208	7.65206	-0.0099843
12/08/15	7.64303	7.64246	0.000568365
13/08/15	7.64175	7.64341	-0.00165726
14/08/15	7.64566	7.64213	0.00352309
17/08/15	7.65085	7.64604	0.00481665
18/08/15	7.64822	7.65124	-0.00301022
19/08/15	7.63994	7.64861	-0.00867038
20/08/15	7.61861	7.64032	-0.0217072
21/08/15	7.58624	7.61899	-0.0327505
24/08/15	7.54603	7.58662	-0.0405927
25/08/15	7.53241	7.54641	-0.0139955
26/08/15	7.57071	7.5328	0.0379101
27/08/15	7.59471	7.57109	0.023626
28/08/15	7.59532	7.59509	0.000227313
31/08/15	7.58689	7.5957	-0.00880832
01/09/15	7.55687	7.58728	-0.0304039
02/09/15	7.575	7.55725	0.0177464
03/09/15	7.57616	7.57538	0.000782877
04/09/15	7.56072	7.57655	-0.0158295
08/09/15	7.58549	7.5611	0.0243924
09/09/15	7.57149	7.58587	-0.0143763
10/09/15	7.57676	7.57188	0.00488284

11/09/15	7.58124	7.57714	0.00409577
14/09/15	7.57714	7.58162	-0.00447928
15/09/15	7.58989	7.57752	0.0123684
16/09/15	7.59855	7.59027	0.0082865
17/09/15	7.59599	7.59894	-0.00294558
18/09/15	7.57969	7.59637	-0.0166775
21/09/15	7.58425	7.58008	0.00417415
22/09/15	7.57185	7.58463	-0.0127762
23/09/15	7.5698	7.57224	-0.00243198
24/09/15	7.56644	7.57019	-0.00374989
25/09/15	7.56597	7.56682	-0.00084714
28/09/15	7.53997	7.56635	-0.0263824
29/09/15	7.5412	7.54035	0.000850855
30/09/15	7.5601	7.54158	0.0185147
01/10/15	7.56207	7.56048	0.0015907
02/10/15	7.57628	7.56245	0.0138326
05/10/15	7.59441	7.57666	0.0177434
06/10/15	7.59081	7.59479	-0.00397593
07/10/15	7.59882	7.59119	0.00762228
08/10/15	7.6076	7.5992	0.00839854
09/10/15	7.60832	7.60798	0.00034361
12/10/15	7.60959	7.6087	0.000893426
13/10/15	7.60275	7.60998	-0.00723006
14/10/15	7.59802	7.60313	-0.00510867
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19/10/15	7.61759	7.6177	-0.000110729
20/10/15	7.61617	7.61797	-0.00180334
21/10/15	7.61033	7.61655	-0.00622369
22/10/15	7.62682	7.61071	0.0161096
23/10/15	7.63779	7.6272	0.0105887
26/10/15	7.63587	7.63817	-0.00229617
27/10/15	7.63332	7.63625	-0.00293862
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03/11/15	7.65434	7.652	0.00234311
04/11/15	7.65079	7.65472	-0.00393291
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09/11/15	7.63944	7.64969	-0.0102525
10/11/15	7.64095	7.63982	0.00112822
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12/11/15	7.62363	7.6381	-0.0144704
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16/11/15	7.62715	7.61274	0.0144121
17/11/15	7.62581	7.62753	-0.00172152
18/11/15	7.64184	7.62619	0.015652
19/11/15	7.64072	7.64222	-0.00150498
20/11/15	7.64452	7.6411	0.00342172
23/11/15	7.64329	7.6449	-0.00161686
24/11/15	7.64451	7.64367	0.000840012
25/11/15	7.64438	7.64489	-0.000510379
27/11/15	7.64497	7.64476	0.000212203
30/11/15	7.64032	7.64535	-0.00503304
01/12/15	7.65094	7.6407	0.0102427
02/12/15	7.63989	7.65133	-0.0114378
03/12/15	7.62541	7.64027	-0.0148591
04/12/15	7.64573	7.62579	0.0199366
07/12/15	7.63871	7.64611	-0.00739528
08/12/15	7.6322	7.63909	-0.00689229

09/12/15	7.62443	7.63258	-0.00815032
10/12/15	7.62668	7.62481	0.00186762
11/12/15	7.60707	7.62706	-0.0199951
14/12/15	7.61181	7.60745	0.00436305
15/12/15	7.62238	7.61219	0.0101813
16/12/15	7.63679	7.62276	0.0140294
17/12/15	7.62163	7.63717	-0.015536
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21/12/15	7.61142	7.60405	0.00736707
22/12/15	7.6202	7.6118	0.00839686
23/12/15	7.63254	7.62058	0.0119604
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04/01/16	7.60721	7.62302	-0.0158033
05/01/16	7.60922	7.60759	0.00162897
06/01/16	7.59602	7.6096	-0.0135834
07/01/16	7.57203	7.5964	-0.0243671
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11/01/16	7.56199	7.56152	0.00047167
12/01/16	7.56976	7.56237	0.00739128
13/01/16	7.54448	7.57014	-0.0256636
14/01/16	7.56104	7.54486	0.0161768
15/01/16	7.5392	7.56142	-0.022217
19/01/16	7.53973	7.53958	0.000150442
20/01/16	7.52797	7.54012	-0.012144
21/01/16	7.53315	7.52835	0.00480075
22/01/16	7.55323	7.53353	0.0196995
25/01/16	7.53747	7.55362	-0.0161428
26/01/16	7.55152	7.53785	0.013664
27/01/16	7.54059	7.5519	-0.0113042
28/01/16	7.54611	7.54098	0.00513211
29/01/16	7.57057	7.54649	0.0240774
01/02/16	7.57012	7.57095	-0.000824573
02/02/16	7.5512	7.5705	-0.0193022
03/02/16	7.55618	7.55158	0.00459838
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05/02/16	7.53905	7.55809	-0.0190354
08/02/16	7.5248	7.53943	-0.0146363
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10/02/16	7.52395	7.52452	-0.000570207
11/02/16	7.51157	7.52433	-0.0127587
12/02/16	7.5309	7.51195	0.0189488
16/02/16	7.54728	7.53128	0.0160005
17/02/16	7.56363	7.54766	0.0159649
18/02/16	7.55895	7.56401	-0.00505787
19/02/16	7.55892	7.55933	-0.000407272
22/02/16	7.57327	7.5593	0.0139695
23/02/16	7.56074	7.57366	-0.0129138
24/02/16	7.56517	7.56112	0.00404872
25/02/16	7.57646	7.56555	0.0109031
26/02/16	7.57458	7.57684	-0.0022531
29/02/16	7.56643	7.57497	-0.00853537
01/03/16	7.59002	7.56681	0.0232071
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03/03/16	7.5976	7.59449	0.0031114
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08/03/16	7.59048	7.60216	-0.011685
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11/03/16	7.61194	7.59606	0.0158813
14/03/16	7.61067	7.61232	-0.00164301
15/03/16	7.60884	7.61106	-0.00221987
16/03/16	7.61442	7.60922	0.00520349
17/03/16	7.62099	7.6148	0.00619234
18/03/16	7.62539	7.62138	0.00401473
21/03/16	7.62638	7.62577	0.000603854
22/03/16	7.6255	7.62676	-0.00125901
23/03/16	7.61909	7.62588	-0.00678775
24/03/16	7.61871	7.61947	-0.000759381
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29/03/16	7.62804	7.61964	0.00839677
30/03/16	7.63238	7.62842	0.00395964
31/03/16	7.63034	7.63276	-0.00242308
01/04/16	7.63665	7.63072	0.00592972
04/04/16	7.63343	7.63703	-0.00359472
05/04/16	7.62324	7.63381	-0.0105775
06/04/16	7.63369	7.62362	0.0100716
07/04/16	7.62164	7.63407	-0.0124293
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12/04/16	7.6313	7.62206	0.00923452
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15/04/16	7.64047	7.64184	-0.00136601
18/04/16	7.64699	7.64086	0.00613849
19/04/16	7.65007	7.64738	0.0026985
20/04/16	7.65083	7.65045	0.000380016
21/04/16	7.64563	7.65122	-0.0055888
22/04/16	7.64568	7.64601	-0.00033338
25/04/16	7.64386	7.64606	-0.00219493
26/04/16	7.64573	7.64424	0.00148976
27/04/16	7.64738	7.64611	0.00126676
28/04/16	7.63811	7.64776	-0.00965487
29/04/16	7.63303	7.63849	-0.00545719
02/05/16	7.64081	7.63341	0.00739837
03/05/16	7.6321	7.64119	-0.00909574
04/05/16	7.62614	7.63248	-0.00633582
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06/05/16	7.62907	7.62628	0.00278837
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13/05/16	7.62394	7.63284	-0.00889567
16/05/16	7.63369	7.62432	0.00936774
17/05/16	7.62423	7.63407	-0.0098371
18/05/16	7.62444	7.62461	-0.000176081
19/05/16	7.62072	7.62482	-0.00409483
20/05/16	7.62673	7.62111	0.00562022
23/05/16	7.62464	7.62711	-0.00246887
24/05/16	7.63823	7.62502	0.0132074
25/05/16	7.64518	7.63861	0.00656929
26/05/16	7.64497	7.64556	-0.000591704
27/05/16	7.64924	7.64535	0.00389646
31/05/16	7.64824	7.64963	-0.00138701
01/06/16	7.64937	7.64862	0.00075316
02/06/16	7.65219	7.64975	0.00243946
03/06/16	7.64928	7.65258	-0.0032973
06/06/16	7.65416	7.64966	0.00450409
07/06/16	7.65545	7.65454	0.000907377

08/06/16	7.65876	7.65583	0.00292286
09/06/16	7.65704	7.65914	-0.00210047
10/06/16	7.64782	7.65742	-0.00959877
13/06/16	7.63967	7.6482	-0.00852954
14/06/16	7.63787	7.64005	-0.00218174
15/06/16	7.63603	7.63825	-0.00222365
16/06/16	7.63916	7.63641	0.00274685
17/06/16	7.63589	7.63954	-0.00364452
20/06/16	7.64168	7.63627	0.00541014
21/06/16	7.64439	7.64207	0.00232715
22/06/16	7.64274	7.64477	-0.00203417
23/06/16	7.65602	7.64312	0.0128943
24/06/16	7.61943	7.6564	-0.036962
27/06/16	7.60117	7.61982	-0.0186435
28/06/16	7.61879	7.60155	0.0172329
29/06/16	7.63568	7.61917	0.016508
30/06/16	7.64915	7.63606	0.0130926
01/07/16	7.6511	7.64953	0.00156547
05/07/16	7.64423	7.65148	-0.00725227
06/07/16	7.64956	7.64461	0.00495745
07/07/16	7.64869	7.64995	-0.0012532
08/07/16	7.66383	7.64907	0.0147569
11/07/16	7.66723	7.66421	0.00302158
12/07/16	7.67422	7.66761	0.0066036
13/07/16	7.67435	7.6746	-0.00024648
14/07/16	7.6796	7.67473	0.00486418
15/07/16	7.67867	7.67998	-0.00131062
18/07/16	7.68105	7.67905	0.00199822
19/07/16	7.67961	7.68143	-0.00181744
20/07/16	7.68387	7.67999	0.00387997
21/07/16	7.68025	7.68425	-0.00400031
22/07/16	7.6848	7.68064	0.00416239
25/07/16	7.68178	7.68518	-0.00339726
26/07/16	7.6821	7.68216	-0.000058506
27/07/16	7.68091	7.68249	-0.0015805
28/07/16	7.68251	7.68129	0.00122368
29/07/16	7.68414	7.68289	0.00124874
01/08/16	7.68287	7.68452	-0.00165183
02/08/16	7.67649	7.68325	-0.00676318
03/08/16	7.67962	7.67687	0.0027478
04/08/16	7.67983	7.68	-0.000168689
05/08/16	7.6884	7.68021	0.00818546
08/08/16	7.68749	7.68878	-0.00128882
09/08/16	7.68788	7.68787	0.00000847916
10/08/16	7.68501	7.68826	-0.00325004
11/08/16	7.68973	7.68539	0.00434218
12/08/16	7.68894	7.69011	-0.0011776
15/08/16	7.69173	7.68932	0.00240778
16/08/16	7.68623	7.69211	-0.00587538
17/08/16	7.6881	7.68661	0.00148561
18/08/16	7.6903	7.68848	0.00181596
19/08/16	7.68885	7.69068	-0.00182255
22/08/16	7.68829	7.68924	-0.00094472
23/08/16	7.69024	7.68867	0.00156863
24/08/16	7.68499	7.69062	-0.00563529
25/08/16	7.68362	7.68537	-0.0017474
26/08/16	7.68204	7.684	-0.0019613
29/08/16	7.68725	7.68242	0.00483319
30/08/16	7.6853	7.68764	-0.00233683
31/08/16	7.68292	7.68568	-0.00275993
01/09/16	7.68288	7.6833	-0.000422624
02/09/16	7.68707	7.68326	0.003811

06/09/16	7.69005	7.68745	0.002596
07/09/16	7.6899	7.69043	-0.000527634
08/09/16	7.68768	7.69028	-0.00260673
09/09/16	7.66285	7.68806	-0.025209
12/09/16	7.67742	7.66323	0.0141891
13/09/16	7.66248	7.6778	-0.015323
14/09/16	7.66189	7.66286	-0.000969088
15/09/16	7.67195	7.66227	0.00967728
16/09/16	7.66817	7.67233	-0.00416067
19/09/16	7.66815	7.66855	-0.000399842
20/09/16	7.66845	7.66853	-0.0000821448
21/09/16	7.67931	7.66883	0.0104768
22/09/16	7.68579	7.67969	0.00609751
23/09/16	7.68003	7.68617	-0.00613453
26/09/16	7.67141	7.68041	-0.00900609
27/09/16	7.67783	7.67179	0.00604226
28/09/16	7.68311	7.67821	0.00490134
29/09/16	7.67375	7.68349	-0.00974637
30/09/16	7.68168	7.67413	0.00755515
03/10/16	7.67842	7.68207	-0.00364726
04/10/16	7.67345	7.6788	-0.00534912
05/10/16	7.67774	7.67383	0.00390625
06/10/16	7.67822	7.67812	0.000100206
07/10/16	7.67496	7.6786	-0.00364003
10/10/16	7.67956	7.67534	0.00421409
11/10/16	7.66703	7.67994	-0.0129058
12/10/16	7.66818	7.66741	0.000764694
13/10/16	7.66507	7.66856	-0.00348532
14/10/16	7.66528	7.66545	-0.000179655
17/10/16	7.66223	7.66566	-0.00342386
18/10/16	7.66837	7.66261	0.00576027
19/10/16	7.67056	7.66876	0.00180833
20/10/16	7.66919	7.67095	-0.00175791
21/10/16	7.6691	7.66957	-0.000465384
24/10/16	7.67384	7.66948	0.00435736
25/10/16	7.67004	7.67422	-0.0041862
26/10/16	7.66829	7.67042	-0.00212317
27/10/16	7.6653	7.66868	-0.00337243
28/10/16	7.66219	7.66568	-0.00349438
31/10/16	7.66207	7.66257	-0.000503523
01/11/16	7.65526	7.66245	-0.00719126
02/11/16	7.64871	7.65564	-0.00692812
03/11/16	7.64428	7.64909	-0.00481445
04/11/16	7.64261	7.64466	-0.00204876
07/11/16	7.66459	7.64299	0.021599
08/11/16	7.66836	7.66497	0.00338364
09/11/16	7.67937	7.66874	0.0106349
10/11/16	7.68132	7.67975	0.00156761
11/11/16	7.67992	7.6817	-0.00178017
14/11/16	7.67981	7.6803	-0.000496748
15/11/16	7.68726	7.68019	0.00707172
16/11/16	7.68568	7.68764	-0.00196476
17/11/16	7.69034	7.68606	0.00428423
18/11/16	7.68795	7.69072	-0.00277089
21/11/16	7.69538	7.68833	0.00705246
22/11/16	7.69755	7.69577	0.00178185
23/11/16	7.69836	7.69793	0.00042646
25/11/16	7.70226	7.69874	0.00352551
28/11/16	7.69699	7.70264	-0.00564963
29/11/16	7.69833	7.69738	0.000953164
30/11/16	7.69567	7.69871	-0.00303817
01/12/16	7.69215	7.69605	-0.00390296

02/12/16	7.69255	7.69253	0.0000156892
05/12/16	7.69835	7.69293	0.00542319
06/12/16	7.70176	7.69873	0.00302385
07/12/16	7.71483	7.70214	0.0126961
08/12/16	7.71699	7.71521	0.00177578
09/12/16	7.72291	7.71737	0.00554018
12/12/16	7.72177	7.72329	-0.00151932
13/12/16	7.72829	7.72216	0.00613724
14/12/16	7.72014	7.72867	-0.00853153
15/12/16	7.72402	7.72052	0.00349447
16/12/16	7.72227	7.7244	-0.0021334
19/12/16	7.72424	7.72265	0.00159193
20/12/16	7.72787	7.72462	0.00324967
21/12/16	7.72541	7.72825	-0.00284162
22/12/16	7.72354	7.72579	-0.00224595
23/12/16	7.7248	7.72393	0.000869694
27/12/16	7.72704	7.72518	0.00186461
28/12/16	7.71865	7.72742	-0.00877288
29/12/16	7.71836	7.71903	-0.000674586
30/12/16	7.71371	7.71874	-0.00502907
03/01/17	7.72216	7.71409	0.00806953
04/01/17	7.72787	7.72254	0.00532473
05/01/17	7.72709	7.72825	-0.00115221
06/01/17	7.73061	7.72748	0.00312955
09/01/17	7.72705	7.73099	-0.00393614
10/01/17	7.72705	7.72743	-0.000381239
11/01/17	7.72988	7.72743	0.0024444
12/01/17	7.72773	7.73026	-0.00252835
13/01/17	7.72958	7.72811	0.00146689
17/01/17	7.72661	7.72996	-0.00335315
18/01/17	7.72837	7.72699	0.00138096
19/01/17	7.72475	7.72875	-0.00399708
20/01/17	7.72811	7.72513	0.00297935
23/01/17	7.72542	7.72849	-0.00307499
24/01/17	7.73196	7.7258	0.0061619
25/01/17	7.73996	7.73234	0.00761281
26/01/17	7.73922	7.74034	-0.00111689
27/01/17	7.73835	7.7396	-0.00124808
30/01/17	7.73233	7.73873	-0.00640891
31/01/17	7.73144	7.73271	-0.00127154
01/02/17	7.73173	7.73182	-0.0000829194
02/02/17	7.7323	7.73211	0.000188908
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06/02/17	7.73742	7.73992	-0.00249884
07/02/17	7.73765	7.73781	-0.000154435
08/02/17	7.73834	7.73803	0.000311844
09/02/17	7.74408	7.73873	0.00535483
10/02/17	7.74764	7.74446	0.00317847
13/02/17	7.75287	7.74802	0.00485089
14/02/17	7.75687	7.75325	0.00361809
15/02/17	7.76185	7.75725	0.00459865
16/02/17	7.76099	7.76223	-0.00124573
17/02/17	7.76266	7.76137	0.00129591
21/02/17	7.76869	7.76305	0.00564861
22/02/17	7.76761	7.76908	-0.00146402
23/02/17	7.76803	7.76799	0.0000376608
24/02/17	7.76952	7.76841	0.00111101
27/02/17	7.77054	7.7699	0.000636227
28/02/17	7.76796	7.77092	-0.00296294
01/03/17	7.78154	7.76834	0.0132
02/03/17	7.77566	7.78192	-0.00625836
03/03/17	7.77617	7.77604	0.000122512

06/03/17	7.77288	7.77655	-0.00366386
07/03/17	7.76997	7.77326	-0.00329886
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10/03/17	7.77174	7.76886	0.0028821
13/03/17	7.77211	7.77212	-0.0000146729
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15/03/17	7.77706	7.7691	0.00795864
16/03/17	7.77544	7.77744	-0.00200927
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23/03/17	7.76045	7.76189	-0.00144207
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27/03/17	7.75859	7.75999	-0.00140135
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29/03/17	7.7669	7.76619	0.000703498
30/03/17	7.76983	7.76728	0.00254957
31/03/17	7.76757	7.77021	-0.00263883
03/04/17	7.76593	7.76795	-0.00202471
04/04/17	7.76648	7.76631	0.000178127
05/04/17	7.76343	7.76687	-0.00344078
06/04/17	7.76535	7.76381	0.00154641
07/04/17	7.76453	7.76573	-0.00120871
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13/04/17	7.75317	7.76039	-0.00721926
17/04/17	7.76175	7.75355	0.00819523
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19/04/17	7.75712	7.75922	-0.00209906
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21/04/17	7.76161	7.76503	-0.00342093
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25/04/17	7.77847	7.77278	0.00569098
26/04/17	7.77798	7.77885	-0.00086706
27/04/17	7.77853	7.77836	0.000171529
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01/05/17	7.77835	7.777	0.00134955
02/05/17	7.77954	7.77873	0.000807105
03/05/17	7.77827	7.77992	-0.00165341
04/05/17	7.77885	7.77865	0.000200695
05/05/17	7.78293	7.77923	0.00369912
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10/05/17	7.78307	7.78232	0.000748724
11/05/17	7.7809	7.78345	-0.00254639
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15/05/17	7.78419	7.77981	0.0043839
16/05/17	7.7835	7.78457	-0.00106837
17/05/17	7.76516	7.78388	-0.0187267
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19/05/17	7.77558	7.76922	0.00636346
22/05/17	7.78073	7.77596	0.00476563
23/05/17	7.78257	7.78111	0.00145495
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26/05/17	7.78979	7.78986	-0.0000707367
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01/06/17	7.79567	7.78851	0.00716136

02/06/17	7.79937	7.79605	0.00331964
05/06/17	7.79815	7.79975	-0.00159965
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08/06/17	7.79721	7.79732	-0.00011407
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19/06/17	7.80525	7.79732	0.00793134
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21/06/17	7.79795	7.79892	-0.000964053
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23/06/17	7.79906	7.79788	0.00117846
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27/06/17	7.79127	7.79975	-0.00848682
28/06/17	7.80004	7.79165	0.00838826
29/06/17	7.7914	7.80042	-0.00901846
30/06/17	7.79293	7.79178	0.00115082
03/07/17	7.79524	7.79331	0.00192693
05/07/17	7.79669	7.79562	0.00107099
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14/07/17	7.80762	7.80334	0.00428138
17/07/17	7.80757	7.808	-0.000434153
18/07/17	7.80816	7.80795	0.00021644
19/07/17	7.81352	7.80855	0.00497702
20/07/17	7.81337	7.8139	-0.00053491
21/07/17	7.813	7.81375	-0.000749178
24/07/17	7.81194	7.81338	-0.00144554
25/07/17	7.81486	7.81232	0.00253767
26/07/17	7.81514	7.81524	-0.0000986146
27/07/17	7.81417	7.81552	-0.0013544
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31/07/17	7.81209	7.8132	-0.00110965
01/08/17	7.81454	7.81248	0.00206488
02/08/17	7.81503	7.81492	0.000111289
03/08/17	7.81285	7.81541	-0.00256728
04/08/17	7.81473	7.81323	0.00150608
07/08/17	7.81638	7.81512	0.00126461
08/08/17	7.81396	7.81676	-0.00279859
09/08/17	7.8136	7.81434	-0.000744913
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11/08/17	7.80029	7.7994	0.000893518
14/08/17	7.81029	7.80068	0.00961241
15/08/17	7.80979	7.81067	-0.000880171
16/08/17	7.81121	7.81017	0.00103786
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18/08/17	7.79381	7.79603	-0.00221829
21/08/17	7.79498	7.79419	0.000780737
22/08/17	7.80487	7.79536	0.00951046
23/08/17	7.80141	7.80525	-0.00384081
24/08/17	7.79933	7.80179	-0.00245786
25/08/17	7.801	7.79971	0.00129023
28/08/17	7.80149	7.80138	0.000105715
29/08/17	7.80233	7.80187	0.000461228

30/08/17	7.80694	7.80271	0.00422329
31/08/17	7.81264	7.80732	0.00532343
01/09/17	7.81462	7.81302	0.00159934
05/09/17	7.80704	7.815	-0.0079607
06/09/17	7.81017	7.80742	0.0027426
07/09/17	7.80999	7.81055	-0.00055969
08/09/17	7.8085	7.81037	-0.0018712
11/09/17	7.81928	7.80888	0.0103997
12/09/17	7.82264	7.81966	0.00297706
13/09/17	7.82339	7.82302	0.000375596
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15/09/17	7.82414	7.82267	0.00146424
18/09/17	7.82559	7.82452	0.00107362
19/09/17	7.8267	7.82597	0.000728341
20/09/17	7.82734	7.82708	0.000252908
21/09/17	7.82429	7.82772	-0.0034318
22/09/17	7.82493	7.82467	0.000266345
25/09/17	7.82271	7.82531	-0.00260576
26/09/17	7.82278	7.82309	-0.000309074
27/09/17	7.82686	7.82316	0.00369558
28/09/17	7.82806	7.82724	0.000822652
29/09/17	7.83176	7.82844	0.00331702
02/10/17	7.83563	7.83214	0.00348528
03/10/17	7.83778	7.83601	0.00177527
04/10/17	7.83903	7.83816	0.000864705
05/10/17	7.84466	7.83941	0.00524967
06/10/17	7.84359	7.84504	-0.00145545
09/10/17	7.84178	7.84397	-0.0021873
10/10/17	7.8441	7.84216	0.00193848
11/10/17	7.8459	7.84448	0.00142064
12/10/17	7.84421	7.84628	-0.00206942
13/10/17	7.84509	7.84459	0.000496483
16/10/17	7.84684	7.84547	0.00136798
17/10/17	7.84751	7.84722	0.000291114
18/10/17	7.84825	7.84789	0.000360821
19/10/17	7.84858	7.84864	-0.0000532944
20/10/17	7.85369	7.84896	0.00472256
23/10/17	7.84971	7.85407	-0.00436163
24/10/17	7.85132	7.85009	0.00123536
25/10/17	7.84665	7.8517	-0.00505519
26/10/17	7.84792	7.84703	0.000888901
27/10/17	7.85596	7.8483	0.00765937
30/10/17	7.85276	7.85634	-0.00357882
31/10/17	7.85371	7.85314	0.000562775
01/11/17	7.8553	7.85409	0.00120961
02/11/17	7.85549	7.85568	-0.00019129
03/11/17	7.85858	7.85587	0.00271105
06/11/17	7.85985	7.85896	0.000889205
07/11/17	7.85966	7.86023	-0.000570359
08/11/17	7.8611	7.86004	0.00106138
09/11/17	7.85733	7.86148	-0.00415022
10/11/17	7.85644	7.85772	-0.00127929
13/11/17	7.85742	7.85682	0.000601912
14/11/17	7.85511	7.8578	-0.00269352
15/11/17	7.84957	7.85549	-0.00592224
16/11/17	7.85773	7.84995	0.00778141
17/11/17	7.8551	7.85811	-0.00301066
20/11/17	7.85637	7.85548	0.000893631
21/11/17	7.86289	7.85675	0.0061386
22/11/17	7.86214	7.86327	-0.00113178
24/11/17	7.8642	7.86252	0.00167275
27/11/17	7.86381	7.86458	-0.00076557

28/11/17	7.87361	7.86419	0.00941909
29/11/17	7.87324	7.87399	-0.000750533
30/11/17	7.8814	7.87362	0.00777635
01/12/17	7.87937	7.88178	-0.00240782
04/12/17	7.87832	7.87976	-0.00143395
05/12/17	7.87458	7.8787	-0.00412763
06/12/17	7.87446	7.87496	-0.00049535
07/12/17	7.87739	7.87484	0.00254683
08/12/17	7.88288	7.87777	0.00510996
11/12/17	7.88608	7.88326	0.0028156
12/12/17	7.88763	7.88646	0.00116649
13/12/17	7.88715	7.88801	-0.000854307
14/12/17	7.88307	7.88753	-0.00446041
15/12/17	7.89201	7.88345	0.00855307
18/12/17	7.89736	7.89239	0.00496724
19/12/17	7.89412	7.89774	-0.00361674

		Lower 95.0%	*Upper 95.0%*
Period	*Forecast*	*Limit*	*Limit*
04/01/20	8.0892	8.07299	8.10541
06/01/20	8.08959	8.06666	8.11251
08/01/20	8.08997	8.06189	8.11804
10/01/20	8.09035	8.05793	8.12277
12/01/20	8.09073	8.05448	8.12697
14/01/20	8.09111	8.05141	8.13082
16/01/20	8.09149	8.0486	8.13438
18/01/20	8.09187	8.04603	8.13772
20/01/20	8.09225	8.04363	8.14088
22/01/20	8.09264	8.04138	8.14389
24/01/20	8.09302	8.03926	8.14678
26/01/20	8.0934	8.03725	8.14955
28/01/20	8.09378	8.03533	8.15222
30/01/20	8.09416	8.03351	8.15481
01/02/20	8.09454	8.03176	8.15732
03/02/20	8.09492	8.03008	8.15976
05/02/20	8.0953	8.02847	8.16214
07/02/20	8.09569	8.02691	8.16446
09/02/20	8.09607	8.02541	8.16672
11/02/20	8.09645	8.02396	8.16894
13/02/20	8.09683	8.02255	8.17111
15/02/20	8.09721	8.02118	8.17324
17/02/20	8.09759	8.01985	8.17533
19/02/20	8.09797	8.01856	8.17738
21/02/20	8.09835	8.01731	8.1794
23/02/20	8.09873	8.01608	8.18139
25/02/20	8.09912	8.01489	8.18334
27/02/20	8.0995	8.01372	8.18527
29/02/20	8.09988	8.01259	8.18717
02/03/20	8.10026	8.01148	8.18904
04/03/20	8.10064	8.01039	8.19089
06/03/20	8.10102	8.00933	8.19272
08/03/20	8.1014	8.00829	8.19452
10/03/20	8.10178	8.00727	8.1963
12/03/20	8.10217	8.00627	8.19806
14/03/20	8.10255	8.00529	8.1998
16/03/20	8.10293	8.00433	8.20153
18/03/20	8.10331	8.00339	8.20323
20/03/20	8.10369	8.00246	8.20492
22/03/20	8.10407	8.00155	8.20659
24/03/20	8.10445	8.00066	8.20825
26/03/20	8.10483	7.99978	8.20988

28/03/20	8.10522	7.99892	8.21151
30/03/20	8.1056	7.99808	8.21312
01/04/20	8.10598	7.99724	8.21472
03/04/20	8.10636	7.99642	8.2163
05/04/20	8.10674	7.99561	8.21787
07/04/20	8.10712	7.99482	8.21943
09/04/20	8.1075	7.99404	8.22097
11/04/20	8.10788	7.99327	8.2225
13/04/20	8.10827	7.99251	8.22403
15/04/20	8.10865	7.99176	8.22554
17/04/20	8.10903	7.99102	8.22704
19/04/20	8.10941	7.99029	8.22853
21/04/20	8.10979	7.98958	8.23
23/04/20	8.11017	7.98887	8.23147
25/04/20	8.11055	7.98817	8.23293
27/04/20	8.11093	7.98749	8.23438
29/04/20	8.11132	7.98681	8.23582
01/05/20	8.1117	7.98614	8.23726

Note:
This table shows the forecasted values for S&P 500. During the period where actual data is available, it also displays the predicted values from the fitted model and the residuals (data-forecast). For time periods beyond the end of the series, it shows 95.0% prediction limits for the forecasts. These limits show where the true data value at a selected future time is likely to be with 95.0% confidence, assuming the fitted model is appropriate for the data.