Summer 8-2023

Two Essays on Investor Sentiment

Amin Amoulashkarian
Old Dominion University, a.amoulashkarian@gmail.com

TWO ESSAYS ON INVESTOR SENTIMENT

by:

Amin Amoulashkarian
B.Sc. in Aerospace Engineering, Sharif University, Tehran, Iran 2013
MBA, Sharif University, Tehran, Iran 2017

A Dissertation Submitted to the Faculty of
Old Dominion University in Partial Fulfillment of the
Requirements for the Degree of

DOCTOR OF PHILOSOPHY

BUSINESSS ADMINISTRATION – FINANCE

OLD DOMINION UNIVERSITY
August 2023

Approved by:

Mohammad Najand (Chair)

Mobina Shafaati (Member)

David Selover (Member)

ABSTRACT

TWO ESSAYS ON INDUSTRY INVESTOR SENTIMENT

Amin Amoulashkarian
Old Dominion University, 2023
Director: Dr. Mohamad Najand

The body of literature on investor sentiment underlines its impact on future stock returns, with general consensus that investor sentiments and future returns are negatively correlated (Baker and Wurgler, 2006; Brown and Cliff, 2004). This extends to the notion that a bullish investor would expect returns to be above average, while a bearish investor anticipates below-average returns (Brown and Cliff, 2004).

The first essay proposes a model to examine the influence of unexpected volatility of investor sentiment on the equity risk premium. Assumptions underpinning the model include risk-averse investors, homogeneous expectations regarding asset returns and price changes, and sentiment-influenced expectations of asset returns. The model also presumes continuous-time stochastic (Weiner) processes for asset returns and sentiment. The developed model is rooted in several principles, including the Efficient Market Hypothesis, Martingale theory, and the impact of uncertain sentiment change on stock returns. Utilizing Thomson Reuters MarketPsych Indices for data analysis, the model tests sentiment metrics against the performance of the S&P 500. The results provide insights into the dynamics of investor sentiment and its impact on equity risk premium, laying the groundwork for further empirical investigation. In the first essay, we evaluate the link between industry tournament incentives and investment inefficiency. We find that firms with higher tournament incentives exhibit higher investment inefficiency. Additionally, cross-sectional tests suggest that these effects operate at least in part through both a financing channel and a monitoring channel. Taken together, our results suggest that industry tournament incentives place pressure on CEOs and affect the efficiency of firm investments.

In the second essay, we examines the phenomenon of sentiment transmission across stock markets, focusing on the influence of U.S. investors' sentiment on G7 countries. The study utilizes data from the Global Finance database, including stock indices for G7 countries and two measures

of sentiment for the U.S. market: news sentiment and social media sentiment. News sentiment captures the impact of positive and negative news articles on market sentiment, while social media sentiment reflects the influence of social media posts on market sentiment. The analysis employs a vector autoregression (VAR) model and Multivariate GARCH model to understand the interdependence of these variables and how changes in U.S. investors' sentiment affect other markets. The study highlights the increasing prevalence and significant impact of sentiment transmission due to the global interconnectedness of markets, amplified by financial innovations like ETFs. The findings contribute to a better understanding of sentiment transmission and its implications for global financial markets, providing insights for policymakers and market participants.

I dedicate my dissertation to my family and the close friends who have stood by me throughout this journey. My heartfelt thanks go to my wonderful wife. Her consistent belief in my abilities and endless encouragement have been instrumental to my progress. I'm also incredibly grateful to my father and mother for their constant love and support. Their wisdom and patience have been my guiding lights, helping me to navigate through this academic adventure. This significant achievement wouldn't have been possible without their enduring presence and unshakeable belief in me. Furthermore, I dedicate this dissertation to the invaluable assistance offered by many faculty and staff members at the Strome College of Business.

ACKNOWLEDGEMENTS

There are several individuals whose steadfast support has been instrumental throughout this journey, for whom I reserve my sincerest gratitude. At the forefront of this group is my esteemed supervisor, Dr. Mohammad Najand, to whom I owe the possibility of this work. Dr. Najand has generously devoted countless hours to thoughtful reflection, meticulous reading, and above all, exhibited an extraordinary level of patience throughout this process. The wisdom and insights he imparted have been invaluable to my journey towards achieving this Ph.D. His guidance and mentorship will be treasured always, a beacon that illuminated the path of my academic pursuit.

In addition, my appreciation extends to the members of my dissertation committee, Dr. David Selover and Dr. Mobina Shafaati. Their generosity in sharing their profound expertise and time has enriched my dissertation. Their review and insightful feedback provided me with a heightened understanding and a fresh perspective, enhancing the quality of my research work. Their contribution to my dissertation journey leaves me grateful and indebted to them.

TABLE OF CONTENTS

Page

LIST OF TABLES VII

LIST OF FIGURES IX

LIST OF GRAPHS X

ESSAY 1: ASSET PRICING MODELS AND INVESTOR SENTIMENT 1

Introduction 1

Literature Review 2

Model Development 5

Data and Methodology 12

Descriptive Statistics 12

Stock Returns Volatility, Sentiment and GARCH Models 14

Causality and CALIS Procedure 19

Unobserved Components Models (UCM) and cyclicality of Sentiment 22

References 25

ESSAY 2: MODELING THE TRANSMISSION OF SENTIMENT ACROSS DIFFERENT MARKETS: A MULTIVARIATE DYNAMIC APPROACH 66

Introduction 66

Literature Review 67

Data and Methodology 70

Multivariate Time Series Analysis Using VARMAX 70

Granger Causality Wald Test for the VAR Model 73

Plots of the Impulse Response. 74

Cumulative Effects 75

Effects of Orthogonal Shocks 75

The US Sentiment Spillover Analysis Using VARMAX 76

Granger Causality Wald Test for the SVAR Model 77

PATH Analysis. 77

Multivariate GARCH Analysis. 78

References. 82

VITA. 132

LIST OF TABLES

Table Page

1.1 Summary Statistics....32
1.2 Moments for Variable SPR....33
1.3 Moments for Variable Sentiment....34
1.4 Basic Statistical Measures for SPR....35
1.5 Basic Statistical Measures for Sentiment....36
1.6 Basic Statistical Measures for SPR....37
1.7 Basic Statistical Measures for Sentiment....38
1.8 Ordinary Least Squares Estimates Dependent Variable Sentiment....39
1.9 OLS Parameter Estimates Dependent Variable Sentiment....40
1. 10 Estimates of Autoregressive Parameters Dependent Variable Sentiment....41
1. 11 GARCH Estimates Dependent Variable Sentiment....42
1. 12 GARCH Parameter Estimates Dependent Variable Sentiment....43
1. 13 Ordinary Least Squares Estimates Dependent Variable SPR....44
1. 14 OLS Parameter Estimates Dependent Variable SPR....45
1. 15 Estimates of Autoregressive Parameters Dependent Variable SPR....46
1. 16 GARCH Estimates Dependent Variable SPR....47
1. 17 GARCH Parameter Estimates Dependent Variable SPR....48
1. 18 SBC & AIC Criteria....49
1. 19 Ordinary Least Squares Estimates Dependent Variable RP....50
1. 20 OLS Parameter Estimates Dependent Variable RP....51
1. 21 GARCH Estimates Dependent Variable RP....52
1. 22 GARCH-M Parameter Estimates Dependent Variable RP....53
1. 23 PATH List....54
1. 24 Variance Parameters....55
1. 25 Covariances Among Exogenous Variables....56
1. 26 Squared Multiple Correlations....57
1. 27 UCM Final Estimates of the Free Parameters....58
1. 28 UCM Fit Statistics Based on Residuals....59
2.1 Descriptive Statistics....85
2.2 Model Parameter Estimates of VAR(5) for R-US....86
2.3 Model Parameter Estimates of VAR(5) for R-Japan....87
2.4 Model Parameter Estimates of VAR(5) for R-UK....88
2.5 Model Parameter Estimates of VAR(5) for R-France....89
2.6 Model Parameter Estimates of VAR(5) for R-Germany....90

2.7 Model Parameter Estimates of VAR(5) for R-Italy....................91
2.8 Model Parameter Estimates of VAR(5) for R-Canada....................92
2.9 Granger-Causality Wald Test for the R-US....................93
2. 10 Model Parameter Estimates of VARX(5,0) for R-US....................94
2. 11 Model Parameter Estimates of VARX(5,0) for R-Japan....................95
2. 12 Model Parameter Estimates of VARX(5,0) for R-UK....................96
2. 13 Model Parameter Estimates of VARX(5,0) for R-France....................97
2. 14 Model Parameter Estimates of VARX(5,0) for R-Germany....................98
2. 15 Model Parameter Estimates of VARX(5,0) for R-Italy....................99
2. 16 Model Parameter Estimates of VARX(5,0) for R-Canada....................100
2. 17 Granger-Causality Test for the US Sentiment....................101
2. 18 PATH List....................102
2. 19 GARCH (1,1) Model Parameter for US Sentiment & US Return....................103
2. 20 GARCH (1,1) Model Parameter for US Sentiment & Japan Return....................104
2. 21 GARCH (1,1) Model Parameter for US Sentiment & UK Return....................105
2. 22 GARCH (1,1) Model Parameter for US Sentiment & France Return....................106
2. 23 GARCH (1,1) Model Parameter for US Sentiment & Germany Return....................107
2. 24 GARCH (1,1) Model Parameter for US Sentiment & Italy Return....................108
2. 25 GARCH (1,1) Model Parameter for US Sentiment & Canada Return....................109

LIST OF FIGURES

Figure Page

1.1 Fit Diagnostics for Sentiment 60

1.2 Fit Diagnostics for SPR 61

1.3 Fit Diagnostics for RP 62

1.4 PATH Analysis for Unsentimentvol, Unsprvol RP 63

1.5 Smoothed Trend for RP 64

1.6 Forecasts for RP. 65

LIST OF GRAPHS

Graph Page

2. 1 Response to Impulse in R-US. 110
2. 2 Response to Impulse in R-Japan 111
2. 3 Response to Impulse in R-UK 112
2. 4 Response to Impulse in R-France 113
2. 5 Response to Impulse in R-Germany 114
2. 6 Response to Impulse in R-Italy 115
2. 7 Response to Impulse in R-Canada 116
2. 8 Accumulated Response to Impulse in R-US 117
2. 9 Accumulated Response to Impulse in R-Japan 118
2. 10 Accumulated Response to Impulse in R-UK 119
2. 11 Accumulated Response to Impulse in R-France 120
2. 12 Accumulated Response to Impulse in R-Germany 121
2. 13 Accumulated Response to Impulse in R-Italy 122
2. 14 Accumulated Response to Impulse in R-Canada 123
2. 15 Response to Orthogonalized Impulse in R-US 124
2. 16 Response to Orthogonalized Impulse in R-Japan 125
2. 17 Response to Orthogonalized Impulse in R-UK 126
2. 18 Response to Orthogonalized Impulse in R-France 127
2. 19 Response to Orthogonalized Impulse in R-Germany 128
2. 20 Response to Orthogonalized Impulse in R-Italy 129
2. 21 Response to Orthogonalized Impulse in R-Canada 130
2. 22 PATH Analysis 131

ESSAY 1: ASSET PRICING MODELS AND INVESTOR SENTIMENT

Introduction

Classical finance theory initially posited that investor sentiment had no substantial influence on stock prices, realized returns, or expected returns. Nonetheless, recent research contradicts this notion, illustrating that investor sentiment, when broadly defined, considerably impacts stock prices and returns cross-sectionally (Baker & Wurgler, 2006). This has spurred an increased interest in comprehending and quantifying investor sentiment, with the Investor Sentiment Index becoming a prevalent instrument (González-Sánchez & Morales, 2021).

The primary empirical discovery of the Baker & Wurgler's (2006) paper reveals that future stock returns' cross-section depends on sentiment proxies at the beginning of the period. Notably, several firm characteristics with no unconditional predictive capacity display robust conditional patterns that only surface after factoring in sentiment. Moreover other papers emphasize the literature's evolution in acknowledging the asymmetrical consequences of negative and positive news on investor sentiment (Bowman, 1983) and the temporal asymmetry between recession and expansion periods (DeLong & Shleifer, 1990; Heidinger & Gatzert, 2016; Kumar & Lee, 2006).

Despite heightened interest in investor sentiment's explanatory power, consensus regarding the construction of sentiment indexes and the inclusion of specific variables or information remains elusive (Chan, 2017). Certain information providers and financial institutions, such as Reuters and Bloomberg, have endeavored to tackle this challenge by creating their investor sentiment indexes; however, many of these indexes have not been validated beyond their study samples (Tetlock, 2007; García, 2013; Xiong, Meng & Lee, 2020).

The findings from the Baker & Wurgler (2006) indicated potential future research directions in corporate finance and asset pricing, encompassing a more comprehensive understanding of sentiment's function in security issuance and the provision of firm characteristics that appear conditionally pertinent to share prices. Furthermore, the subsequent multiple papers acknowledged the exploration of investor sentiment's impact on volatility and trading volume while differentiating between small and institutional investors (Tetlock, 2007; García, 2013; Verma & Verma, 2007; Renault, 2007; Johnman, Vanstone & Gep, 2017).

The remainder of the paper is organized as follows. Section 2 reviews related literature.

Section 3 develops the model. Section 4, 5 and 6 presents data and methodology.

Literature Review

Most of the research in the financial literature reports the relationship between investor sentiment and financial markets (Baker, Wurgler, & Yuan, 2007; Renault, 2017). The main focus of the literature for the market variable is the return asset, but there are some studies that apply trading volume (Pineiro-Chousa, 2016; Gonzalez Sanchez, 2018)and volatility (Chiou, 2010; Antweiler, 2004).

Shen et al.(2023) supports the idea that investor emotions influence stock returns. It investigates emotions expressed in news and social media and finds that company-specific media-based emotions significantly impact stock returns across different periods, economic cycles, and market sentiment states. The effect of investor emotions is stronger with frequent media mentions and cannot be replaced by single-dimension sentiment.

In contrast, there is no agreement on the measurement of investor sentiment, and multiple approaches on how to measure it have been introduced in the growing literature (Sun, 2016). Gonzalez-Sanchez & Morales de Vega (2021) have provided an excellent review of the literature on sentiment measuring approaches. According to them, the first approach to investor sentiment is to develop an index that includes market variables (Baker, Wurgler, & Yuan, 2007; Baker M. a., 2006). A key drawback of this method is the possibility of capturing other types of information that are not relevant to investors' perceptions of these types of indices.

The second approach is to create indexes using investor surveys (Da, 2015). There are various indexes of the US market: the University of Michigan Consumer Emotion Index (a monthly index calculated from a consumer confidence survey of a random group of 500 American households (Chung, 2012; Zouaoui, 2011; Lemmon, 2006; Schmeling, 2007; Ho, 2009; Stambaugh, 2012; Fisher, Consumer confidence and stock returns, 2003); the Investor Index and the Daily Emotions Index (an index that identifies the balance between bull and bear investors) (Frijns B. a., 2018); And American Individual Investors Association Survey (Index that provides weekly data on the bullish, bearish, or neutral of a series of financial market surveys over the next six months) (Brown, 2004; Verma R. a., Noise trading and stock market volatility, 2007; Fisher, Investor sentiment and stock returns, 2000; Kurov, Investor sentiment, trading behavior and informational efficiency in index futures markets, 2008; Fong, 2013; Verma R. a., 2009). The monthly index of consumer confidence of the European Commission has been applied to the European Union (Jansen, 2003).

Overall, this survey-based empirical research approach discovers a significant relationship between the market variables and sentiment indices. However, similar to the case in the first approach, there are multiple problems with using this method. For example, these surveys can not be trusted when the motivation for giving an honest answer and the response rate is low (Sun, 2016).

A third approach is to construct sentiment indices based on information offered by the media. Several advantages have been attributed to the application of this approach, like the cheaper cost of acquiring data, availability of more time-frequent data in comparison to the previous methods (daily instead of weekly or monthly in surveys), and the possibility of being applicable to a higher number of stocks. In this method, Based on the sources of news, three forms of application can be identified- first, use of news from an internet search engine, like utilizing Google keywords, while browsing within certain publications on Google (Da, 2015; Dimpfl, 2016); secondly, derivation of news from social media like Twitter and Facebook (Siganos, Facebook's daily sentiment and international stock markets, 2014; Siganos, Facebook's daily sentiment and international stock markets, 2014); and lastly, news obtained from expert financial media such as Wall Street Journal, Bloomberg and Yahoo finance (Garcia, 2013; Tetlock, 2007).

In general, these studies empirically attempt to find a significant relationship between market return and investor media news-based sentiment indices. Moreover, studies highlight the importance of this relationship in the case of firms with higher risk or extreme shares return (Chung, 2012; Corredor, 2013; Baker M. a., 2006). However, similar to the other two approaches, this method suffers from the problem of different impacts and direction of the market return and investor sentiment relationship conditioned on the source of information employed. The frequency effect has been recognized as one of the issues. Due to the growing adoption of investor sentiment indices in empirical research, scholars are increasingly utilizing high-frequency data (such as daily and intraday data) instead of relying solely on monthly or weekly data. This trend is evident in recent works by Renault (2017), Sun (2016), and Gao (2020), who have incorporated high-frequency data into their research, whereas earlier studies by Fang (2009), Hribar (2012), and Frijns B. a. (2017) relied on monthly or weekly data. Some studies show that the frequency of the data matters because it determines the sign of the relationship between the portfolio return and the sentiment (Ding, 2019). In particular, there is a positive relationship between high-frequency-based sentiment and returns and a negative one between low-frequency-sentiment and portfolio returns.

Another body of literature that has been growing simultaneously with investor sentiment indices is the exploration of the link between market return and textual analysis of news (Brigida, 2017). There is no consensus on the explanatory power of these proxies. Some studies note that textual analysis-based proxies are a possible causal mechanism at play (Das, 2005; Tumarkin, 2001). While other studies produce contradictory evidence as a result of the asymmetry between words with negative and positive connotations, various linguistic perceptions among investors, the language of the news release, and the market where the news is from, thus casting further doubt on the use of such proxies (Frijns B. a., 2017; Zhang Y. a., 2012).

There is no clear evidence of whether institutional investor sentiment plays a role in the explanation of market returns (Klemola, 2016). Some studies find that institutional investor sentiment is associated with the behavior of market prices (Lee, 2002; Verma R. a., 2006) while other studies indicate that this sentiment does not appear to play a strong or even any role (Brown, 2004). Some studies illustrate that analysts rely on their knowledge and are inclined to herd less towards the consensus recommendation stemming from higher news coverage of a particular firm (Frijns B. a., 2018). However, they are likely to follow the herd behavior when the stock has had negative news, consistent with the notion that analysts are reluctant to distinguish themselves from the crowd when conveying negative news. This reluctance intensifies among analysts with investment bank affiliations and those covering high trading volume stocks. Consequently, the investor’s size and knowledge or expertise have implications for the explanatory power of investor sentiment.

Overall, Based on the above review of studies of investor sentiment in financial markets, the empirical studies could be categorized into two fundamental characteristics: first, those papers that consider an asset valuation model to measure the relationship between market returns of assets and investor sentiment (Smales, 2015; Pineiro-Chousa, 2016; Kurov, Investor sentiment and the stock market’s reaction to monetary policy, 2010; Teti, 2019), versus those who do not (Ng, 2016; Sabherwal, 2011; Fang, 2009; Tetlock, 2007); and secondly, studies that develop their own sentiment indices (Corredor, 2013; Baker M. a., 2006; Ng, 2016) versus those deploying indices created by specialized investors or economic agents (Tetlock, 2007; Fang, 2009;

Papakyriakou, 2019).

To sum up, all the aforementioned papers emphasize the significance of investor sentiment in financial markets and its notable effect on stock prices and returns. The expanding literature in this area has prompted the creation of diverse methodologies and approaches for measuring investor sentiment and efforts to develop more dependable sentiment indexes. As research in this domain progresses, a more profound comprehension of investor sentiment's role and dynamics in financial markets can be anticipated.

Model Development

The purpose of this section is to develop a model to study the impact of investors' sentiment on the equity risk premium. The model will provide a basis for empirical testing for the impact of sentiment on risky assets. The following assumptions are made to derive the model:

(1) Investors are risk averse, single period expected utility of real terminal wealth maximized.

(2) Investors have homogenous expectations with respect to the rate of assets returns and price changes.

(3) Investors' expectations of asset returns are influenced by their emotions.

(4) Returns on assets and presentiment follow continuous-time stochastic (Weiner) processes.

The first assumption implies that the individuals' utility functions are assumed to be strictly concave. This implies that: (1) they always prefer more wealth to less (the marginal utility of wealth is positive, MU(W)>0), and (2) their marginal utility of wealth decreases as they have more and more wealth (dMU(W)/dW<0). Also since all investors maximize the expected utility of their end-of-period wealth, the model is implicitly a one-period model.

The second assumption implies that investors make decisions based on an identical opportunity set. In other words, no one can be fooled because everyone has the same information at the same time.

The last assumption implies that (a) the capital markets are assumed to be open all the time, and therefore economic agents have the opportunity to trade continuously, (b) asset prices traded in speculative markets satisfy the "Efficient Market Hypothesis" of Fama (1970) and Samuelson (1965). Namely, assets are priced so that the stochastic processes describing the unanticipated parts of their expected value are martingale. The notion that stochastic processes are martingale is generally accepted by financial economists (see for example; Fama (1965), Mandelbrot (1966)). A martingale is a stochastic process (X_i), where for all i = 1,2…

1. $E(|X_i|) < \infty$; and
2. $E(X_{i+1}|X_1, \dots, X_i) = X_i$

This is often called a "fair game" since the expected future value of a variable is equal to its most recent realization. In a market characterized by risk-averse investors, the martingale model is appropriate if the arbitrage profits are to be eliminated. A proof for this proposition is provided by Samuelson (1965). Markets characterized by the absence of arbitrage profits are generally accepted in the finance literature. If investors are risk-averse, the appropriate arbitrage arguments deal not with "profits" of expected returns, but rather with expected utility. It is further assumed that the asset returns are generated by diffusion processes with continuous sample paths and that returns are serially independent and identically distributed through time, i.e., that prices follow a geometric Brownian motion or Wiener process, and hence the prices are lognormally distributes (for a detail discussion see Merton (1975)).

The general Wiener process x is described by the following stochastic differential equation. This equation is often used as a model of the rate of return on stocks (Merton (1973, 1978), Friend, Landskroner, and Losq (1976), Pindyck (1984) among others).

$$dx = adt + bdz \tag{1}$$

Where $dz = \varepsilon\sqrt{dt}$, ε is a standard normal variable with the expected value of zero and variance of 1 and a and b are constants. The process is a Wiener process with drift *a* and variance b^2. The expected value of dx is adt. The drift, a, is often called the expected instantaneous rate of change of x.

We assume that the rate of sentiment flow is stochastic and described by:

$$d(Sentiment) = sent = E(sent)dt + s_{sent}dz \quad (2)$$

Where dz = $\varepsilon\sqrt{dt}$ as mentioned before, with ε a serially uncorrelated and normally distributed random variable with zero mean and unit variance, that is, z is a Wiener process. Thus, over an interval dt, expected sentiment is $E(sent)$ and its variance is s_{sent}^2. Therefore, the standard deviation of the Wiener process of sentiment changes (s_{sent}) represents uncertain sentiment. Substituting for dz, equation (2) can be written as:

$$sent = E(sent)dt + s_{sent}\varepsilon_{sent}\sqrt{dt} \quad (3)$$

Similarly, the dynamic of the real return on equity is described as:

$$r_s = E(r_s)dt + s_s dz_s \quad (4)$$

Where $E(r_s)$ is the expected return on equity per unit of time. Since this research is concerned about the effect of uncertain sentiment change on the stock returns, another term should be added to equation (4) that reflects this effect. This is permissible, as Merton (1975) points out, as long as the added term reflects a specific additional source of uncertainty.

$$r_s = E(r_s)dt + s_s dz_s + \beta_s s_{sent} dz_{sent} \quad (5)$$

Where s_s is the stochastic component of asset returns which is independent of uncertain sentiment change, i.e., $E(\varepsilon_s \varepsilon_{sent}) = 0$ and $\beta_s = cov(r_s, sent)/s_{sent}^2$. Substituting for dz:

$$r_s = E(r_s)dt + s_s dz_s + \beta_s s_{sent} \varepsilon_{sent} \sqrt{dt} \qquad (6)$$

In equation (6) β_s measures the degree of the real stock returns changes with respect to uncertain changes.

Next, following Friend, Landskroner, and Losq (1976), the real wealth dynamic for the investors is derived. It should be pointed out that Friend, Landskroner, and Losq derive the Capital Asset Pricing Model (CAPM) adjusted for the inflation. However, this study derives the effect of uncertain sentiment on the risk premium. Assuming the investors are rational, they adjust their portfolio upon the arrival of new information about any changes in the price level. The real wealth dynamic for the kth investor may be written in a stochastic differential equation form:

$$W_{k,t+dt} = W_{k,t}(1 + \tau_{Fk} r_F dt + \tau_{sk} r_s dt) \qquad (7)$$

$$= \quad W_{k,t} + (\tau_{Fk} r_F dt + \tau_{sk} r_s dt) W_{k,t}$$

Where $W_{k,t}$ = the wealth of the kth investor at time t,

r_F = the real risk-free rate of return,

τ_{sk}= the proportion of the wealth invested in stocks by the kth investor,

τ_{Fk}= the proportion of the wealth invested in the risk-free rate by the kth investor,

The investor's budget constraint is defined as:

$$\tau_{Fk} + \tau_{sk} = 1 \qquad (8)$$

By substituting equation (9) into equation (8), we get:

$$W_{k,t+dt} = W_{k,t} + [r_F dt + \tau_{sk}(r_{s-}r_F)dt]W_{k,t} \tag{9}$$

Differentiating the expected utility of the final real wealth, $W_{k,t+dt}$, with respect to τ_{sk}, the first order condition for the maximum is derived.

$$E[u'(W_{k,t+dt})(r_s - r_F)dt] = 0 \tag{10}$$

Expanding the marginal utility of real wealth function in a Taylor series about $W_{k,t}$; equation (11) is obtained:

$$u'(W_{k,t+dt}) = u'(W_{k,t}) + u''(W_{k,t})(W_{k,t+dt} - W_{k,t}) + \varphi \tag{11}$$

Where φ is the remaining terms in the Taylor series expansion. Pratt (1964) assumes that second order and higher terms are insignificant ($\varphi = 0$). By finding the value of $W_{k,t+dt} - W_{k,t}$ from equation (9) and inserting it into equation (11) and ignoring φ we get:

$$u'(W_{k,t+dt}) = u'(W_{k,t}) + u''(W_{k,t})(W_{k,t})[r_F dt + \tau_{sk}(r_s - r_F)dt] \tag{12}$$

By substituting equation (12) into equation (10),

$$u'(W_{k,t})E(r_s - r_F)dt + u''(W_{k,t})W_{k,t}E[\{r_F dt + \tau_{sk}(r_s - r_F)dt\}(r_s - r_F)dt] = 0 \quad (13)$$

Since $E[r_F dt(r_s - r_F)dt] = \text{cov}(r_F, r_s - r_F)dt$ and $E[\{(r_s - r_F)dt\}^2] = \text{var}(r_s - r_F)dt,$ equation (13) becomes:

$$u'(W_{k,t})E(r_s - r_F)dt + u''(W_{k,t})W_{k,t}\,\text{cov}(r_F, r_s - r_F)dt + \tau_{sk}\,\text{var}(r_s - r_F)dt = 0 \quad (14)$$

Equation (14) can be written in the following form:

$$E(r_s - r_F) = C_k[\text{cov}(r_F, r_s - r_F)] + \tau_{sk}\,\text{var}(r_s - r_F) \quad (15)$$

Where $C_k = -W_{k,t}\{u''(W_{k,t})/u'(W_{k,t})\}$ is the Arrow-Pratt measure of relative risk aversion. Following the aggregation method used by Friend, Landskroner, and Losq (1976), equation (15) is aggregated over individual investors according to their proportions of initial wealth to the total initial wealth. To derive market equilibrium condition, let $\Gamma_k = W_{k,t}/\sum W_{k,t}$ and $\Omega = (\sum \Gamma_k/C_k)$. By multiplying both sides of equation (15) by Ω/C_k and aggregating over all investors, the market equilibrium is derived.

$$E(r_s - r_F) = \Omega\,[cov(r_F, r_s - r_F)] + \tau_{sk} var(r_s - r_F) \quad (16)$$

In equation (16), Ω represents the market price of risk and τ_{sk} is the total value of common stock to the total value of all assets. Furthermore, it can be shown from return generating function [equation (6)] that:

$$cov(\,r_F, r_s - r_F) = s_{sent}^2(\beta_s - 1) \quad (17)$$

and

$$var(\, r_s - r_F) = s_s^2 + s_{sent}^2(\beta_s - 1)^2 \quad (18)$$

By substituting equation (17) and (18) into (16):

$$E(r_s - r_F) = \Omega[s_s^2 + s_{sent}^2(\beta_s^2 - \beta_s)]\tau_s \quad (19)$$

Following Ross (1976), it is assumed that the net supply of the risk-free asset is zero, i.e., $\tau_s = 1$
, then equation (20) becomes:

$$E(r_s - r_F) = \Omega[s_s^2 + s_{sent}^2(\beta_s^2 - \beta_s)] \quad (20)$$

By taking the first derivative of (20) with respect to s_{sent}^2,

$$dE(r_s - r_F)/ds_{sent}^2 = \Omega[(\beta_s^2 - \beta_s)] > 0 \quad (21)$$

Where R_S is the nominal return on stocks and R_F is the nominal return on risk-free rate:

$$E(r_s - r_F) = E(R_s - R_F) \quad (22)$$

Thus equation (20) becomes:

$$E(R_s - R_F) = \Omega[s_s^2 + s_{sent}^2(\beta_s^2 - \beta_s)] \tag{23}$$

Equation (23) states that the equity risk premium is affected by the risk of common stocks s_s^2 unexpected sentiment volatility (s_{sent}) and the degree of responsiveness of the stock returns with respect to uncertain sentiment volatility β_s This equation is the basis of my empirical study for measuring the effect of uncertain sentiment on the market risk premium which is conducted in the next chapter.

Data and Methodology

Descriptive Statistics

MarketPsych of Thomson Reuters provides the sentiment data used in our analysis. The Thomson Reuters MarketPsych Indices (TRMI) analyze contents from the news and social media in real time. This allows them to translate the massive amount of professional news and online information into data streams that can be easily digested and used to make decisions that are more in accordance with reality. Three categories of indicators are offered:

• Macroeconomic measures like Earnings Forecast, Interest Rate Forecast, and Long vs. Short

• Emotional markers such as Anger, Fear, and Joy

• Buzz indicators at the asset level, for example, Buzz, and concerning market-impacting subjects related to the asset, such as Litigation, Mergers, and Volatility

These indices are provided as real-time data sequences that can be seamlessly integrated into your investment and trading decision-making processes, whether quantitative or qualitative.

The indicators are refreshed every minute for various entities, including companies, sectors, regions, nations, commodities, energy subjects, indices, and currencies. These can be directly converted into spreadsheets or visualizations that can be observed by traders, risk managers, or analysts. Alternatively, they can be directly integrated into your algorithms for low-frequency or long-term asset allocation or sector rotation decisions.

All TRMIs are constructed from material written throughout a given period of time. It is more accurate to have the index value "NA" (Not Applicable) rather than zero if no relevant material is found for that index during that time period.

All TRMIs are built from articles published throughout a specific time frame. If no relevant content is located for a certain index within the given time period, it is preferable to have the index value show as "NA" (Not Applicable) rather than zero.

TRMI sentiment extends between -1 and 1, representing the net balance of positive references against negative references. The daily data covers the period from January 1, 1998, to December 31, 2021. As an indicator of market returns, we utilize the log returns on the S&P 500 index, sourced from the Kenneth R. French Data Library database.

Table 1 provides summary statistics for the full sample of 6164 daily observations from January 1, 1998, to December 31, 2021. Among the variables, SPR is the log of the daily SP500 index returns, RF is the daily risk-free rate; RP is the risk premium that comes from deducting the RF from the SPR; LPR is the lag of risk premium (RP), SPRVol is the volatility of SPR calculated by SPR to the power of two; and Sentimentvol is the sentiment volatility that is sentiment to the power of two.

[Insert Table 1 here]

In the next tables summaries of the SPR and sentiment variables are represented. These tables are useful for visualizing the distribution of the variables and detecting any outliers or unusual patterns.

[Insert Table 2 through 7 here]

Stock Returns Volatility, Sentiment and GARCH Models

The fluctuation of stock returns presents a significant and complex challenge in the field (Zhou, 2016). There are two primary characteristics of this issue: the first is the time-dependent nature of volatility, and the second is the occurrence of abrupt and substantial increases or decreases in stock returns within a short timeframe, a phenomenon known as "jumping behavior" (Chu, 2021; Liu, 2020).

Time series plots frequently reveal a pattern of stability interrupted by periods of substantial variation. This is especially noticeable in financial time series, where the market conditions often remain steady with minimal day-to-day changes. However, at times, drastic shifts occur, leading to consecutive days of larger market movements. These shifts could follow significant announcements, such as financial reports, or suggest a market crisis requiring the establishment of a new equilibrium.

This pattern of fluctuation isn't exclusive to financial data; it's observed in other domains too. For instance, meteorological data may exhibit long periods of stable weather conditions, punctuated by rapid changes. This type of behavior challenges the assumption of independent residuals in time series models because it implies inconsistent variance or changing volatility throughout the observation period.

From a mathematical standpoint, such observations suggest the inadequacy of the estimated model. Theoretically, this inadequacy implies inefficiency in the model's estimation method, and the reported standard deviations of the estimated parameters, as well as the distribution of test statistics, are likely to be inaccurate.

This shortfall might not pose a significant problem for general forecasting or parameter estimation tasks. However, in financial modeling, assessing risk is crucial, and it's often quantitatively measured as variance. Hence, GARCH models treat the variance of a time series as a time series itself, aimed at forecasting future variances. In other words, these models are employed for predicting future risk.

With the growing emphasis on risk reporting by financial institutions, especially following the 2008 financial crisis and subsequent regulations like Solvency II for insurance companies, this aspect has gained substantial importance.

While ARIMA or VARMA models may adequately address the autocorrelation structure of residuals, they often overlook other forms of dependence. Variance clustering, a higher-order dependence than autocorrelation, is one such overlooked feature. The forthcoming section discusses models that extend beyond handling the autocorrelation structure of time series values to modeling the variance of a time series.

These models can be complex due to the abundance of parameters and the large variance of estimated variance. These complexities can result in unstable estimation procedures and occasional issues. In certain scenarios, the estimation process may need fine-tuning, for instance, by specifying initial values for the parameters in the VARMAX procedure in the SAS that is used as the main econometric software in this essay.

Focusing on the GARCH Model, it treats the variance $\mathrm{var}(x_t)$ as stochastic. The series $\mathrm{var}(x_t)$ is treated as a time series and modeled in the same form as the observed series. Although the variance $\mathrm{var}(x_t)$ is not directly observable like the original time series x_t, formulating a model for var(x_t) offers a statistical model for the observed time series. The parameters of the model for var(x_t) are estimated alongside other parameters in the model.

The core concept is that the variance var(x_t) at time t can be predicted using the conditional expectation based on the previously observed values of the time series x_{t-1}, x_{t-2}, and so on. The assumption is that the mean value of x_t is zero, implying that var(x_t) = E[x_t^2]. The conditional variance, usually denoted as h_t, is defined as E[x_t^2 | past values] = h_t. A GARCH(p,q) model is defined by an expression for h_t as follows:

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i x_{t-i}^2 + \sum_{j=1}^{p} \gamma_j h_{(t-j)}$$

This formulation, in a way, parallels the concept of an ARMA(p,q) model applied to the time series h_t or x_t^2. The values for p and q are frequently selected as 1 due to their tendency to provide a satisfactory fit in many instances. However, more complex model orders often create computational challenges in parameter estimation algorithms due to an increased parameter count.

Various constraints are applied to the parameters to ensure that the conditional variance is correctly defined as a positive number. A typical condition is the non-negativity requirement:

ω > 0, $\alpha_i \geq 0$, $\gamma_j \geq 0$.

Additionally, there are limitations on the actual size of the coefficients. When p = 0, the GARCH(p,q) model simplifies to the ARCH(q) process. When both p and q equal 0, there are no GARCH effects present. The series then has a constant variance ω, rendering the model homoscedastic.

Often, the GARCH model for a time series is used for the residuals of a time series model, like the univariate ARMA models previously discussed. In such cases, it is helpful to represent the residuals εt of the ARMA model as follows:

$$\varepsilon_{t=} e_t \sqrt{h_t}$$

Here, e_t is independent and follows a standard normal distribution. The conditional variance of the residuals, represented as h_t, is defined as follows:

$$h_t = \omega + \sum_{i_1=1}^{q} \alpha_i \varepsilon_{(t-i)}^2 + \sum_{j=1}^{p} \gamma_j h_{t-j}$$

Certain conditions are imposed on the model parameters as below:

$$\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \gamma_j < 1$$

These restrictions are essential to verify that the unconditional variance and autocovariances are finite and constant over time. When the GARCH process is stationary, the unconditional variance of ε_t is calculated as follows:

$$Var(\varepsilon_t) = \frac{\omega}{1 - \sum_{i=1}^{q} \alpha_i - \sum_{j=1}^{p} \gamma_j}$$

PROC AUTOREG employs this expression for ht as the default parameterization. In PROC VARMAX, the parameterizations are primarily designed to suit generalizations to a multivariate setting. Therefore, in PROC VARMAX, a specific option must be engaged to apply this parameterization.

To test equation 23 , first we need to calculate the unexpected volatility of the risk premium and sentiment variables.

Choosing to model sentiment unexpected volatility with a GARCH(1,1) allows us to account for these key empirical characteristics of volatility clustering and leverage effects in financial time series data. By first predicting the sentiment volatility using the GARCH model, and then deducting this predicted value from the observed sentiment volatility (variable Sentimentvol in our dataset), we can isolate the unexpected component of sentiment volatility. The unexpected portion essentially represents the unexplained or unpredictable aspect of volatility. Moreover, the fact that the GARCH model accounts for past shocks in its volatility predictions implies that any remaining discrepancies between predicted and observed volatility truly reflect unexpected volatility events. Therefore, this methodology provides a more comprehensive, nuanced, and accurate understanding of volatility behavior in financial time series data. The following is the table results:

[Insert Table 8 through 12 here]

[Insert Figure 1 here]

The same process is repeated to capture the unexpected market risk premium. Therefore, Unexpected risk premium volatility = Predicted risk premium volatility – Observed risk premium volatility.

[Insert Table 13 through 17 here]

[Insert Figure 2 here]

In the quest for determining the most optimal GARCH model variant for testing equation 23, a suite of GARCH-family models have been estimated using SAS.

We ran nine variations of GARCH models - GARCH (1,1), Stationary GARCH (1,1), AR1 GARCH (1,1), Integrated GARCH (1,1), Exponential GARCH (1,1), GARCH-M (1,1), Quadratic GARCH (1,1), Threshold GARCH (1,1), and Power GARCH (1,1). These variations aim to capture different nuances in volatility patterns, such as long-memory effects, asymmetry in shocks, and non-constant volatility over time.

The models were evaluated using Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC), two common measures of model quality. Both criteria penalize the complexity of the model (in terms of the number of parameters), while rewarding the goodness of fit. Lower values for both criteria indicate a better model.

Table 18 outlines the SBC and AIC for each of the models run in the code. Based on these numbers, it seems that the best model according to both AIC and SBC is the GARCH M (1,1) model, as it has the lowest (or most negative) values for both criteria. This suggests that this model provides the best fit for the data while maintaining the least complexity among all tested models. Moreover, it is crucial to consider the difference in AIC or SBC values between models. When the difference is less than 2, the models are generally considered to have similar performance.

The quadratic, power, and exponential GARCH models are closely following the GARCH-M model. Their AIC and SBC values are not substantially higher, indicating that these models also fit the data fairly well. It is worth noting that the relative ranking of the models is identical when sorted by either AIC or SBC, which suggests a high level of agreement between these two criteria.

[Insert Table 18 here]

The GARCH-M (1,1) model, otherwise known as the GARCH-in-Mean model, is an extension of the GARCH model. GARCH-M was later developed to explicitly allow for volatility to influence the mean of the return series, essentially capturing the risk-return trade-off. One of the notable papers that introduced the GARCH-M model is Engle, Lilien and Robins' "Estimating

Time Varying Risk Premia in the Term Structure: The ARCH-M Model" (1987).

The GARCH-M model incorporates the conditional variance, a measure of risk, directly into the mean equation. This addition implies that the expected return on an asset is a function of the expected risk on that asset, a notion consistent with many financial theories. For example, in financial markets, it is often observed that periods of high volatility are associated with lower returns and vice versa. The GARCH-M model is designed to capture this observed behavior.

We ran a GARCH-M (1,1) model, which includes one lag of the error term and one lag of the conditional variance in the volatility equation. The GARCH-M model also includes an additional term in the mean equation that links the mean return to the conditional variance.

Now, looking at the table 19, the Ordinary Least Squares Estimates (OLS) section presents the results for the mean equation. Only Unsentimentvol is statistically significant at the 5% level, indicating it has a significant impact on RP.

The GARCH Estimates table provides the results for the volatility equation. Here, both predictors are significant, suggesting both have a significant influence on the volatility of RP. Furthermore, the ARCH1 parameter estimate (0.2149) and the GARCH1 parameter estimate (0.7476) are statistically significant, indicating past errors and past volatilities significantly affect current volatility. The parameter DELTA (0.000279) is also statistically significant, suggesting a positive relationship between risk and return.

In the results presented, the Ordinary Least Squares (OLS) model's R-squared is 0.0244, indicating that this model explains about 2.44% of the variation in the dependent variable, RP. The low R-squared may suggest that the OLS model is not capturing much of the variation in the data.

On the other hand, the GARCH-M (1,1) model has an R-squared of 0.0708, which means it explains about 7.08% of the variation in RP. While this is also relatively low, it is notably higher than the R-squared of the OLS model. The higher R-squared value for the GARCH-M model compared to the OLS model suggests that the GARCH-M model provides a better fit to the data, capturing more of the variation in RP.

[Insert Table 19 through 22 here]
[Insert Figure 3 here]

Causality and CALIS Procedure

The CALIS procedure (Covariance Analysis of Linear Structural Equations) is a SAS software procedure that can perform various forms of linear structural equation modeling, such as path analysis, confirmatory factor analysis, and general structural equation modeling.

In the finance domain, the CALIS procedure is mainly used to study the interdependencies among multiple variables, evaluate theoretical models, and explore the influence of different financial indicators on each other. This can help analysts gain insights into the relationships and cause-effect scenarios between financial variables and parameters, which is critical for decision making in finance.

CALIS can be used to model financial risk factors such as market risk, credit risk, and operational risk. Structural equation modeling can be used to examine the relationships and influence of these risk factors on overall financial performance and risk exposure. For example, it can reveal how much the operational risk affects the credit risk, and how these together impact the overall risk of a firm.

CALIS can also be used in validating asset pricing models. For example, the Fama-French three-factor model, which uses three factors - market risk, size effect, and book-to-market effect - to explain stock returns, can be validated using this procedure.

The CALIS procedure of SAS is a powerful tool that helps analysts and decision makers in the finance industry to validate their theoretical models, gain insight into complex interdependencies among financial variables, and make informed decisions. By leveraging this procedure, finance professionals can reveal the latent structures in their data, which can further assist them in achieving optimal risk-return tradeoffs.

Path Analysis is a subset of structural equation modeling that involves specifying and estimating a series of regressions in which we hypothesize that certain variables affect others. In the context of asset pricing models, path analysis allows us to go beyond single-equation models and create more comprehensive models.

For example, we might hypothesize that the country's macroeconomic condition influences the market risk premium, which in turn affects stock returns. We might also believe that company-specific factors, like size and book-to-market ratio, influence the company's stock return directly, but also indirectly through their effect on the market risk premium.

In this case, we would use path analysis to estimate this more complex model. The CALIS procedure allows us to not only estimate the direct effects of each variable on the stock return, but also the indirect effects (for example, the effect of company size on stock return through its effect on the market risk premium).

It is worth noting that while the CALIS procedure provides powerful tools for estimating and validating asset pricing models, its results are always subject to the quality and appropriateness of the data, and the assumptions made in setting up the models.

We applied PATH analysis to our model to examine the relationships between the dependent variable RP and the independent variables Unsprvol and Unsentimentvol.

The following is the interpretation of the tables and the graph provided:

The path list provides the estimated coefficients (Estimate) and their statistical significance (t Value and Pr > |t|) for the relationships between the independent and dependent variables.

The effect of Unsprvol on RP is positive and statistically significant, with an estimated coefficient of 0.04916. This means that a unit increase in Unsprvol would, on average, increase RP by 0.04916, given other factors are held constant.

Unsentimentvol also has a statistically significant effect on RP, although the size of its coefficient (1.13443E-7) is extremely small. This implies that the effect of Unsentimentvol on RP is minute, but significant.

Regarding the variance parameters, table 24 includes the variances of the independent variables and the residual (error) variance of the dependent variable. The variance of Unsprvol is 32.30964, and that of Unsentimentvol is extremely large (809751465), suggesting a high level of dispersion in these variables. The error variance of RP (1.08610) represents the variability in RP that cannot be explained by Unsprvol and Unsentimentvol.

Table 25 presents the estimated covariance between Unsprvol and Unsentimentvol. A negative covariance (-4219) is reported, indicating that these two variables tend to move in opposite directions. In other words, when Unsprvol increases, Unsentimentvol tends to decrease, and vice versa.

In table 26 R-squared value for the model is 0.0670, which means that approximately 6.7% of the variability in RP is explained by Unsprvol and Unsentimentvol.

Overall, these results show that both Unsprvol and Unsentimentvol significantly affect RP, but they explain a relatively small proportion of its variability.

[Insert Table 23 through 26 here]

[Insert Figure 4 here]

Unobserved Components Models (UCM) and cyclicality of Sentiment

Unobserved Components Models (UCM) procedure, also known as the PROC UCM in SAS, is a powerful tool used for time series analysis. UCM decomposes a time series into components such as trend, seasonal, cyclic, and irregular components, which might not be directly observed in the data. This decomposition allows for a more flexible and granular analysis of the time series and helps in capturing the complex structure within the data more accurately.

UCM is particularly beneficial when the time series data exhibits certain patterns or components, such as a rising or falling trend, predictable seasonal fluctuations, recurring cycles, and irregular movements. For example, retail sales data might have a rising trend, seasonal peaks during certain times of the year, and irregular fluctuations due to unforeseen events or market changes.

The UCM procedure provides several advantages:

Flexibility**:** The UCM can handle a wide variety of time series patterns, including constant or time-varying trends, constant or time-varying seasonality, autocorrelated residuals, and recurring cycles of variable length.

Interpretability: The UCM decomposes a time series into distinct, interpretable components. Each component can be examined and interpreted separately, giving a clear understanding of the underlying patterns and structures in the data.

Model Selection: The UCM procedure provides various model selection methods that can be used to choose the best combination of unobserved components that represent the structure in the data.

Forecasting: The UCM procedure can be used to make short-term or long-term forecasts based on the estimated components and their associated parameters.

[Insert Table 27 through 28 here]

Using the UCM procedure, a model was constructed for the variable RP, incorporating Unsentimentvol and Unsprvol as explanatory variables. The model specified level, slope, seasonal (with a cycle of length 5 days), and cyclical components. Final estimates of the parameters were then generated.

The left side table above is the final estimates of the free parameters of the Unobserved Components Model (UCM) that we have run on our data.

The level component is a representation of the constant term in the model. The error variance of the level component is essentially zero (1.55972E-11) and not statistically significant (p-value 0.9987), meaning that there is very little variation around the constant term in the model.

The slope component represents the trend in the model. The error variance of the slope component is also essentially zero (3.36642E-24) and not statistically significant (p-value 1.0000), indicating that there's no significant trend in the series. This suggests that the data points do not systematically increase or decrease over time.

The season component captures the seasonal effects in the data. The error variance for the season component is close to zero (9.75719E-10) and not statistically significant (p-value 0.9881). This indicates that there is very little variation around the seasonal effects in the model, suggesting that there isn't significant seasonality in the data.

The cycle component represents the cyclical effects in the data. The error variance for the cycle component is 1.66652 and highly significant (p-value < .0001), suggesting that the series does exhibit significant cyclical effects. The damping factor and the period for the cycle component, though, are not statistically significant, suggesting that the cycle does not damp over time, and the period of the cycle is constant.

Explanatory Variables:

The coefficient for Unsprvol is 0.01583 and is statistically significant (p-value < .0001), indicating that this variable has a significant positive impact on RP. This implies that a unit increase in Unsprvol would, on average, increase RP by 0.01583, assuming other factors remain constant. However, the coefficient for Unsentimentvol is -2.23361E-7 and not statistically significant (p-value 0.7808), meaning that changes in Unsentimentvol do not have a statistically significant impact on RP.

In summary, the results suggest that there is significant cyclical variation in the dependent variable RP, and that Unsprvol has a significant positive impact on RP. However, there is no significant level, slope, or seasonal variation in RP, and Unsentimentvol does not have a significant impact on RP. These insights can guide subsequent analyses or model refinement efforts.

These estimates help in understanding the behavior of the time series. The model estimates the variability associated with the trend (level and slope), seasonal and cyclic components of the time series. These components, taken together, are what gives the time series its unique characteristics and allow for forecasting future values. The larger the error variances, the more difficult it can be to forecast accurately as the component's future values have more uncertainty. However, this is part of the trade-off in using a UCM, which aims to balance the model's complexity and interpretability with the desire for accurate predictions.

For the right-side table, the Random Walk R-Square of 0.52716 suggests that the UCM has significantly better predictive accuracy than a simple random walk model.

The Random Walk R-Square is a fit statistic that compares the predictive accuracy of the Unobserved Components Model (UCM) to the accuracy of a simple random walk model. A random walk model is a model where each future point is expected to be equal to the current point plus a random error term. It's one of the simplest models for time series, and often serves as a kind of baseline. If the model does not perform better than a random walk, it might not be very useful.

The RWRSq is calculated as (1 - (UCM's Mean Squared Error / Random Walk's Mean Squared Error)). A higher RWRSq (closer to 1) indicates that the UCM has higher predictive accuracy compared to the random walk model.

Below, the forecast graph for RP shows a fluctuating line around zero, given the closeness of the forecast values to zero. The uncertainty in the forecast is represented by a shaded area corresponding to the 95% confidence intervals, which is relatively wide due to the large standard errors.

The Smoothed Trend graph for RP would illustrate the estimated trend component from the UCM, essentially a smoother version of the actual data. Based on the results from the UCM, we would expect this to be fairly flat, as the slope component was not statistically significant.

[Insert Figure 5 and 6 here]

References

Amihud, Y. a. (1986). Asset pricing and the bid-ask spread. *Journal of financial Economics, 17*(2), 223--249.

Antoniou, C. a. (2013). Cognitive dissonance, sentiment, and momentum. *Journal of Financial and Quantitative Analysis, 48*(1), 245--275.

Antweiler, W. a. (2004). Is all that talk just noise? The information content of internet stock message boards. *The Journal of finance, 59*(3), 1259--1294.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The journal of Finance*, *61*(4), 1645-1680.

Baker, M. a. (2012). Global, local, and contagious investor sentiment. *Journal of financial economics, 104*(2), 272--287.

Baker, M., Wurgler, J., & Yuan, Y. (2007). Investor sentiment in the stock market. *Journal of economic perspectives*(21(2)), 129-152.

Brigida, M. a. (2017). Fake news. *The North American Journal of Economics and Finance, 42*, 564--573.

Brown, G. W. (2004). Investor sentiment and the near-term stock market. *Journal of empirical finance, 11*(1), 1--27.

Chiou, W.-J. P.-F. (2010). Stock return, risk, and legal environment around the world. *International Review of Economics \& Finance*, *19*(1), 95--105.

Chung, S.-L. a.-H.-Y. (2012). When does investor sentiment predict stock returns? *Journal of Empirical Finance*, *19*(12), 217--240.

Chu, G., Li, X., Shen, D., & Zhang, Y. (2021). Stock crashes and jumps reactions to information demand and supply: an intraday analysis. Asia-Pacific Financial Markets, 28, 397-427.

Christie, A. A. (1982). The stochastic behavior of common stock variances: Value, leverage and interest rate effects. Journal of financial Economics, 10(4), 407-432.

Corredor, P. a. (2013). Investor sentiment effect in stock markets: Stock characteristics or country-specific factors? *International Review of Economics \& Finance*, *27,* 572--591.

D'avolio, G. (2002). The market for borrowing stock. *Journal of financial economics, 66*(2-3), 271--306.

Da, Z. a. (2015). The sum of all FEARS investor sentiment and asset prices. *The Review of Financial Studies, 28*(1), 1--32.

Das, S. a.-J. (2005). eInformation: A clinical study of investor discussion and sentiment. *Financial Management, 34*(3), 103--137.

Dimpfl, T. a. (2016). Can internet search queries help to predict stock market volatility? *European Financial Management, 22*(2), 171--192.

Ding, W. a. (2019). Investor sentiment and the cross-section of stock returns: new theory and evidence. *Review of Quantitative Finance and Accounting, 53*(2), 493--525.

Engle, R. F., Lilien, D. M., & Robins, R. P. (1987). Estimating time varying risk premia in the term structure: The ARCH-M model. *Econometrica: journal of the Econometric Society*, 391-407.

Fang, L. a. (2009). Media coverage and the cross-section of stock returns. *The Journal of Finance, 64*(5), 2023--2052.

Fisher, K. L. (2000). Investor sentiment and stock returns. *Financial Analysts Journal, 56*(2), 16--23.

Fisher, K. L. (2003). Consumer confidence and stock returns. *The Journal of Portfolio Management, 30*(1), 115--127.

Fong, W. M. (2013). Risk preferences, investor sentiment and lottery stocks: A stochastic dominance approach. *Journal of Behavioral Finance, 14*(1), 42--52.

Frijns, B. a. (2017). Excess stock return comovements and the role of investor sentiment. *Journal of International Financial Markets, Institutions and Money, 49*, 74--87.

Frijns, B. a. (2018). Herding in analysts' recommendations: The role of media. *Journal of Banking \& Finance, 91*, 1--18.

Gao, B. a. (2020). Intraday sentiment and market returns. *International Review of Economics \& Finance, 69*, 48--62.

Garcia, D. (2013). Sentiment during recessions. *The Journal of Finance, 68*(3), 1267--1300.

Gonzalez Sanchez, M. a. (2018). Corporate reputation and firms' performance: Evidence from Spain. *Corporate Social Responsibility and Environmental Management, 25*(6), 1231--1245.

González-Sánchez, M., & Morales de Vega, M. E. (2021). Influence of Bloomberg's Investor Sentiment Index: Evidence from European Union Financial Sector. Mathematics, 9(4), 297.

Ho, C. a.-H. (2009). Investor sentiment as conditioning information in asset pricing. *Journal of Banking \& Finance, 33*(5), 892--903.

Hribar, P. a. (2012). Investor sentiment and analysts' earnings forecast errors. *Management Science, 58*(2), 293--307.

Jansen, W. J. (2003). The stock market and consumer confidence: European evidence. *Economics letters, 79*(1), 89--98.

Klemola, A. a. (2016). Changes in Investors' Market Attention and Near-Term Stock Market Returns. *Journal of Behavioral Finance, 17*(1), 18--30.

Kumar, A. a. (2006). Retail investor sentiment and return comovements. *The Journal of Finance, 61*(5), 2451--2486.

Kurov, A. (2008). Investor sentiment, trading behavior and informational efficiency in index futures markets. *Financial Review, 43*(1), 107--127.

Kurov, A. (2010). Investor sentiment and the stock market's reaction to monetary policy. *Journal of Banking \& Finance, 34*(1), 139--149.

Lee, W. Y. (2002). Stock market volatility, excess returns, and the role of investor sentiment. *Journal of banking \& Finance, 26*(12), 2277--2299.

Lemmon, M. a. (2006). Consumer confidence and asset prices: Some empirical evidence. *The Review of Financial Studies, 19*(4), 1499--1529.

Liu, G., Wang, Y., Chen, X., Zhang, Y., & Shang, Y. (2020). Forecasting volatility of the Chinese stock markets using TVP HAR-type models. Physica A: Statistical Mechanics and its Applications, 542, 123445.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. Econometrica: Journal of the econometric society, 347-370.

Ng, J. a.-M. (2016). Media coverage and the stock market valuation of TARP participating banks. *European Accounting Review, 25*(2), 347--371.

Nyman, R. a. (2021). News and narratives in financial systems: exploiting big data for systemic risk assessment. *Journal of Economic Dynamics and Control, 127*, 104119.

Papakyriakou, P. a. (2019). The impact of terrorist attacks in G7 countries on international stock markets and the role of investor sentiment. *Journal of International Financial Markets, Institutions and Money, 61,* 143--160.

Pineiro-Chousa, J. R.-C.-P. (2016). Examining the influence of stock market variables on microblogging sentiment. *Journal of Business Research*, *69*(6), 2087--2092.

Renault, T. (2017). Intraday online investor sentiment and return patterns in the US stock market. *Journal of Banking \& Finance, 84,* 25--40.

Sabherwal, S. a. (2011). Do internet stock message boards influence trading? Evidence from heavily discussed stocks with no fundamental news. *Journal of Business Finance \& Accounting, 38*(9-10), 1209--1237.

Schmeling, M. (2007). Institutional and individual sentiment: smart money and noise trader risk? *International Journal of Forecasting, 23*(1), 127--145.

Schwert, G. W. (1989). Why does stock market volatility change over time?. The journal of finance, 44(5), 1115-1153.

Shen, J., Najand, M., & Chen, C. (2023). The Influence of Emotions on Cross-Section Returns: T ests for Cognitive Appraisal Theory. *Journal of Behavioral Finance*, 1-16.

Sibley, S. E. (2016). The information content of the sentiment index. *Journal of Banking \& Finance, 62*, 164--179.

Siganos, A. a.-N. (2014). Facebook's daily sentiment and international stock markets. *Journal of Economic Behavior \& Organization, 107*, 730--743.

Siganos, A. a.-N. (2017). Divergence of sentiment and stock market trading. *Journal of Banking \& Finance, 78*, 130--141.

Smales, L. A. (2015). Asymmetric volatility response to news sentiment in gold futures. *Journal of International Financial Markets, Institutions and Money, 34*, 161--172.

Stambaugh, R. F. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics, 104*(2), 288--302.

Sun, L. a. (2016). Stock return predictability and investor sentiment: A high-frequency perspective. *Journal of Banking \& Finance*, *73*, 147--164.

Teti, E. a. (2019). The relationship between twitter and stock prices. Evidence from the US technology industry. *Technological Forecasting and Social Change, 149*, 119747.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of finance*, *62*(3), 1139--1168.

Tumarkin, R. a. (2001). News or noise? Internet postings and stock prices. *Financial Analysts Journal*, *57*(3), 41--51.

Verma, R. a. (2006). The impact of US individual and institutional investor sentiment on foreign stock markets. *The Journal of Behavioral Finance*, *7*(3), 128--144.

Verma, R. a. (2007). Noise trading and stock market volatility. *Journal of Multinational Financial Management*, *17*(3), 231--243.

Verma, R. a. (2009). The impact of individual and institutional investor sentiment on the market price of risk. *The Quarterly Review of Economics and Finance*, *49*(3), 1129--1145.

Verma, R. a. (n.d.). Are survey forecasts of individual and institutional investor sentiments rational? *International Review of Financial Analysis*, *17*(5), 1139--1155.

W. Johnk, D. a. (2015). Time-varying market price of risk and investor sentiment: Evidence from a multivariate GARCH model. *Journal of behavioral finance*, *16*(2), 105--119.

Wang, J., Chen, P., Wang, J., Guo, X., & Wang, X. (2023). Monetary Policy, Investor Sentiment, and the Asymmetric Jump Risk of Chinese Stock Market. IEEE Transactions on Computational Social Systems.

Wang, Y.-H. a. (2006). The relationships between sentiment, returns and volatility. *International Journal of Forecasting*, *22*(1), 109--123.

Wurgler, J. a. (2002). Does arbitrage flatten demand curves for stocks? *The Journal of Business, 75*(4), 583--608.

Xiong, X., Meng, Y., Li, X., & Shen, D. (2020). Can overnight return really serve as a proxy for f firm-specific investor sentiment? Cross-country evidence. *Journal of International Financial Markets, Institutions and Money*, *64*, 101173.

Zhang, Y. a. (2010). Are day traders bias free?—evidence from internet stock message boards. *Journal of Economics and Finance, 34*(1), 96--112.

Zhang, Y. a. (2012). Measuring effects on stock returns of sentiment indexes created from stock message boards. *Journal of Financial Research, 35*(1), 79--114.

Zhou, T., Gao, S., Wang, J., Chu, C., Todo, Y., & Tang, Z. (2016). Financial time series p rediction using a dendritic neuron model. *Knowledge-Based Systems*, *105*, 214-224.

Zouaoui, M. a. (2011). How does investor sentiment affect stock market crises? Evidence from panel data. *Financial Review, 46*(4), 723--747.

Table 1

Summary Statistic

Variable	Label	*N*	*Mean*	*Std Dev*	*Minimum*	*Maximum*
Mkt_RF	Market return - Risk-free rate	6164	0.031102	1.25532260	-12	11.35
RF	Risk-free rate	6164	0.006840	0.00762007	0	0.0260000
Sentiment	TRMI sentiment measure using news and social media data	6040	-0.0205839	0.04069180	-0.1915960	0.1257000
SPR	Logarithmic stock price return (continuesly compunded)	6263	0.0003003	0.01250140	-0.1276046	0.1095818
RP	Market risk Premium (SPR-RF)	6007	-0.0067185	0.01469150	-0.136811	0.1023199
SPRVol	Stock price return volatilty = SPR^2	6263	0.0001563	0.00053327	0	0.0162829
Sentimentvol	Sentiment volatilty = sentiment^2	6040	0.0020792	0.00284240	0.000000	0.0368090

Table 2

Moments

Variable: SPR

N	6039	**Sum Weights**	6039.0
Mean	0.0334709	**Sum Observations**	202.1
Std Deviation	1.237501	**Variance**	1.5
Skewness	-0.392575	**Kurtosis**	10.4
Uncorrected SS	9253.4228	**Corrected SS**	9246.6573
Coeff Variation	3697.2446	**Std Error Mean**	0.01592

Table 3
Moments

Variable: Sentiment

N	5037	**Sum Weights**	5037.0
Mean	0.69008	**Sum Observations**	3475.9629
Std Deviation	95.30337	**Variance**	9082.733
Skewness	0.102165	**Kurtosis**	4.948949
Uncorrected SS	45743042	**Corrected SS**	45740643.2
Coeff Variation	13810.363	**Std Error Mean**	1.3428339

Table 4

Basic Statistical Measures

Variable: SPR

Locations		Variability	
Mean	0.033471	**Std Deviation**	1.23750
Median	0.071296	**Variance**	1.53141
Mode	0	**Range**	23.71864
		Interquartile Range	1.08516

Table 5
Basic Statistical Measures

Variable: Sentiment

Locations		Variability	
Mean	0.690086	**Std Deviation**	95.30337
Median	0.64468	**Variance**	9083
Mode	.	**Range**	1384
		Interquartile Range	79.50687

Table 6
Basic Statistical Measures
Variable: SPR

Tests	Statistic		P Value	
Student's t	t	2.101863	Pr >|t|	0.03560
Sign	M	257.5	Pr >=|M|	<.0001
Signed Rank	S	715585	Pr >= |S|	<.0001

Table 7

Basic Statistical Measures

Variable: Sentiment

Tests	Statistic		P Value	
Student's t	**t**	0.513903	**Pr >|t|**	0.60730
Sign	**M**	21.5	**Pr >=|M|**	0.5540
Signed Rank	**S**	39360.5	**Pr >= |S|**	0.7030

Table 8
Ordinary Least Squares Estimates
Dependent Variable: Sentiment

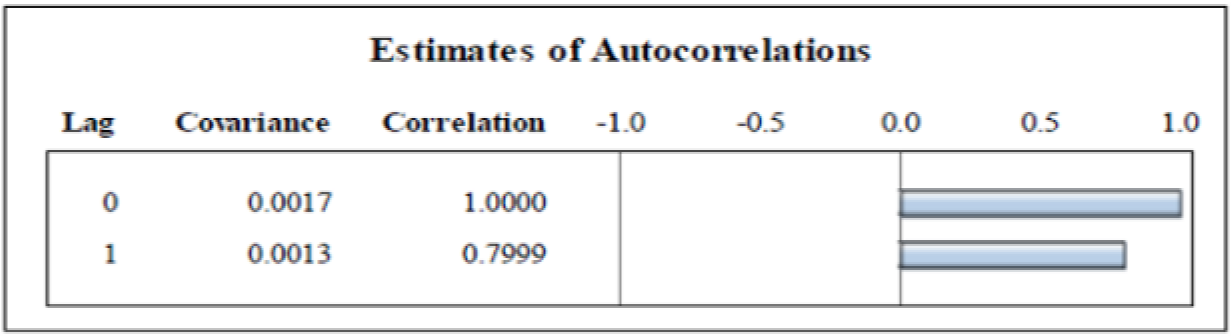
SSE	9.9995239	**DFE**	6039.00000
MSE	0.00166	**Root MSE**	0.04069
SBC	-21528.392	**AIC**	-21535.098
MAE	0.0325188	**AICC**	-21535.098
MAPE	298.04516	**HQC**	-21532.77
Durbin-Watson	0.4001	**Total R-Square**	0.0000

Table 9
Parameter Estimates

Variable	DF	Estimate	Standard Error	t Value	Approx Pr> |t|
Intercept	1	-0.0206	0.000524	-39.310000	<.0001

Table 10
Estimates of Autoregressive Parameters

Lag	Coefficient	Standard Error	t Value	Preliminary MSE
1	-0.79991	0.007723	-103.570000	0.000596



Estimates of Autocorrelations

Lag	Covariance	Correlation	-1.0 -0.5 0.0 0.5 1.0
0	0.0017	1.0000	
1	0.0013	0.7999	

Table 11

GARCH Estimates

Dependent Variable: Sentiment

SSE	3.60641603	**Observations**	6040
MSE	0.0005971	**Uncond Var**	0.000662
Log Likelihood	14074.7609	**Total R-Square**	0.6393
SBC	-28105.991	**AIC**	-28139.522
MAE	0.01861034	**AICC**	-28139.512
MAPE	266.203773	**HQC**	-28127.822
Pr > ChiSq	<.0001	**Normality Test**	207.0759

Table 12

Parameter Estimates

Dependent Variable: Sentiment

Variable	DF	Estimate	Standard Error	t Value	Approx Pr> |t|
Intercept	1	-0.0253	0.001477	-17.11	<.0001
AR1	1	-0.8025	0.008285	-96.85	0.0002
ARCH0	1	2.507E-06	6.638E-07	3.78	<.0001
ARCH1	1	0.0296	0.002578	11.47	<.0001
GARCH1	1	0.9667	0.003038	318.15	<.0001

Table 13

Ordinary Least Squares Estimates

Dependent Variable: SPR

SSE	0.9786622	**DFE**	6262
MSE	0.0001563	**Root MSE**	0.01250
SBC	-37106.461	**AIC**	-37113.203
MAE	0.0083192	**AICC**	-37113.203
MAPE	115.45895	**HQC**	-37110.867
Durbin-Watson	2.1971	**Total R-Square**	0.0000

Table 14
Parameter Estimates

Dependent Variable: SPR

Variable	DF	Estimate	Standard Error	t Value	Approx Pr> |t|
Intercept	1	0.0003	0.000158	1.90	0.0573

Table 15

Estimates of Autoregressive Parameters

Depndent Variable: SPR

Lag	Coefficient	Standard Error	t Value	Preliminary MSE
1	0.098567	0.012576	7.84	0.000155

Estimates of Autocorrelations

Lag	Covariance	Correlation
0	0.0002	1.0000
1	-0.0000154	-0.0986

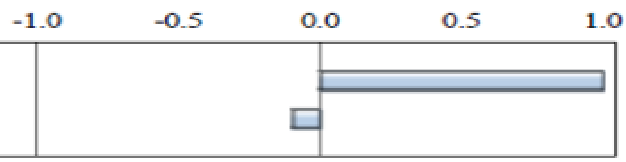


Table 16

GARCH Estimates

Dependent Variable: SPR

SSE	0.97223086	**Observations**	6263
MSE	0.0001552	**Uncond Var**	0.000166
Log Likelihood	20039.4723	**Total R-Square**	0.0066
SBC	-40035.232	**AIC**	-40068.945
MAE	0.00828608	**AICC**	-40068.935
MAPE	144.1717	**HQC**	-40057.263
Pr > ChiSq	<.0001	**Normality Test**	1229.9244

Table 17

Parameter Estimates

Dependent Variable: SPR

Variable	DF	Estimate	Standard Error	t Value	Approx Pr> |t|
Intercept	1	0.000693	0.000101	6.8	<.0001
AR1	1	0.0533	0.0141	3.78	0.0002
ARCH0	1	2.237E-06	1.877E-07	11.91	<.0001
ARCH1	1	0.123	0.006649	18.5	<.0001
GARCH1	1	0.8636	0.006827	126.49	<.0001

Table 18

Schwarz Bayesian Criterion (SBC)
Akaike Information Criterion (AIC)

In GARCH model tables, SBC and AIC stand for Schwarz Bayesian Criterion and Akaike Information Criterion, respectively. Both are statistical measures used to compare the goodness-of-fit of different statistical models applied to the same data set.
Schwarz Bayesian Criterion (SBC): Also known as the Bayesian Information Criterion (BIC), it is used for model selection among a finite set of models. The model with the lowest SBC is considered the best. The SBC is generally defined for a given model as: SBC = ln(n)k - 2ln(L) SBC introduces a penalty term for the complexity of the model to avoid overfitting.
Where:
n = number of observations,
k = number of parameters estimated by the model,
L = maximized value of the likelihood function for the estimated model.

Akaike Information Criterion (AIC): Similar to SBC, the AIC is a measure of the relative quality of a statistical model for a given set of data. As a method of model selection, AIC estimates the quality of each model, relative to each of the other models. The model that has the lowest AIC is usually chosen. The AIC is calculated as: AIC = 2k - 2ln(L)
Where the terms mean the same as in the SBC formula.
Like SBC, AIC also penalizes complexity to prevent overfitting, but it does so to a lesser extent.

	Model	*SBC*	*AIC*
1	AR1 GARCH(1,1)	-13881.8	-13915.6
2	I GARCH (1,1)	-14478.0	-14495.1
3	ST GARCH (1,1)	-14579.5	-14607.9
4	GARCH (1,1)	-14579.9	-14608.3
5	T GARCH (1,1)	-14617.5	-14651.6
6	E GARCH (1,1)	-14625.2	-14659.3
7	P GARCH (1,1)	-14637.0	-14676.8
8	Q GARCH (1,1)	-14643.0	-14677.1
9	GARCH M (1,1)	-14648.5	-14682.6

Table 19
Ordinary Least Squares Estimates
Dependent Variable: RP

SSE	0.23888771	**DFE**	6262
MSE	0.0001103	**Root MSE**	0.01050
SBC	-13582.527	**AIC**	-13593.889
MAE	0.0069388	**AICC**	-13593.884
MAPE	210.078965	**HQC**	-13589.734
Durbin-Watson	1.9843	**Total R-Square**	0.0244

Table 20
Parameter Estimates

Dependent Variable: RP

Variable	Estimate	t Value	Approx Pr> |t|
Unsprvol	4.1224	0.6	0.5479
Unsentimentvol	0.034	7.32	<.0001

Table 21
GARCH Estimates
Dependent Variable: RP

SSE	0.22752496	**Observations**	6263
MSE	0.000105	**Uncond Var**	.
Log Likelihood	7347.29144	**Total R-Square**	0.0708
SBC	-14648.496	**AIC**	-14682.583
MAE	0.00681792	**AICC**	-14682.544
MAPE	261.232431	**HQC**	-14670.118
Pr > ChiSq	<.0001	**Normality Test**	294.1945

Table 22
GARCH-M (1,1) Model Parameter Estimates
Dependent Variable: RP

Variable	Estimate	t Value	Pr > |t|
Unsprvol	2.9255	10.08	0.0001
Unsentimentvol	0.0345	6.85	0.0001
ARCH0	4.18E-06	8.24	0.0001
ARCH1	0.2149	12.14	0.0001
GARCH1	0.7476	44.03	0.0001
DELTA	0.000279	12.37	0.0001

Table 23
PATH List

Path			Estimate	t Value	Pr > |t|
RP	**<===**	**Unsprvol**	0.04916	11.5882	<.0001
RP	**<===**	**Unsentimentvol**	1.13E-07	Infty	.

Table 24

Variance Parameters

Variance Type	Variable	Estimate	t Value	Pr > |t|
Exogenous	Unsprvol	32.30964	30.5904	<.0001
	Unsentimentvol	809751465	.	.
Error	RP	1.0861	30.5696	<.0001

Table 25

Covariances Among Exogenous Variables

Var1	Var2	Estimate	t Value	Pr > |t|
Unsentimentvol	**Unsprvol**	-4219	-3.85E+08	<.0001

Table 26

Squared Multiple Correlations			
Variable	**Error Variance**	**Total Variance**	**R-Square**
RP	1.0861	1.16416	0.067

Table 27

Final Estimates of the Free Parameters

Component	Parameter	Estimate	t Value	Approx Pr > |t|
Level	**Error Variance**	1.56E-11	0	0.9987
Slope	**Error Variance**	3.37E-24	0	1
Season	**Error Variance**	9.76E-10	0.01	0.9881
Cycle	**Damping Factor**	1.05E-07	0	1
Cycle	**Period**	34651	.	.
Cycle	**Error Variance**	1.66652	47.05	<.0001
Unsentimentvol	**Coefficient**	-2.23E-07	-0.28	0.7808
Unsprvol	**Coefficient**	0.01583	4.49	<.0001

Table 28
Fit Statistics Based on Residuals

Mean Squared Error	1.73924
Root Mean Squared Error	1.3188
Mean Absolute Percentage Error	168.2726
Maximum Percent Error	55965
R-Square	-0.03887
Adjusted R-Square	-0.04002
Random Walk R-Square	0.52716
Amemiya's Adjusted R-Square	-0.04164

Figure 1

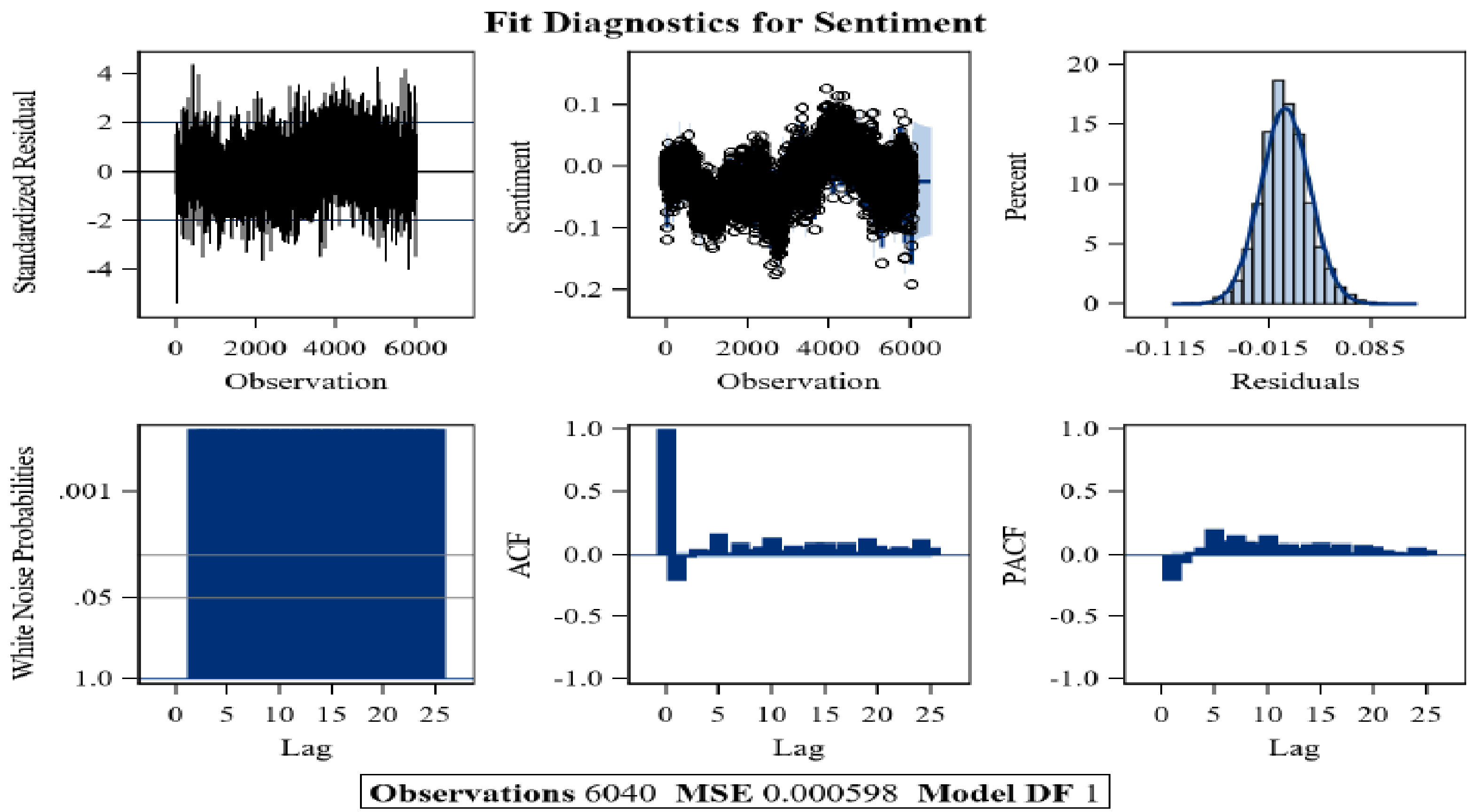
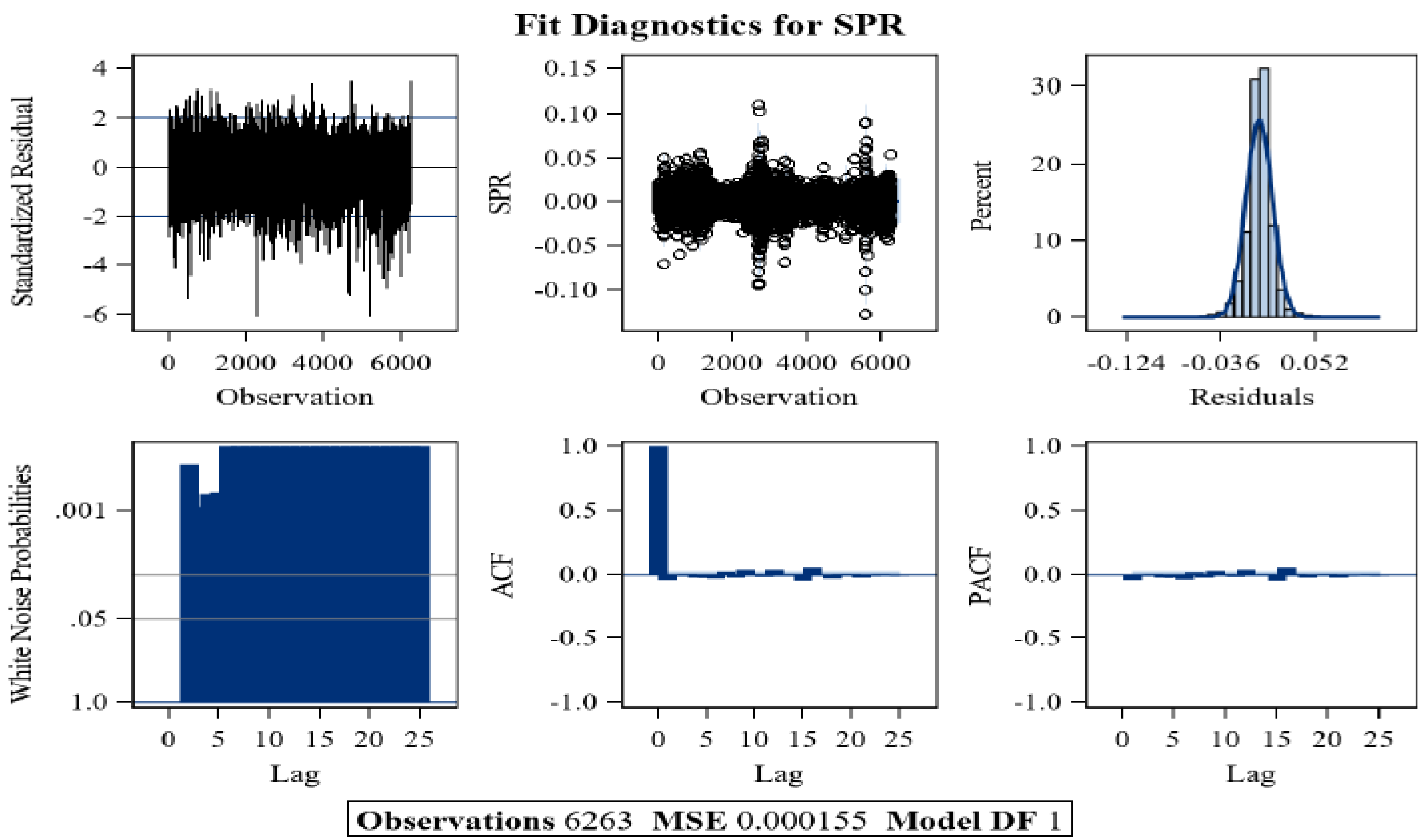

Fit Diagnostics for Sentiment
Standardized Residual
4
2
0
-2
-4
0 2000 4000 6000
Observation
Sentiment
0.1
0.0
-0.1
-0.2
0 2000 4000 6000
Observation
Percent
20
15
10
5
0
-0.115 -0.015 0.085
Residuals
White Noise Probabilities
.001
.05
1.0
0 5 10 15 20 25
Lag
ACF
1.0
0.5
0.0
-0.5
-1.0
0 5 10 15 20 25
Lag
PACF
1.0
0.5
0.0
-0.5
-1.0
0 5 10 15 20 25
Lag
Observations 6040 MSE 0.000598 Model DF 1

Figure 2



Fit Diagnostics for SPR
Standardized Residual
4
2
0
-2
-4
-6
0 2000 4000 6000
Observation
SPR
0.15
0.10
0.05
0.00
-0.05
-0.10
0 2000 4000 6000
Observation
Percent
30
20
10
0
-0.124 -0.036 0.052
Residuals
White Noise Probabilities
.001
.05
1.0
0 5 10 15 20 25
Lag
ACF
1.0
0.5
0.0
-0.5
-1.0
0 5 10 15 20 25
Lag
PACF
1.0
0.5
0.0
-0.5
-1.0
0 5 10 15 20 25
Lag
Observations 6263 MSE 0.000155 Model DF 1

Figure 3

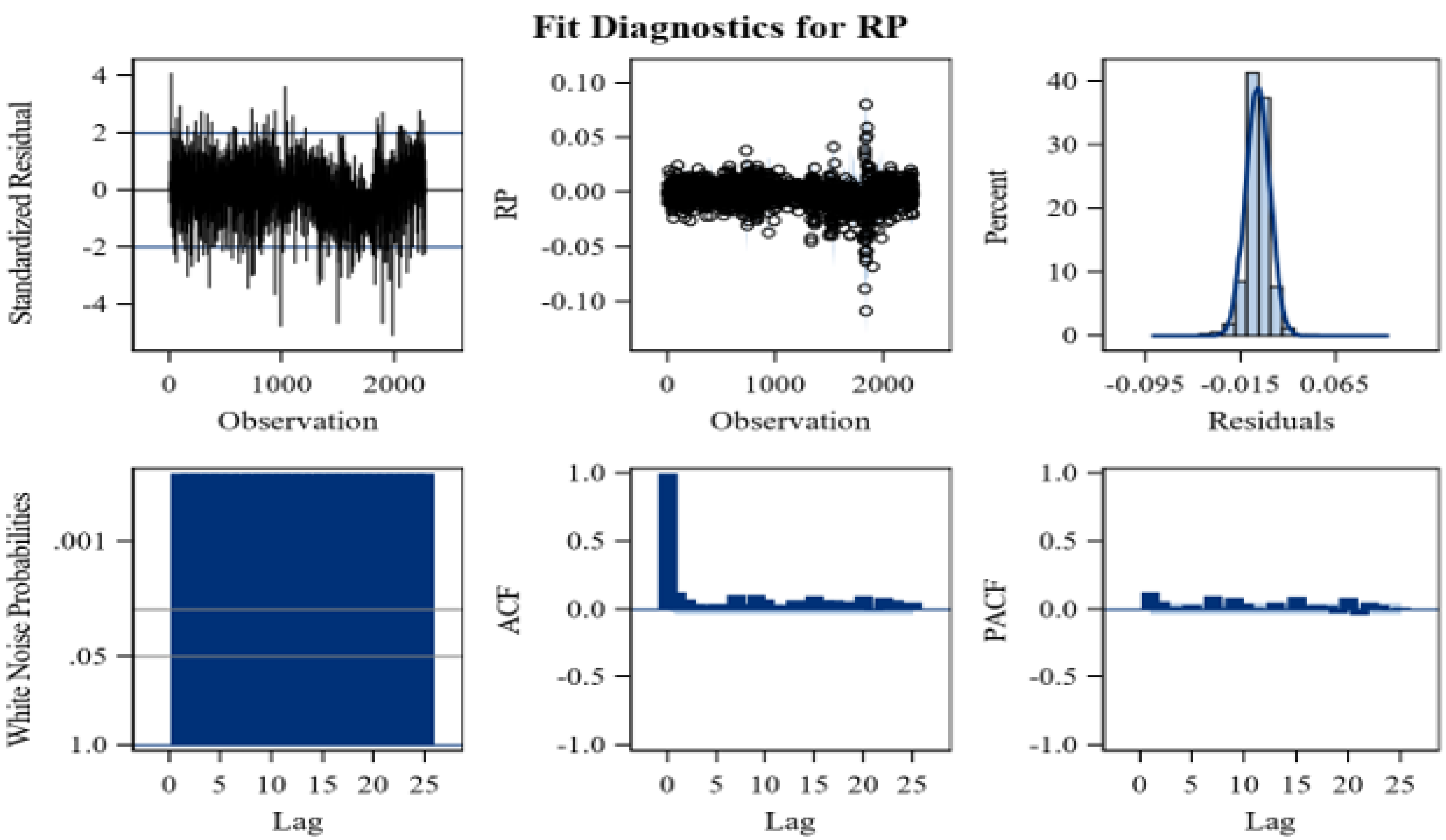

Fit Diagnostics for RP
Standardized Residual
4
2
0
-2
-4
0 1000 2000
Observation
RP
0.10
0.05
0.00
-0.05
-0.10
0 1000 2000
Observation
Percent
40
30
20
10
0
-0.095 -0.015 0.065
Residuals
White Noise Probabilities
.001
.05
1.0
0 5 10 15 20 25
Lag
ACF
1.0
0.5
0.0
-0.5
-1.0
0 5 10 15 20 25
Lag
PACF
1.0
0.5
0.0
-0.5
-1.0
0 5 10 15 20 25
Lag

Figure 4

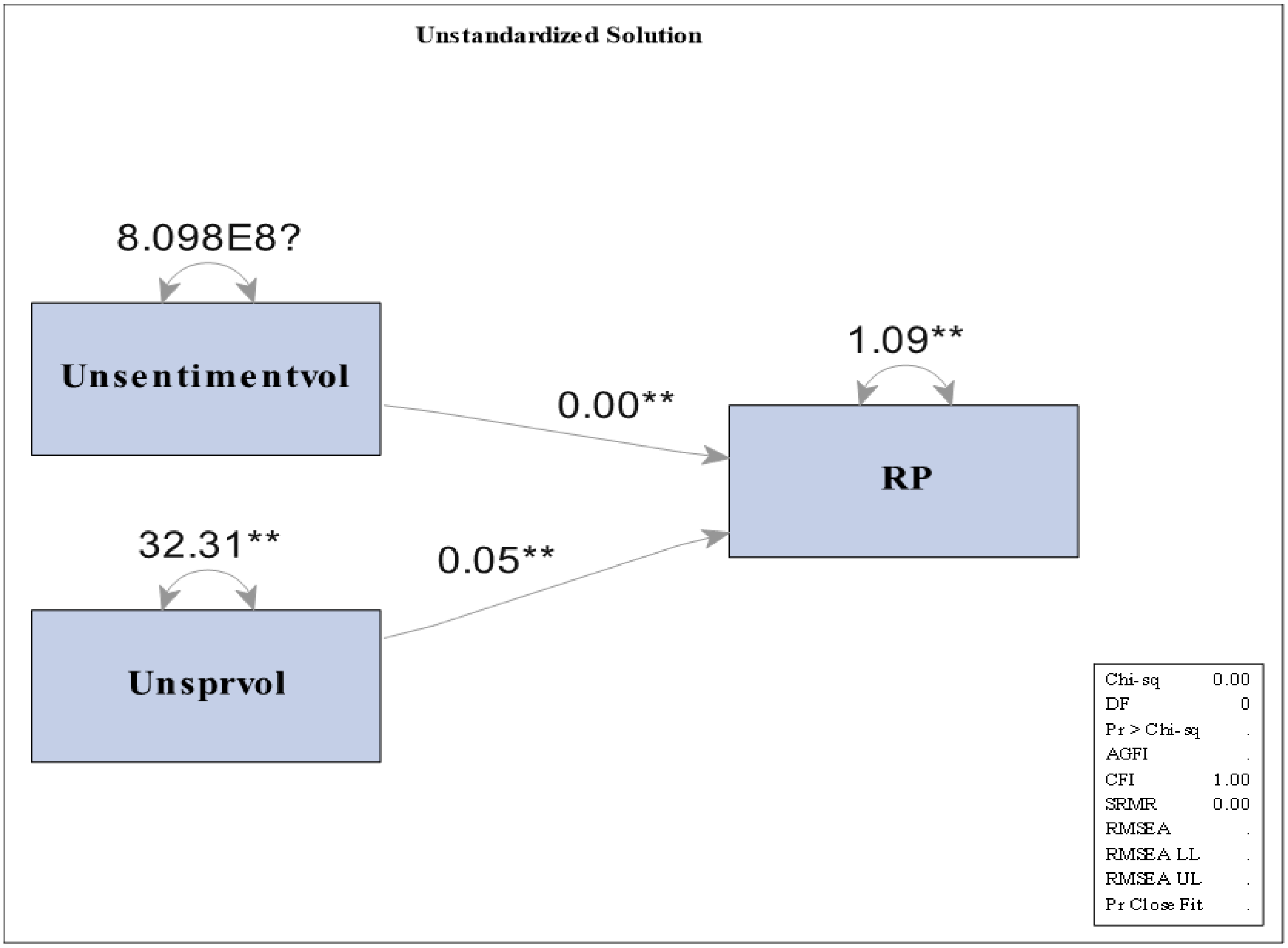

Unstandardized Solution
8.098E8?
Unsentimentvol
1.09**
0.00**
RP
32.31**
0.05**
Unsprvol
Chi-sq 0.00
DF 0
Pr > Chi-sq .
AGFI .
CFI 1.00
SRMR 0.00
RMSEA .
RMSEA LL .
RMSEA UL .
Pr Close Fit .

Figure 5

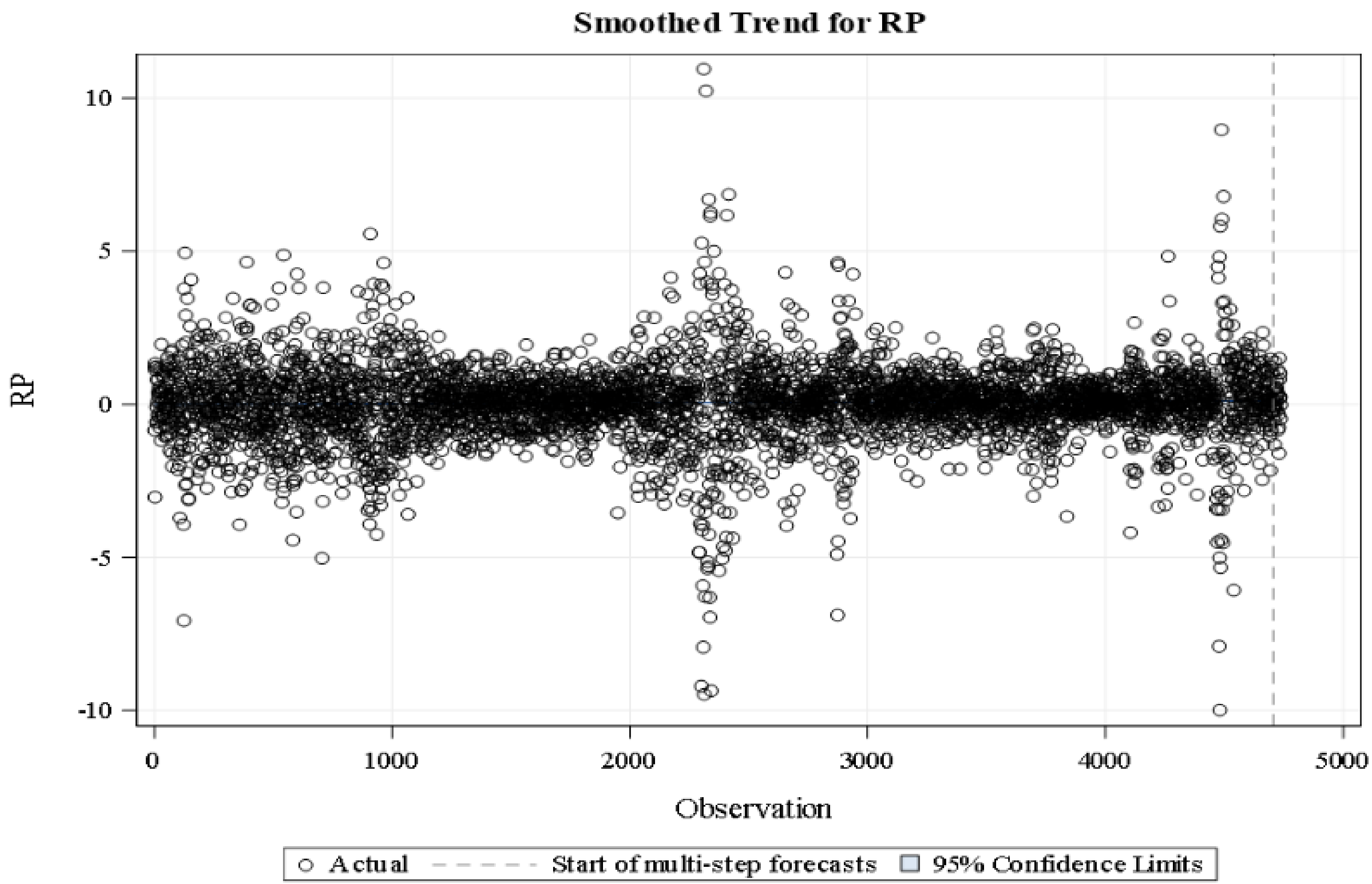
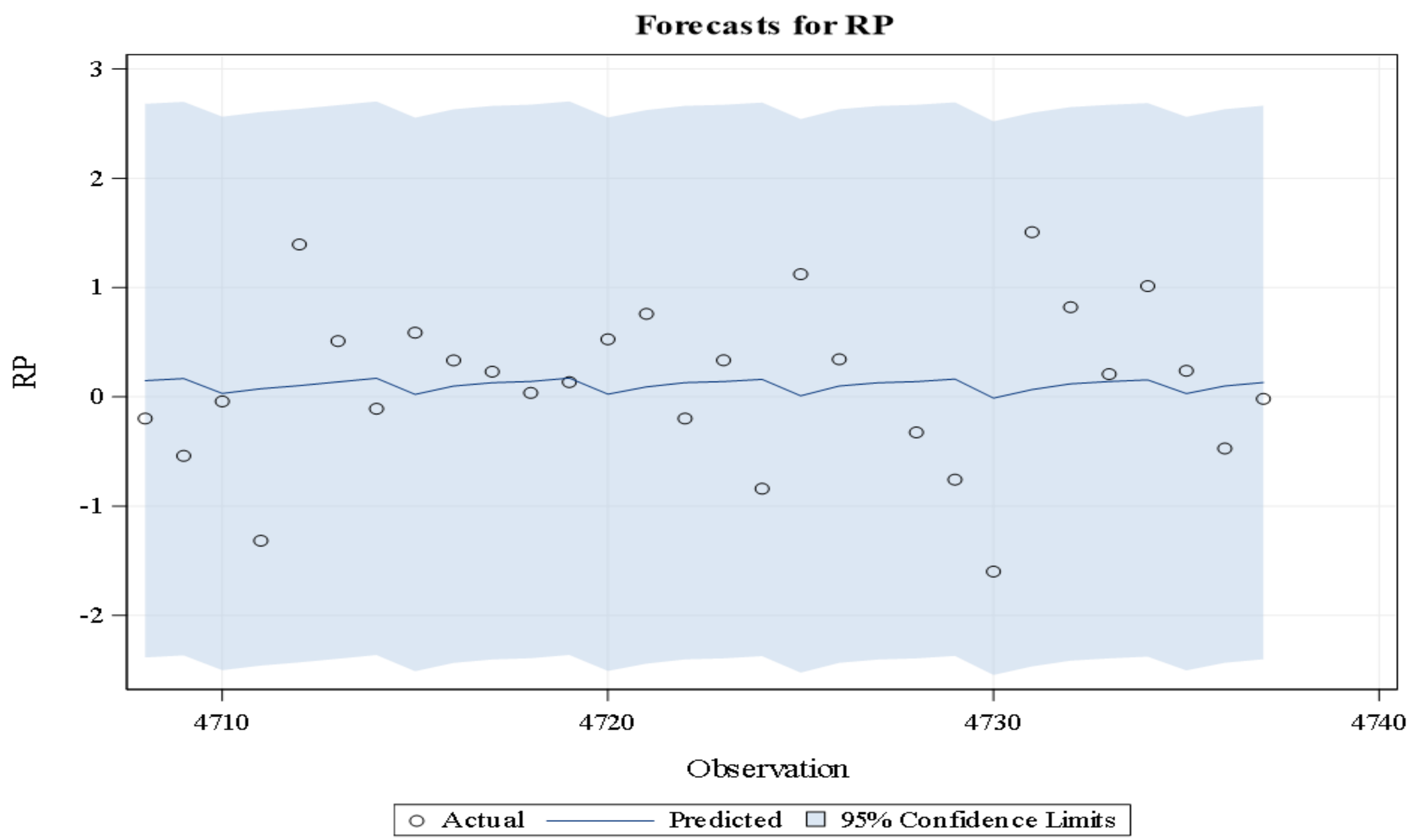

Smoothed Trend for RP
RP
10
5
0
-5
-10
0
1000
2000
3000
4000
5000
Observation
Actual
Start of multi-step forecasts
95% Confidence Limits

Figure 6



Forecasts for RP
RP
3
2
1
0
-1
-2
4710
4720
4730
4740
Observation
Actual
Predicted
95% Confidence Limits

ESSAY 2: MODELING THE TRANSMISSION OF SENTIMENT ACROSS DIFFERENT MARKETS: A MULTIVARIATE DYNAMIC APPROACH

Introduction

Sentiment transmission across stock markets refers to the phenomenon where emotions and perceptions of market participants in one stock market influence those in another market. The transmission can occur through various channels, including news, social media, and economic indicators. Sentiment transmission can have significant implications for global financial markets and can affect the decisions of investors, traders, and policymakers.

The global interconnectedness of financial markets has made sentiment transmission across markets more prevalent in recent years. With the advent of technology, information can be transmitted across borders almost instantly, enabling investors to quickly respond to market changes and news from other regions. For instance, a major event in one market can trigger panic in other markets, leading to a sell-off of stocks and other assets. The transmission of sentiment can be amplified by financial innovations such as algorithmic trading and exchange-traded funds (ETFs), which can exacerbate market movements.

One of the most significant channels for sentiment transmission is the news media. News outlets often report on major economic events such as interest rate decisions, GDP growth, and corporate earnings reports. Positive news can generate optimism among investors, leading to a rise in stock prices. In contrast, negative news can create fear and uncertainty, leading to a sell-off of stocks. The impact of news on sentiment transmission is particularly evident during times of crisis when the news can shape market sentiment.

Social media is another channel for sentiment transmission across markets. Social media platforms such as Twitter and Reddit have become popular sources of market information and analysis. Traders and investors use social media to share their opinions and insights, which can influence the sentiment of other market participants. Social media can also amplify the impact of news on market sentiment, as news stories can quickly go viral on social media platforms. Economic indicators can also affect sentiment transmission across markets. Economic indicators such as inflation, unemployment, and consumer confidence can provide insights into the health of the economy and the prospects for corporate earnings. Positive economic indicators can generate optimism among investors, leading to a rise in stock prices. In contrast, negative economic indicators can create fear and uncertainty, leading to a sell-off of stocks.

Sentiment transmission can have significant implications for global financial markets. A rise in sentiment in one market can lead to a rise in sentiment in other markets, leading to a global bull market. Conversely, a decline in sentiment in one market can lead to a decline in sentiment in other markets, leading to a global bear market. The impact of sentiment transmission can be amplified by financial innovations such as ETFs, which can create correlations between different asset classes and markets.

In conclusion, sentiment transmission across stock markets is a complex phenomenon that is influenced by various channels, including news, social media, and economic indicators. The global interconnectedness of financial markets has made sentiment transmission more prevalent in recent years, and the impact of sentiment transmission can be amplified by financial innovations such as ETFs. The implications of sentiment transmission for global financial markets are significant, and policymakers and market participants need to be aware of the potential impact of sentiment transmission on their investment decisions.

Literature Review

The body of literature on investor sentiment underlines its impact on future stock returns, with general consensus that investor sentiments and future returns are negatively correlated (Baker and Wurgler, 2006; Brown and Cliff, 2004). This extends to the notion that a bullish investor would expect returns to be above average, while a bearish investor anticipates below-average returns (Brown and Cliff, 2004). Research has illustrated how these sentiment levels can propagate to impact not only domestic returns but also the aggregate market returns of countries within the G6, alongside value and growth stock returns. In order to investigate this, a monthly individual investor survey is employed as a proxy for individual investor sentiment.

Schmeling (2009) established the global prevalence of this phenomenon by examining investor sentiments across 18 countries. However, the effect of investor sentiment is not uniform. It is more pronounced in countries with less market integrity and those more culturally susceptible to herd-like behavior and overreaction (Schmeling, 2009). Similarly, studies have shown that value stocks are more significantly affected by investor sentiment compared to growth stocks

(Bathia and Bredin, 2016). Such disparities suggest that while investor sentiment certainly plays a role in global financial markets, its impact can vary.

A particularly influential factor in these global markets is the US, due to its substantial effect on asset prices (Froot et al., 2001; Grinblatt and Keloharju, 2000). This impact extends to international stock market returns, as numerous studies have illustrated (Tandon and Urich, 1987; Becker et al., 1995; Canova, 2005; Mackowiak, 2007; Foerster and Schmitz, 1997). The response of these markets to US-originated shocks is immediate and pervasive.

Specifically, the sentiment spillover from the US is a key determinant of stock returns in the UK (Verma and Soydemir, 2006; Hudson and Green, 2015). These sentiments significantly impact UK stock returns, to the point where domestic sentiments have become largely irrelevant (Hudson and Green, 2015). Contrary to this, Bathia et al. (2016) argue that US investor sentiment doesn't play a significant role in the G7 countries' stock returns, indicating the influence of US sentiments may differ from market to market.

Studies have shown, for example, that the US stock market significantly affects emerging stock markets at varying degrees (Soydemir, 2000). The US market has also been found to be more influential than the Japanese market in transmitting returns and volatilities to the Asian markets (Liu and Pan, 1997).

However, the propagation of US investor sentiment is not straightforward. Grossmann et al. (2007) found that the price of American Depositary Receipts (ADRs) and the price of the underlying asset are more responsive to US consumer sentiments than to the sentiments of the country from which the underlying asset originates. Moreover, investor sentiments are not always perfectly correlated. For instance, Bai (2014) found that investor sentiments are contagious, but their impact is not constant.

Furthermore, not all shocks originating from the US are influential. Forbes and Rigobon (2002) did not find any evidence of contagion during three periods of market turmoil, suggesting that high levels of co-movement across many stock markets during tumultuous periods are due to a continuation of strong cross-market linkages, rather than a significant shift in these linkages. This underlines the complexity of the influence of US sentiments on global markets.

Interestingly, there is also some evidence that the impact of US investor sentiments can shift over time. Bai (2014) divided his sample into periods before and after the global financial crisis and found that the influence of US sentiments on sample markets significantly diminished after the crisis. This finding implies that the relationship between US investor sentiments and international stock returns is not static and may be influenced by larger economic conditions.

The importance of investor sentiments has led to the development of various measures to assess it, including closed-end fund discount, fund flow, put-call ratio, dividend premium, and IPO first-day returns (e.g., Zweig (1973), Lee et al. (1991), Warther (1995), Frazzini and Lamont (2006), Easley et al. (1998), Pan and Poteshman (2006), Baker and Wurgler (2006, 2007), Ritter (2003), Ljungqvist (2006)). Of these, investors' surveys have been found to be particularly useful and consistent in forecasting future stock returns.

It should be noted that there is debate in the literature on whether shifts in the level of investor sentiment are fully irrational (where investors mainly trade on noise rather than fundamentals) or a combination of both rational and irrational (Black, 1986; De Long et al., 1990).

Data and Methodology

We utilize the Global Finance database to obtain stock indices for G7 countries except US and two measures of sentiment for the U.S. market from Thomson Reuters MarketPsych Indices (TRMI) database similar to essay one.

The first sentiment variable measures the sentiment of news articles related to the market, such as earnings reports, regulatory changes, and geopolitical events. Positive news can increase market sentiment, while negative news can decrease market sentiment.

The second sentiment variable measures the sentiment of social media posts related to the market, such as tweets, Reddit posts, and blog articles. Positive social media sentiment can increase market sentiment, while negative social media sentiment can decrease market sentiment.

To model sentiment transmission across different markets, we use a vector autoregression (VAR) model. The VAR model allows us to estimate the interdependence of multiple time series variables, which is useful for understanding how changes in one variable affect other variables in the system. Moreover, we applied structural equation modeling (SEM) to examine the direction of relationships among the US sentiment and Countries' return variables through PATH analysis. Finally, we utilized multivariate GARCH models to address the changing variance and excess kurtosis issues of the log returns and fit a more appropriate model to explore whether the US sentiment affect other 6 countries' return.

The following table provides summary statistics for the full sample of 4976 daily observations from January 1, 1998, to December 31, 2021.

[Insert Table 1 about here]

Multivariate Time Series Analysis Using Vector AutoRegressive Moving Average Models with Exogenous Variables (VARMAX)

Multivariate time series analysis takes into account multiple, or k number of, individual time series simultaneously. Each series is observed at time t and is denoted by X_{jt}, where j ranges from 1 to k and t from 1 to T. The total number of observations, also referred to as the length of the series, is given the notation T. Using matrix notation, this k-dimensional observation can be represented as a column vector X_t:

$$X_t = \begin{pmatrix} X_{1t} \\ X_{kt} \end{pmatrix}$$

The rationale behind modeling these k series concurrently is due to the potential interactive dynamics that might not be captured by treating each series independently. One critical characteristic of multivariate time series is the requirement for all series to exhibit simultaneous stationarity, meaning their combined distribution remains stable over time. This idea is an expansion of the concept from univariate analysis. When extended to cover more than one time series, it asserts that any lagged dependencies between series should remain constant throughout the entire data period, and no series should display trends.

Transformations like differencing are often applied to non-stationary series to attain stationarity, akin to the methods used in univariate models. For example, while price indices in multiple countries may show trends due to inflation, a series of annual changes in these prices might be fairly stable and reflect the average yearly inflation rate across the observed countries.

When a multivariate series is stationary, it can be represented by a Vector Autoregressive Moving Average (VARMA) model, an expansion of the Autoregressive Moving Average (ARMA) models.

$$X_{t\_}\alpha_1 X_{t-1} - .. - \alpha_p X_{t-p} = c + \varepsilon_t - \beta_1 \varepsilon_{t-1} - ... - \beta_q \varepsilon_{t-q}$$

The VARMA(p, q) model replicates the ARMA model definition, with the only variance being that all terms are represented as vectors or matrices, not merely scalar values. Therefore, those familiar with univariate time series modeling will find this model easy to comprehend.

The interpretation of the multivariate model is also a simple extension of the univariate model. In this context, the parameter vector c is a k-dimensional column vector. The mean vector μ is calculated when p is greater than 0, whereas it only represents the mean value for each k series when p equals 0.

$$\boldsymbol{\mu} = (\boldsymbol{I} - \boldsymbol{\alpha_1} - .. - \boldsymbol{\alpha_p})^{-\mathbf{1}}\mathbf{c}$$

The coefficients in the VARMA(p, q) model are represented as k × k matrices, which can encompass k^2 parameters.

$$\alpha_m = \begin{pmatrix} \alpha_{m11} & \cdots & \alpha_{m1k} \\ \vdots & \ddots & \vdots \\ \alpha_{mk1} & \cdots & \alpha_{mkk} \end{pmatrix}$$

The model's formulation for a specific component X_{jt} can become complex even for small values of the model orders p and q. The expression will include lagged values of all observed components of the time series and lagged values of all error components. This complexity could potentially lead to over-parameterization; hence, several refinements have been suggested primarily to minimize the number of parameters. Various interpretations of the model thus evolve over time.

The interrelationships among different series, considering lagged impacts, are represented by the off-diagonal elements of the coefficient matrices α_m and β_m. The diagonal elements of these coefficient matrices correspond to the univariate ARMA models for each individual series.

As it is established in the literature, the US stock market leads other G7 countries. To test this interconnection within global economies, this study employs a multivariate Vector AutoRegressive (VAR) model, a tool that unravels the dynamic interdependencies among multiple time series variables. The approach, particularly when used with economic or financial data, unveils the mutual influences and causal relationships that might be concealed in the complex network of international financial markets.

The core of this section revolves around implementing the VAR model, designed to analyze the return rates of G7 economies. The 'PROC VARMAX' procedure, a SAS feature that enables VAR and VARMA model creation, forms the foundation of our methodology. Specifically, our VAR model includes return rate variables and looks at the previous five values of each variable.

The subsequent table presents the parameter estimates for our VAR (5) models, lending weight to our hypothesis that the US market exerts a leading influence on the other six countries. This is corroborated by the fact that the parameter estimates associated with US returns are significant in the majority of instances.

Taking the US return VAR model as an example, only the five lags of the US yield a t-value exceeding 2, signaling their statistical significance. Turning to Japan's return, all US lags, barring the first, exhibit significance. In the case of the remaining five nations, every US lag is significant, underscoring the dominance of the US market.

Additionally, there is an evident interdependence among the European markets, as several of their respective parameter estimates prove significant.

[Insert Table 2 through 8 here]

Granger Causality Wald Test for the VAR Model

As part of this study investigating global economic linkages, we have utilized the Granger-Causality Wald Test, a statistical tool that helps in determining causal relationships between time series variables. This test posits that if a variable X "Granger-causes" (or GC) a variable Y, then changes in X should precede changes in Y. In other words, X should have significant predictive power over Y.

The Wald test is an additional statistical test used to examine the joint significance of the coefficients. In the context of the Granger causality test, the Wald variant is used to test the joint hypothesis that the coefficients on the lagged X variables are all zero. If this hypothesis can be rejected, then it can be said that X Granger-causes Y.

The benefit of using the Wald test for Granger causality is that it can be more robust and flexible, allowing for the testing of multiple coefficients and multiple equations simultaneously.

In the context of this study, the Granger-Causality Wald Test is leveraged to examine the causal relationship between the United States' market returns and those of six other countries.

The US market returns is being investigated for its predictive power, while the market returns of the other six countries are being examined for their dependency on the US market.

[Insert Table 9 here]

The Granger-Causality Wald Test table result shows that the chi-square statistic is 43.38, and the p-value (Pr > ChiSq) is 0.0443. The p-value being less than 0.05 suggests that we can reject the null hypothesis that the lagged values of the US returns do not Granger-cause the returns of the other six markets.

In this test, the group1 variable is the United States return (R_US), and the group2 variables are returns from Japan, the United Kingdom, France, Germany, Italy, and Canada (R_Japan, R_UK, R_France, R_Germany, R_Italy, R_Canada). The rejection of the null hypothesis indicates a significant causal effect from R_US to the other six market returns. This result is consistent with our earlier premise of the US market leading the other six economies.

This finding provides robust statistical evidence of the influential role of the US market on these economies. It emphasizes the interconnectedness of global financial markets, and the dominance of the US market in shaping global financial trends, lending credence to the effectiveness of the multivariate Vector AutoRegressive (VAR) model in uncovering such relationships. The ability to identify such influential markets could offer valuable insights to investors, policymakers, and researchers in their economic forecasting, policy formulation, and academic pursuits respectively.

Plots of the Impulse Response

The infinite moving average representation's coefficients portray the reactions of a series to a shock occurring beyond the same period. By default, SAS displays these coefficients for lags up to 12. In the analysis of multivariate series, these coefficients or 'impulse responses' signify that a substantial input error term at a particular point in time triggers changes in all other series in subsequent periods.

$$X_{1t} = \varepsilon_{1t} + a_1\varepsilon_{1t-1} + a_2\varepsilon_{1t-2+}a_3\varepsilon_{1t-3} + a_4\varepsilon_{2t-1+}a_5\varepsilon_{2t-2} + a_6\varepsilon_{2t-3} + \cdots$$

$$X_{2t} = \varepsilon_{2t} + b_1\varepsilon_{1t-1} + b_2\varepsilon_{1t-2+}b_3\varepsilon_{1t-3} + b_4\varepsilon_{2t-1+}b_5\varepsilon_{2t-2} + b_6\varepsilon_{2t-3} + \cdots$$

Take, for instance, a two-by-two matrix for lag representation from 1 to 3, expressed as two distinct equations. According to the model, an increase in X_{1t} for a single period, represented by ε_{1t} = .1 (approximating to a 10% rise), induces subsequent price hikes by a factor of a_1 × .1. Thus, a further increase of 0.1a_1% occurs in the next year, and two periods later, a surge of a_2 × .1 or 0.1a_2%.

Simultaneously, X_{2t} experiences a rise by b_1 × .1 or 0.1b_1% in the following period. Two periods later, it increases by b_2 × .1 or 0.1b_2%. The direct effect of X_{1t}'s increase on X_{2t} is not explicitly observed through these parameters. The immediate period's impact is modeled by the correlation between error process terms ε_{1t} and ε_{2t}.

This model representation through an infinite series incorporates many coefficients in output tables. Yet, the structure becomes clearer when visualized through graphs, like those produced by PROC VARMAX, as opposed to scanning numerous figures in output tables. The impulse responses are plotted against increasing lag lengths and can be observed in the subsequent figures.

[Insert Graph 1 through 7 here]

Cumulative Effects

These effects are also cumulative, with the total impact on each series calculated as the sum of effects up to a specific lead value. In this study, these figures represent the aggregate impact on the series following a sudden shock to one of them.

Below are plots for the cumulative effects. For instance, a shock to the R-US series (i.e., a large value of the error term ε_{1t}) results in a total effect of 0.85 times the immediate impact on the R_US series after four years. This corresponds to a multiplicative effect of 0.85, implying a 1% increase in US return in one year leads to nearly a 0.85% rise in US return in the following years.

However, a shock to the US return series, ε1t, also influences the return series of other countries. For instance, the Japan return is affected by 0.5% after four years, as the graph for accumulated response to impulse in R_US at lag four displays a coefficient of nearly 0.5.

[Insert Graph 8 through 14 here]

Effects of Orthogonal Shocks

The output's third section highlights the impact of an orthogonal shock on one of the series. The concept rests on the premise that the error term exists solely in one series and does not contribute to the error in the other series due to the correlation of the error terms. These plots illustrate the changes in all series in the years following a unique event in just one of the series.

This effect is computed through an orthogonalization of the error terms' correlation matrix Σ. The covariance matrix is factored as Σ = PPT, where P can be interpreted as a lower triangular matrix. In this representation, the error processes are standardized to variance 1, and individual error processes are independent. The orthogonalized impulse response is defined as the coefficients to these orthogonalized errors. In the output series, these coefficients are represented as an infinite series in lagged values of orthogonalized errors.

[Insert Graph 15 through 21 here]

US Sentiment Spillover Analysis Using Vector AutoRegressive Moving Average Models with Exogenous Variables (VARMAX)

Several studies have probed the global impact of US investor sentiment on the stock returns of other countries (Verma & Soydemir, 2006; Bathia and Bredin 2016). The empirical evidence suggests a high degree of integration among global stock markets, with similar factors driving their performance, a finding that was corroborated in the preceding section of our study.

Given that our analysis incorporates the stock returns of the G7 nations, recognized for their highly advanced stock markets, it stands to reason that the influence of US sentiment on global stock returns would be prominent. To validate this supposition, we employed the Structural VAR (SVAR) methodology, incorporating US sentiment as an exogenous variable in our VAR(5) model.

The Structural Vector Autoregression (SVAR) model presents a refined mechanism for scrutinizing intricate systems characterized by multiple interrelated variables evolving over time. This model extends the traditional Vector Autoregression (VAR) framework, which is frequently utilized in finance and macroeconomics to comprehend the time-dependent coevolution of a system of variables.

The SVAR model takes the VAR model a step further by integrating economic theory into the model's architecture. It does this by imposing what are known as structural restrictions on the model. These are constraints based on a priori economic information that we have reason to believe holds true.

The role of exogenous variables in the VARMAX framework cannot be overstated. Exogenous variables, also referred to as independent or predictor variables, are variables external to the model that are not generated by the system. In VARMAX, exogenous variables are assumed to affect the endogenous variables but remain unaffected by them. The inclusion of these variables allows the model to account for influences coming from outside the multivariate system being analyzed.

In our study by including the U.S. sentiment as an exogenous variable in a VAR model, we have made an assumption about the structure of the model — that the U.S. sentiment influences the other variables in the model but is not influenced by them within the same time period.

The following are the result tables of our model that shows a significant effect of the US sentiment on the return of all G7 countries.

[Insert Table 10 through 16 here]

Granger Causality Wald Test for the SVAR Model

In order to comprehend the temporal dynamics between the sentiment of investors in the United States and the stock returns of the G7 nations, a Granger causality test was conducted.

The rational behind it is similar to one for the VAR model. However, the structure of our analysis in this section involved treating US sentiment as an independent variable (Group 1) since we are assuming that the US sentiment is an exogenous variable and the stock returns of Japan, the United Kingdom, France, Germany, Italy, and Canada as dependent variables (Group 2). This structure allowed us to investigate whether changes in US sentiment could anticipate variations in the stock returns of these G7 countries.

The principal findings of this section are encapsulated in the Granger-Causality Wald Test. The p-value (Pr > ChiSq) of the test was found to be less than 0.0001. This is significantly smaller than the standard threshold of 0.05, and therefore, allows us to reject the null hypothesis of the test. The null hypothesis for the Granger causality test suggests no predictive capacity of US sentiment over the G7 stock returns. Therefore, we can infer that US sentiment does provide meaningful predictive information regarding the stock returns of these countries.

[Insert Table 17 here]

PATH Analysis

In the first essay of this dissertation, we employed the SAS CALIS procedure for Path Analysis to investigate the causal relationships between US return and unexpected sentiment volatility and unexpected stock return volatility to test our model. We continue the exploration of the causal relationships between the US sentiment and returns on various countries' indices, using PATH analysis.

The CALIS procedure in SAS, combined with PATH analysis, facilitated the estimation of the direct effects of the US sentiment on each of the indices of interest. The results present intriguing insights into how changes in US sentiment could be associated with alterations in the selected indices.

[Insert Table 18 here]

The US_sentiment ===> R_US path analysis revealed a notable negative relationship. The estimated path coefficient of -3.18075 indicates that a unit increase in US sentiment corresponds to a decrease of approximately 3.18 units in R_US. This inverse relationship is statistically significant, as substantiated by a t-statistic of -4.9391 and a p-value less than 0.0001. These results corroborate our hypothesis in Essay 1, which postulated a potential negative impact of US sentiment on R_US.

For the R_US ===> R_Japan path, a unit increase in R_US was found to result in an approximately 0.06452 unit increase in R_Japan. With a t-statistic of 3.7734 and a p-value of 0.0002, the positive relationship is highly statistically significant.

The path analysis results of R_US with indices from other countries (R_UK, R_France, R_Germany, R_Italy, and R_Canada) were also statistically significant. Each of these paths yielded a positive path coefficient and a p-value less than 0.0001, implying that R_US exerts a significant positive impact on these indices.

[Insert Figure 1 here]

Multivariate GARCH Analysis

Upon examining Table 1, which presents the descriptive statistics of our key variables, a pattern emerges. The returns of all countries under study display a pronounced excess kurtosis. This observed characteristic in the return distribution highlights the idiosyncratic property of our data: it exhibits heteroskedasticity, a phenomenon where the variability of the error terms is not constant. Considering this non-constant variance in our dataset a more appropriate approach in modeling the data to explore influence of sentiment from one country on the return of another country might be multivariate GARCH models.

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, introduced by Robert Engle in 1982 and further extended by Tim Bollerslev in 1986, is a potent tool for modelling and forecasting financial volatility. While highly valuable, the GARCH model is inherently univariate, only considering one time series at a time. To capture interdependencies and volatilities of multiple time series simultaneously, Multivariate GARCH (MGARCH) models have been developed.

Multivariate GARCH models offer an extension to the univariate GARCH models for a multivariate context. These models allow for time-varying covariance between series. Thus, they permit modelling of changing variances and correlations amongst multiple time series. This allows simultaneous examination of several assets, thereby enhancing our understanding of their interconnectedness.

This section presents a detailed discussion on applying the VARMAX procedure to compute parameters of GARCH models for multivariate time series, adhering to the same theoretical framework provided for the univariate scenario in Essay 1.

Scholars have proposed multiple conceptual frameworks for multivariate GARCH models, such as BEKK, CCC, and DCC. BEKK parameterization essentially extends the GARCH model to multivariate expressions using matrix structures. In contrast, CCC and DCC parameterizations amalgamate individual GARCH models, which allow modeling of multivariate scenarios with few additional parameters. These parameterizations also cater to different GARCH model interpretations for individual univariate series, including but not limited to PGARCH and TGARCH.

The Constant Conditional Correlation (CCC) parameterization merges unique GARCH models for different time series, utilizing a fixed correlation between each pair. This yields a model of relative simplicity: a single parameter is employed to model the interplay between two variance processes. This model introduces fewer parameters than other methods, thereby avoiding potential numerical instabilities.

The correlations amongst the k series are amalgamated into a k × k matrix, represented by S. Any element in the (i,j) position is indicated as S_{ij}, where i, j = 1, . . . , k. Each series' GARCH models independently define conditional variances. The conditional variance for the ith series is depicted as h_{iit}, an extension of the notation from Essay 1, with an extra i subscript included for matrix notation consistency. The model for the conditional variances, h_{iit}, can be a typical GARCH model, although alternative models like QGACH and TGARCH are also permissible. The interrelationship among the series is then portrayed by the covariance, h_{ijt}, based on historical values. The conditional covariance is defined as follows:

$$h_{ijt} = Cov_t(\varepsilon_{it}, \varepsilon_{jt}) = s_{ij}\sqrt{h_{iit}h_{jjt}}$$

In this parameterization, the constant correlation is multiplied by the two conditional standard deviations to outline the conditional covariance. This structure introduces a single parameter for each pair of series, in contrast to univariate GARCH models for separate series, assuming independent volatility structures. For a bivariate situation, a CCC-GARCH(1,1) model incorporates three parameters per univariate GARCH model and one additional parameter signifying the series correlation, totaling seven parameters.

A logical strategy to develop a CCC model is to calculate GARCH models for each series individually, that is, calculating parameters in the k unique models.

$$h_{iit} = \omega + \sum_{i_1=1}^{q} \alpha_{i_1} \varepsilon_{i(t-i_1)}^2 + \sum_{j=1}^{p} \gamma_j h_{ii(t-j)}$$

The CCC model's computation can be executed by k individual applications of PROC VARMAX for each series. The correlations s_{ij} in the matrix S can subsequently be estimated through empirical correlation.

$$s_{ij} = \frac{1}{T} \sum_{t=1}^{T} \frac{\varepsilon_{it}}{\sqrt{h_{iit}}} \frac{\varepsilon_{jt}}{\sqrt{h_{ijt}}}$$

The series of PROC VARMAX commands employed in SAS aimed to model the interplay between US sentiment and the returns of each of seven different countries as paired relationships. Each procedure entails the specification of a MGARCH model with a Constant Conditional Correlation (CCC) form. In these models, a GARCH process of order (1,1) is stipulated, encapsulating a first-order autoregressive part and a first order moving average part for the conditional variances.

As an illustration, referring to Table 19, where we applied a dual GARCH(1,1) model with Constant Conditional Correlation (CCC) parameterization. The uniqueness of this parameterization is its single covariance parameter, capturing the relationship between the two series. Under this CCC-GARCH(1,1) structure, we formulated two individual GARCH(1,1) models—one for each series. The formulae for the estimated parameters are:

For the series representing US sentiment:

$$h_{1,t} = 0.00003 + 0.161\varepsilon_{1,t-1} + 0.791h_{1,t-1}$$

For the series denoting US returns:

$$h_{2,t} = 0.028 + 0.124\varepsilon_{2,t-1} + 0.856h_{2,t-1}$$

Following the estimation, we combined the conditional variances $h_{1,t}$ and $h_{2,t}$ of these series using a constant correlation factor, s_{12}, through the following equation:

$$h_{12t} = Cov_t(\varepsilon_{1t}, \varepsilon_{2t}) = s_{12}\sqrt{h_{11t}h_{22t}}$$

In this scenario, the derived constant correlation was -0.0697, which is represented as CCC_1_2 in Table 19.

[Insert Table 19 through 25 here]

In the Multivariate GARCH models, parameter estimates obtained from Tables 19 through 25 provide essential insights into the influence of US sentiment on various international returns. All parameters' estimates across all models are statistically significant, as indicated by their p-values and t values. This statistical significance implies that these parameters are essential to the model and significantly influence the return dynamics of the different countries under study.

The CCC1_2 parameters denote the correlations between the US sentiment and the different international market returns. This finding corroborates the notion of sentiment being a global phenomenon, affecting not just domestic markets, but having far-reaching effects on international financial markets as well.

Furthermore, the parameters GCHC1_1 and GCHC2_2 pertain to the constant conditional correlations of the residuals from the US sentiment and respective country returns. These are small but significant, suggesting a persisting effect on the volatility of the series. ACH1_1_1 and ACH1_2_2 denote the autoregressive parameters for US sentiment and international market returns. The positive estimates for these parameters indicate that both the sentiment and returns exhibit significant persistence. The parameters GCH1_1_1 and GCH1_2_2 represent the GARCH parameters for the volatility equations. These high estimates imply that past volatility plays a significant role in predicting future volatility in both the US sentiment and international market returns.

In essence, the parameter estimates confirm the interdependencies and influence of US sentiment on international market returns, capturing both the spillover of volatility and return dynamics. These findings are critical to understanding the underlying intricacies of global market dynamics and can have significant implications for international financial risk management and investment strategies.

References

Bai, Y. (2014). Cross-border sentiment: an empirical analysis on EU stock markets. *Applied Financial Economics*, *24*(4), 259-290.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The journal of Finance*, *61*(4), 1645-1680.

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of economic perspectives*, *21*(2), 129-151.

Bathia, D., Bredin, D., & Nitzsche, D. (2016). International sentiment spillovers in equity returns. *International Journal of Finance & Economics*, *21*(4), 332-359.

Becker, K. G., Finnerty, J. E., & Friedman, J. (1995). Economic news and equity market linkages between the US and UK. *Journal of Banking & Finance*, *19*(7), 1191-1210.

Black, F. (1986). Noise. *The journal of finance*, *41*(3), 528-543.

Brown, G. W., & Cliff, M. T. (2004). Investor sentiment and the near-term stock market. *Journal of empirical finance*, *11*(1), 1-27.

Canova, F. (2005). The transmission of US shocks to Latin America. *Journal of Applied econometrics*, *20*(2), 229-251.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of political Economy*, *98*(4), 703-738.

Engle, R. F., & Kroner, K. F. (1995). Multivariate simultaneous generalized ARCH. *Econometric theory*, *11*(1), 122-150.

Engle, R. F., Lilien, D. M., & Robins, R. P. (1987). Estimating time varying risk premia in the term structure: The ARCH-M model. *Econometrica: journal of the Econometric Society*, 391-407.

Easley, D., O'hara, M., & Srinivas, P. S. (1998). Option volume and stock prices: Evidence on where informed traders trade. *The Journal of Finance*, *53*(2), 431-465.

Foerster, S. R., & Schmitz, J. J. (1997). The transmission of US election cycles to international stock returns. *Journal of International Business Studies*, *28*, 1-13.

Forbes, K. J., & Rigobon, R. (2002). No contagion, only interdependence: measuring stock market comovements. *The journal of Finance*, *57*(5), 2223-2261.

Frazzini, A., & Lamont, O. A. (2008). Dumb money: Mutual fund flows and the cross-section of stock returns. *Journal of financial economics*, *88*(2), 299-322.

Froot, K. A., O'connell, P. G., & Seasholes, M. S. (2001). The portfolio flows of international *investors. Journal of financial Economics, 59(2), 151-193.*

Grinblatt, M., & Keloharju, M. (2000). The investment behavior and performance of various investor types: a study of Finland's unique data set. *Journal of financial economics, 55(1), 43-67.*

Grossmann, A., Ozuna, T., & Simpson, M. W. (2007). ADR mispricing: Do costly arbitrage and consumer sentiment explain the price deviation?. *Journal of International Financial Markets, Institutions and Money*, 17(4), 361-371.

Hudson, Y., & Green, C. J. (2015). Is investor sentiment contagious? International sentiment and UK equity returns. *Journal of Behavioral and Experimental Finance, 5, 46-59.*

Lee, C. M., Shleifer, A., & Thaler, R. H. (1991). Investor sentiment and the closed-end fund puzzle. The journal of finance, 46(1), 75-109.

Liu, Y. A., & Pan, M. S. (1997). Mean and volatility spillover effects in the US and Pacific-Basin stock markets. Multinational Finance Journal, 1(1), 47-62.

Ljungqvist, A., 2006. IPO Underpricing. *Handbook of Corporate Finance: Empirical Corporate Finance Chapter 7. Elsevier/North-Holland Publication.*

Maćkowiak, B. (2007). External shocks, US monetary policy and macroeconomic fluctuations in emerging markets. *Journal of monetary economics*, 54(8), 2512-2520.

Milhøj, A. *(2016)*. Multiple Time Series Modeling Using the SAS® VARMAX Procedure. *SAS Institute.*

Pan, J., & Poteshman, A. M. (2006). The information in option volume for future stock prices. *The Review of Financial Studies*, 19(3), 871-908.

Ritter, J. R. (2003). Investment banking and securities issuance. *In Handbook of the Economics of Finance (Vol. 1, pp. 255-306). Elsevier.*

Schmeling, M. (2009). Investor sentiment and stock returns: Some international evidence. *Journal of empirical finance*, 16(3), 394-408.

Soydemir, G. (2000). International transmission mechanism of stock market movements: evidence from emerging equity markets. *Journal of Forecasting*, *19*(3), 149-176.

Tandon, K., & Urich, T. (1987). International market response to announcements of US macroeconomic data. *Journal of International Money and Finance*, *6*(1), 71-83.

Verma, R., & Soydemir, G. (2006). The impact of US individual and institutional investor sentiment on foreign stock markets. *The Journal of Behavioral Finance*, *7*(3), 128-144.

Warther, V. A. (1995). Aggregate mutual fund flows and security returns. *Journal of financial* *economics*, *39*(2-3), 209-235.

Zweig, M. E. (1973). An investor expectations stock price predictive model using closed-end fund premiums. *The Journal of Finance*, *28*(1), 67-78.

Table 1

Summary Statistic

Variable	Label	*N*	*Mean*	*Std Dev*	*Skewness*	*Kurtosis*	*Minimum*	*Maximum*
US_sentiment	TRMI sentiment measure using news and social media data	4976	0.037169	0.02699810	0.90283445	0.90283445	0.000029	0.1915960
R_US	log(US_Closed/lag(US_Closed))*100	4976	0.028963	1.22933630	-0.35116530	10.51354300	-12.760460	10.9581838
R_Japan	log(JPN_Closed/lag(JPN_Closed))*100	4976	-0.0140532	1.48478580	-0.54675370	5.62003818	-12.111026	9.4941467
R_UK	log(UK_Closed/lag(UK_Closed))*100	4976	-0.018482	1.19068170	-0.46337460	7.22851780	-11.511706	8.6664227
R_France	log(FRN_Closed/lag(FRN_Closed))*10(	4976	-0.0068101	1.44735080	-0.38693890	5.90696776	-13.098349	9.2207981
R_Germany	log(GER_Closed/lag(GER_Closed))*10(	4976	-0.009687	1.49825100	-0.38150580	5.34257220	-13.056095	10.6852385
R_Italy	log(ITA_Closed/lag(ITA_Closed))*100	4976	-0.017936	1.52773050	-0.75539720	33.55082340	-24.033959	24.5825949
R_Canada	log(CAN_Closed/lag(CAN_Closed))*10(	4976	0.0049984	1.11743050	-1.15514220	-1.15514220	-13.175803	11.2945340

Table 2
Model Parameter Estimates
VAR (5)

Equation	Estimate	t Value	Pr > |t|	Variable
R_US	0.0333	1.91	0.0561	1
	-0.0859	-5.72	0.0001	R_US(t-1)
	-0.01879	-1.37	0.1718	R_Japan(t-1)
	0.01503	0.48	0.6332	R_UK(t-1)
	-0.04985	-1.4	0.1627	R_France(t-1)
	0.04476	1.71	0.0879	R_Germany(t-1)
	0.00314	0.15	0.881	R_Italy(t-1)
	0.01184	0.56	0.5722	R_Canada(t-1)
	-0.03152	-2.07	0.0384	R_US(t-2)
	0.00383	0.27	0.7847	R_Japan(t-2)
	-0.05152	-1.63	0.1026	R_UK(t-2)
	0.02638	0.73	0.4627	R_France(t-2)
	0.03404	1.28	0.1997	R_Germany(t-2)
	-0.02564	-1.22	0.2214	R_Italy(t-2)
	0.02067	0.95	0.3399	R_Canada(t-2)
	0.02352	1.54	0.1245	R_US(t-3)
	-0.00343	-0.25	0.8062	R_Japan(t-3)
	0.04485	1.42	0.155	R_UK(t-3)
	-0.01075	-0.3	0.7648	R_France(t-3)
	-0.01749	-0.66	0.5099	R_Germany(t-3)
	0.01203	0.57	0.5664	R_Italy(t-3)
	0.00007	0	0.9975	R_Canada(t-3)
	-0.04116	-2.51	0.0121	R_US(t-4)
	-0.01529	-1.1	0.273	R_Japan(t-4)
	-0.0074	-0.23	0.8146	R_UK(t-4)
	-0.0031	-0.09	0.9312	R_France(t-4)
	0.00986	0.37	0.7086	R_Germany(t-4)
	0.03312	1.58	0.1137	R_Italy(t-4)
	0.01314	0.62	0.5335	R_Canada(t-4)
	-0.03189	-1.96	0.0503	R_US(t-5)
	0.00348	0.27	0.7855	R_Japan(t-5)
	-0.02361	-0.76	0.4496	R_UK(t-5)
	0.00048	0.01	0.9893	R_France(t-5)
	-0.03142	-1.2	0.229	R_Germany(t-5)
	-0.00017	-0.01	0.9936	R_Italy(t-5)
	0.00882	0.42	0.6725	R_Canada(t-5)

Table 3
Model Parameter Estimates
VAR (5)

Equation	Estimate	t Value	Pr > |t|	Variable
R_Japan	-0.02998	-1.57	0.1154	1
	0.01235	0.75	0.4517	R_US(t-1)
	-0.20148	-13.41	0.0001	R_Japan(t-1)
	0.03267	0.95	0.3422	R_UK(t-1)
	0.05347	1.37	0.1704	R_France(t-1)
	0.12266	4.28	0.0001	R_Germany(t-1)
	0.03852	1.68	0.0929	R_Italy(t-1)
	0.27875	12.18	0.0001	R_Canada(t-1)
	0.05747	3.46	0.0006	R_US(t-2)
	-0.0081	-0.53	0.5964	R_Japan(t-2)
	-0.02656	-0.77	0.441	R_UK(t-2)
	0.01883	0.48	0.6313	R_France(t-2)
	0.0404	1.39	0.1635	R_Germany(t-2)
	-0.02176	-0.95	0.3422	R_Italy(t-2)
	-0.01671	-0.71	0.48	R_Canada(t-2)
	0.2015	12.05	0.0001	R_US(t-3)
	-0.04479	-2.94	0.0033	R_Japan(t-3)
	0.02087	0.61	0.5446	R_UK(t-3)
	0.01634	0.42	0.6773	R_France(t-3)
	-0.04508	-1.55	0.1201	R_Germany(t-3)
	-0.02293	-1	0.317	R_Italy(t-3)
	0.00206	0.09	0.9287	R_Canada(t-3)
	0.08338	4.65	0.0001	R_US(t-4)
	-0.03465	-2.27	0.023	R_Japan(t-4)
	-0.06241	-1.81	0.0704	R_UK(t-4)
	-0.02494	-0.64	0.5246	R_France(t-4)
	0.02949	1.02	0.3065	R_Germany(t-4)
	0.06096	2.67	0.0077	R_Italy(t-4)
	-0.0076	-0.33	0.7417	R_Canada(t-4)
	0.0764	4.29	0.0001	R_US(t-5)
	-0.01252	-0.9	0.3699	R_Japan(t-5)
	0.01323	0.39	0.698	R_UK(t-5)
	-0.01169	-0.3	0.7637	R_France(t-5)
	0.03578	1.25	0.2099	R_Germany(t-5)
	-0.00817	-0.36	0.7208	R_Italy(t-5)
	-0.04416	-1.94	0.0528	R_Canada(t-5)

Table 4
Model Parameter Estimates
VAR (5)

Equation	Estimate	t Value	Pr > |t|	Variable
R_UK	-0.04434	-2.78	0.0054	1
	0.11379	8.28	0.0001	R_US(t-1)
	-0.01521	-1.21	0.2265	R_Japan(t-1)
	-0.09308	-3.23	0.0012	R_UK(t-1)
	-0.10357	-3.17	0.0015	R_France(t-1)
	0.04907	2.05	0.0408	R_Germany(t-1)
	-0.03917	-2.04	0.0413	R_Italy(t-1)
	0.22724	11.85	0.0001	R_Canada(t-1)
	0.11339	8.14	0.0001	R_US(t-2)
	-0.00334	-0.26	0.7941	R_Japan(t-2)
	-0.0437	-1.51	0.1301	R_UK(t-2)
	0.01746	0.53	0.5951	R_France(t-2)
	-0.06937	-2.86	0.0043	R_Germany(t-2)
	0.00342	0.18	0.8587	R_Italy(t-2)
	0.00388	0.2	0.8449	R_Canada(t-2)
	0.24543	17.53	0.0001	R_US(t-3)
	-0.01239	-0.97	0.3319	R_Japan(t-3)
	-0.05017	-1.74	0.082	R_UK(t-3)
	-0.00302	-0.09	0.9269	R_France(t-3)
	-0.04859	-2	0.0454	R_Germany(t-3)
	0.00999	0.52	0.6025	R_Italy(t-3)
	0.00195	0.1	0.9193	R_Canada(t-3)
	0.08654	5.77	0.0001	R_US(t-4)
	0.00408	0.32	0.7491	R_Japan(t-4)
	-0.05491	-1.9	0.0573	R_UK(t-4)
	-0.05378	-1.64	0.1013	R_France(t-4)
	0.02375	0.98	0.3254	R_Germany(t-4)
	0.05746	3	0.0027	R_Italy(t-4)
	-0.01927	-1	0.318	R_Canada(t-4)
	0.07103	4.77	0.0001	R_US(t-5)
	-0.02091	-1.79	0.0737	R_Japan(t-5)
	0.00041	0.01	0.9885	R_UK(t-5)
	0.01181	0.36	0.7168	R_France(t-5)
	-0.05631	-2.36	0.0184	R_Germany(t-5)
	-0.00479	-0.25	0.8027	R_Italy(t-5)
	0.03138	1.64	0.1003	R_Canada(t-5)

Table 5
Model Parameter Estimates
VAR (5)

Equation	Estimate	t Value	Pr > |t|	Variable
R_France	-0.03383	-1.74	0.082	1
	0.14252	8.51	0.0001	R_US(t-1)
	-0.00872	-0.57	0.5696	R_Japan(t-1)
	-0.06931	-1.97	0.0485	R_UK(t-1)
	-0.19661	-4.94	0.0001	R_France(t-1)
	0.10344	3.54	0.0004	R_Germany(t-1)
	-0.0277	-1.18	0.2366	R_Italy(t-1)
	0.22541	9.64	0.0001	R_Canada(t-1)
	0.15966	9.4	0.0001	R_US(t-2)
	0.01004	0.64	0.5204	R_Japan(t-2)
	-0.02955	-0.84	0.4013	R_UK(t-2)
	-0.01728	-0.43	0.6663	R_France(t-2)
	-0.08704	-2.94	0.0033	R_Germany(t-2)
	0.02092	0.89	0.3713	R_Italy(t-2)
	0.02631	1.09	0.2763	R_Canada(t-2)
	0.29702	17.39	0.0001	R_US(t-3)
	0.00617	0.4	0.6922	R_Japan(t-3)
	0.00393	0.11	0.911	R_UK(t-3)
	-0.08766	-2.19	0.0288	R_France(t-3)
	-0.06599	-2.23	0.0259	R_Germany(t-3)
	0.04074	1.74	0.0818	R_Italy(t-3)
	0.00743	0.32	0.7519	R_Canada(t-3)
	0.10853	5.93	0.0001	R_US(t-4)
	0.01005	0.65	0.5185	R_Japan(t-4)
	-0.02753	-0.78	0.4344	R_UK(t-4)
	-0.09765	-2.44	0.0147	R_France(t-4)
	0.04474	1.52	0.1288	R_Germany(t-4)
	0.06393	2.74	0.0062	R_Italy(t-4)
	-0.03251	-1.38	0.1672	R_Canada(t-4)
	0.05754	3.17	0.0016	R_US(t-5)
	-0.01814	-1.27	0.2032	R_Japan(t-5)
	0.00395	0.11	0.9096	R_UK(t-5)
	-0.00673	-0.17	0.8655	R_France(t-5)
	-0.05213	-1.79	0.0736	R_Germany(t-5)
	-0.00767	-0.33	0.7426	R_Italy(t-5)
	0.00893	0.38	0.7012	R_Canada(t-5)

Table 6
Model Parameter Estimates
VAR (5)

Equation	Estimate	t Value	Pr > |t|	Variable
R_Germany	-0.03765	-1.86	0.0626	1
	0.14866	8.53	0.0001	R_US(t-1)
	-0.01256	-0.79	0.4309	R_Japan(t-1)
	-0.04752	-1.3	0.1933	R_UK(t-1)
	-0.0531	-1.28	0.1998	R_France(t-1)
	-0.05195	-1.71	0.0877	R_Germany(t-1)
	-0.01462	-0.6	0.548	R_Italy(t-1)
	0.16052	6.6	0.0001	R_Canada(t-1)
	0.16533	9.36	0.0001	R_US(t-2)
	0.00735	0.45	0.6509	R_Japan(t-2)
	-0.07489	-2.05	0.0408	R_UK(t-2)
	0.11064	2.66	0.0079	R_France(t-2)
	-0.1475	-4.79	0.0001	R_Germany(t-2)
	0.00344	0.14	0.8877	R_Italy(t-2)
	0.04222	1.68	0.0929	R_Canada(t-2)
	0.34076	19.19	0.0001	R_US(t-3)
	-0.008	-0.49	0.6211	R_Japan(t-3)
	0.01538	0.42	0.6742	R_UK(t-3)
	-0.05932	-1.42	0.1547	R_France(t-3)
	-0.07072	-2.3	0.0217	R_Germany(t-3)
	0.03439	1.41	0.1576	R_Italy(t-3)
	-0.00881	-0.36	0.7184	R_Canada(t-3)
	0.11418	6	0.0001	R_US(t-4)
	0.00047	0.03	0.977	R_Japan(t-4)
	-0.02957	-0.81	0.4194	R_UK(t-4)
	-0.10904	-2.62	0.0088	R_France(t-4)
	0.06366	2.08	0.0376	R_Germany(t-4)
	0.07172	2.95	0.0032	R_Italy(t-4)
	-0.01374	-0.56	0.5746	R_Canada(t-4)
	0.05265	2.79	0.0053	R_US(t-5)
	0.01173	0.79	0.4287	R_Japan(t-5)
	0.0238	0.66	0.5109	R_UK(t-5)
	-0.00105	-0.03	0.9796	R_France(t-5)
	-0.06055	-2	0.0457	R_Germany(t-5)
	-0.00743	-0.31	0.7597	R_Italy(t-5)
	0.00819	0.34	0.7351	R_Canada(t-5)

Table 7
Model Parameter Estimates
VAR (5)

Equation	Estimate	t Value	Pr > |t|	Variable
R_Italy	-0.04588	-2.2	0.0275	1
	0.10459	5.83	0.0001	R_US(t-1)
	-0.01381	-0.84	0.4002	R_Japan(t-1)
	-0.05866	-1.56	0.1188	R_UK(t-1)
	-0.11443	-2.68	0.0073	R_France(t-1)
	0.05282	1.69	0.0917	R_Germany(t-1)
	-0.04457	-1.78	0.0752	R_Italy(t-1)
	0.18965	7.58	0.0001	R_Canada(t-1)
	0.17559	9.66	0.0001	R_US(t-2)
	0.0104	0.62	0.5338	R_Japan(t-2)
	-0.02231	-0.59	0.5538	R_UK(t-2)
	-0.01605	-0.37	0.7083	R_France(t-2)
	-0.03819	-1.21	0.2282	R_Germany(t-2)
	-0.01179	-0.47	0.6377	R_Italy(t-2)
	0.01249	0.48	0.6292	R_Canada(t-2)
	0.30195	16.52	0.0001	R_US(t-3)
	-0.00233	-0.14	0.8888	R_Japan(t-3)
	-0.00571	-0.15	0.8795	R_UK(t-3)
	-0.07852	-1.83	0.0673	R_France(t-3)
	-0.05092	-1.61	0.1082	R_Germany(t-3)
	0.04095	1.64	0.102	R_Italy(t-3)
	0.01859	0.74	0.4599	R_Canada(t-3)
	0.12199	6.23	0.0001	R_US(t-4)
	0.01233	0.74	0.4593	R_Japan(t-4)
	-0.02546	-0.68	0.4994	R_UK(t-4)
	-0.07992	-1.87	0.0622	R_France(t-4)
	0.03966	1.26	0.2083	R_Germany(t-4)
	0.07242	2.9	0.0038	R_Italy(t-4)
	-0.0106	-0.42	0.674	R_Canada(t-4)
	0.06034	3.1	0.0019	R_US(t-5)
	-0.02105	-1.38	0.1677	R_Japan(t-5)
	-0.00543	-0.15	0.8841	R_UK(t-5)
	0.03629	0.85	0.3931	R_France(t-5)
	-0.05299	-1.7	0.0893	R_Germany(t-5)
	-0.03119	-1.25	0.2121	R_Italy(t-5)
	0.00796	0.32	0.7493	R_Canada(t-5)

Table 8
Model Parameter Estimates
VAR (5)

Equation	Estimate	t Value	Pr > |t|	Variable
R_Canada	-0.00894	-0.6	0.549	1
	0.06574	5.11	0.0001	R_US(t-1)
	0.01374	1.17	0.2432	R_Japan(t-1)
	0.03433	1.27	0.2029	R_UK(t-1)
	-0.08086	-2.65	0.0082	R_France(t-1)
	0.03351	1.49	0.1356	R_Germany(t-1)
	0.00211	0.12	0.9066	R_Italy(t-1)
	-0.02295	-1.28	0.2011	R_Canada(t-1)
	0.06033	4.63	0.0001	R_US(t-2)
	0.01269	1.06	0.2901	R_Japan(t-2)
	-0.0903	-3.34	0.0008	R_UK(t-2)
	0.01567	0.51	0.6105	R_France(t-2)
	-0.00084	-0.04	0.9705	R_Germany(t-2)
	0.02848	1.59	0.1127	R_Italy(t-2)
	-0.03926	-2.12	0.0343	R_Canada(t-2)
	0.33596	25.63	0.0001	R_US(t-3)
	-0.0223	-1.87	0.0621	R_Japan(t-3)
	0.03259	1.21	0.2274	R_UK(t-3)
	-0.01508	-0.49	0.624	R_France(t-3)
	-0.04175	-1.84	0.0663	R_Germany(t-3)
	0.02009	1.12	0.2632	R_Italy(t-3)
	-0.11274	-6.25	0.0001	R_Canada(t-3)
	0.04316	3.07	0.0021	R_US(t-4)
	-0.00453	-0.38	0.7047	R_Japan(t-4)
	-0.02842	-1.05	0.2931	R_UK(t-4)
	-0.02331	-0.76	0.448	R_France(t-4)
	0.03435	1.52	0.1286	R_Germany(t-4)
	0.02344	1.31	0.191	R_Italy(t-4)
	-0.0149	-0.82	0.4094	R_Canada(t-4)
	0.02546	1.83	0.068	R_US(t-5)
	0.00574	0.52	0.6001	R_Japan(t-5)
	0.01326	0.5	0.6197	R_UK(t-5)
	0.01712	0.56	0.5743	R_France(t-5)
	-0.04562	-2.04	0.0414	R_Germany(t-5)
	0.00088	0.05	0.9607	R_Italy(t-5)
	0.01289	0.72	0.4707	R_Canada(t-5)

Table 9

Granger-Causality Wald Test

Group 1 Variables: US

Group 2 Variables: Japan, UK, France, Germany, Italy, Canada

DF	Chi-Square	Pr > ChiSq
30	43.38	0.0443

Table 10
Model Parameter Estimates (Least Square)
VARX(5,0)

Equation	Estimate	t Value	Pr > |t|	Variable
R_US	0.16965	5.65	0.0001	1
	-3.64978	-5.57	0.0001	US_sentiment(t)
	-0.08911	-5.95	0.0001	R_US(t-1)
	-0.01876	-1.37	0.1712	R_Japan(t-1)
	0.01616	0.51	0.6068	R_UK(t-1)
	-0.05085	-1.43	0.1532	R_France(t-1)
	0.04294	1.64	0.1006	R_Germany(t-1)
	0.00378	0.18	0.8565	R_Italy(t-1)
	0.00195	0.09	0.9259	R_Canada(t-1)
	-0.03429	-2.26	0.024	R_US(t-2)
	0.00403	0.29	0.7727	R_Japan(t-2)
	-0.05176	-1.65	0.1	R_UK(t-2)
	0.02455	0.69	0.4931	R_France(t-2)
	0.03559	1.35	0.1786	R_Germany(t-2)
	-0.02651	-1.27	0.2049	R_Italy(t-2)
	0.01862	0.86	0.3886	R_Canada(t-2)
	0.01833	1.2	0.2306	R_US(t-3)
	-0.00356	-0.26	0.798	R_Japan(t-3)
	0.0461	1.47	0.1426	R_UK(t-3)
	-0.01382	-0.39	0.6996	R_France(t-3)
	-0.01479	-0.56	0.5764	R_Germany(t-3)
	0.01056	0.51	0.6136	R_Italy(t-3)
	-0.00435	-0.21	0.8361	R_Canada(t-3)
	-0.04279	-2.62	0.0089	R_US(t-4)
	-0.01414	-1.02	0.3094	R_Japan(t-4)
	-0.00211	-0.07	0.9466	R_UK(t-4)
	-0.00684	-0.19	0.8485	R_France(t-4)
	0.00903	0.34	0.7315	R_Germany(t-4)
	0.03216	1.54	0.1234	R_Italy(t-4)
	0.00881	0.42	0.6755	R_Canada(t-4)
	-0.0352	-2.17	0.0303	R_US(t-5)
	0.00306	0.24	0.8102	R_Japan(t-5)
	-0.02342	-0.75	0.4518	R_UK(t-5)
	-0.00049	-0.01	0.989	R_France(t-5)
	-0.0327	-1.26	0.2092	R_Germany(t-5)
	-0.00029	-0.01	0.9889	R_Italy(t-5)
	0.0074	0.36	0.722	R_Canada(t-5)

Table 11
Model Parameter Estimates (Least Square)
VARX(5,0)

Equation	Estimate	t Value	Pr > |t|	Variable
R_Japan	0.12291	3.75	0.0002	1
	-4.09259	-5.72	0.0001	US_sentiment(t)
	0.00875	0.53	0.5931	R_US(t-1)
	-0.20144	-13.45	0.0001	R_Japan(t-1)
	0.03394	0.99	0.3223	R_UK(t-1)
	0.05235	1.35	0.1782	R_France(t-1)
	0.12062	4.22	0.0001	R_Germany(t-1)
	0.03924	1.72	0.0859	R_Italy(t-1)
	0.26767	11.69	0.0001	R_Canada(t-1)
	0.05437	3.28	0.0011	R_US(t-2)
	-0.00787	-0.52	0.6059	R_Japan(t-2)
	-0.02683	-0.78	0.435	R_UK(t-2)
	0.01678	0.43	0.668	R_France(t-2)
	0.04214	1.46	0.1449	R_Germany(t-2)
	-0.02273	-1	0.3196	R_Italy(t-2)
	-0.01901	-0.81	0.4203	R_Canada(t-2)
	0.19569	11.72	0.0001	R_US(t-3)
	-0.04494	-2.96	0.0031	R_Japan(t-3)
	0.02227	0.65	0.5167	R_UK(t-3)
	0.01289	0.33	0.7419	R_France(t-3)
	-0.04205	-1.45	0.1459	R_Germany(t-3)
	-0.02457	-1.08	0.282	R_Italy(t-3)
	-0.00289	-0.13	0.8997	R_Canada(t-3)
	0.08155	4.56	0.0001	R_US(t-4)
	-0.03335	-2.2	0.0282	R_Japan(t-4)
	-0.05648	-1.64	0.1006	R_UK(t-4)
	-0.02913	-0.75	0.456	R_France(t-4)
	0.02855	0.99	0.3206	R_Germany(t-4)
	0.05989	2.63	0.0087	R_Italy(t-4)
	-0.01245	-0.54	0.5882	R_Canada(t-4)
	0.07269	4.09	0.0001	R_US(t-5)
	-0.01299	-0.93	0.3507	R_Japan(t-5)
	0.01344	0.4	0.6925	R_UK(t-5)
	-0.01277	-0.33	0.7418	R_France(t-5)
	0.03434	1.21	0.2273	R_Germany(t-5)
	-0.00831	-0.36	0.7154	R_Italy(t-5)
	-0.04575	-2.01	0.0442	R_Canada(t-5)

Table 12
Model Parameter Estimates (Least Square)
VARX(5,0)

Equation	Estimate	t Value	Pr > |t|	Variable
R_UK	0.14109	5.16	0.0001	1
	-4.96362	-8.31	0.0001	US_sentiment(t)
	0.10942	8.01	0.0001	R_US(t-1)
	-0.01517	-1.21	0.2247	R_Japan(t-1)
	-0.09155	-3.2	0.0014	R_UK(t-1)
	-0.10493	-3.24	0.0012	R_France(t-1)
	0.0466	1.96	0.0505	R_Germany(t-1)
	-0.0383	-2.01	0.0445	R_Italy(t-1)
	0.2138	11.19	0.0001	R_Canada(t-1)
	0.10963	7.92	0.0001	R_US(t-2)
	-0.00306	-0.24	0.8099	R_Japan(t-2)
	-0.04401	-1.54	0.1248	R_UK(t-2)
	0.01497	0.46	0.6464	R_France(t-2)
	-0.06726	-2.79	0.0053	R_Germany(t-2)
	0.00224	0.12	0.9064	R_Italy(t-2)
	0.00109	0.06	0.9559	R_Canada(t-2)
	0.23837	17.11	0.0001	R_US(t-3)
	-0.01258	-0.99	0.3213	R_Japan(t-3)
	-0.04847	-1.69	0.0907	R_UK(t-3)
	-0.0072	-0.22	0.8255	R_France(t-3)
	-0.04491	-1.86	0.0627	R_Germany(t-3)
	0.008	0.42	0.6747	R_Italy(t-3)
	-0.00405	-0.21	0.8324	R_Canada(t-3)
	0.08432	5.66	0.0001	R_US(t-4)
	0.00565	0.45	0.6558	R_Japan(t-4)
	-0.04771	-1.66	0.0964	R_UK(t-4)
	-0.05887	-1.81	0.071	R_France(t-4)
	0.02261	0.94	0.3457	R_Germany(t-4)
	0.05616	2.95	0.0032	R_Italy(t-4)
	-0.02516	-1.31	0.1897	R_Canada(t-4)
	0.06653	4.49	0.0001	R_US(t-5)
	-0.02148	-1.85	0.0643	R_Japan(t-5)
	0.00066	0.02	0.9813	R_UK(t-5)
	0.0105	0.32	0.7454	R_France(t-5)
	-0.05805	-2.45	0.0144	R_Germany(t-5)
	-0.00495	-0.26	0.7945	R_Italy(t-5)
	0.02945	1.55	0.1205	R_Canada(t-5)

Table 13
Model Parameter Estimates (Least Square)
VARX(5,0)

Equation	Estimate	t Value	Pr > |t|	Variable
R_France	0.20783	6.24	0.0001	1
	-6.469	-8.89	0.0001	US_sentiment(t)
	0.13683	8.22	0.0001	R_US(t-1)
	-0.00866	-0.57	0.5692	R_Japan(t-1)
	-0.06731	-1.93	0.0535	R_UK(t-1)
	-0.19838	-5.02	0.0001	R_France(t-1)
	0.10022	3.45	0.0006	R_Germany(t-1)
	-0.02657	-1.14	0.2527	R_Italy(t-1)
	0.20789	8.93	0.0001	R_Canada(t-1)
	0.15475	9.18	0.0001	R_US(t-2)
	0.01041	0.67	0.5019	R_Japan(t-2)
	-0.02997	-0.86	0.391	R_UK(t-2)
	-0.02053	-0.52	0.6057	R_France(t-2)
	-0.08428	-2.87	0.0041	R_Germany(t-2)
	0.01939	0.84	0.4036	R_Italy(t-2)
	0.02267	0.95	0.3444	R_Canada(t-2)
	0.28783	16.96	0.0001	R_US(t-3)
	0.00592	0.38	0.7016	R_Japan(t-3)
	0.00614	0.18	0.8603	R_UK(t-3)
	-0.09311	-2.34	0.0193	R_France(t-3)
	-0.06119	-2.08	0.0374	R_Germany(t-3)
	0.03814	1.64	0.1005	R_Italy(t-3)
	-0.0004	-0.02	0.9865	R_Canada(t-3)
	0.10564	5.82	0.0001	R_US(t-4)
	0.01209	0.78	0.4336	R_Japan(t-4)
	-0.01815	-0.52	0.6037	R_UK(t-4)
	-0.10427	-2.63	0.0087	R_France(t-4)
	0.04326	1.48	0.1388	R_Germany(t-4)
	0.06223	2.69	0.0073	R_Italy(t-4)
	-0.04018	-1.72	0.0856	R_Canada(t-4)
	0.05167	2.86	0.0042	R_US(t-5)
	-0.01888	-1.34	0.1819	R_Japan(t-5)
	0.00429	0.12	0.9013	R_UK(t-5)
	-0.00844	-0.21	0.8304	R_France(t-5)
	-0.0544	-1.88	0.0599	R_Germany(t-5)
	-0.00789	-0.34	0.7335	R_Italy(t-5)
	0.00642	0.28	0.7811	R_Canada(t-5)

Table 14
Model Parameter Estimates (Least Square)
VARX(5,0)

Equation	Estimate	t Value	Pr > |t|	Variable
R_Germany	0.19723	5.69	0.0001	1
	-6.28749	-8.3	0.0001	US_sentiment(t)
	0.14313	8.27	0.0001	R_US(t-1)
	-0.01251	-0.79	0.4299	R_Japan(t-1)
	-0.04558	-1.26	0.209	R_UK(t-1)
	-0.05482	-1.33	0.1826	R_France(t-1)
	-0.05509	-1.82	0.0683	R_Germany(t-1)
	-0.01352	-0.56	0.576	R_Italy(t-1)
	0.14349	5.92	0.0001	R_Canada(t-1)
	0.16056	9.15	0.0001	R_US(t-2)
	0.00771	0.48	0.6327	R_Japan(t-2)
	-0.0753	-2.07	0.0384	R_UK(t-2)
	0.10748	2.6	0.0094	R_France(t-2)
	-0.14482	-4.74	0.0001	R_Germany(t-2)
	0.00195	0.08	0.9357	R_Italy(t-2)
	0.03869	1.55	0.1211	R_Canada(t-2)
	0.33182	18.78	0.0001	R_US(t-3)
	-0.00824	-0.51	0.6084	R_Japan(t-3)
	0.01752	0.48	0.6295	R_UK(t-3)
	-0.06462	-1.56	0.1186	R_France(t-3)
	-0.06606	-2.16	0.0308	R_Germany(t-3)
	0.03186	1.32	0.1874	R_Italy(t-3)
	-0.01642	-0.68	0.499	R_Canada(t-3)
	0.11137	5.89	0.0001	R_US(t-4)
	0.00245	0.15	0.8787	R_Japan(t-4)
	-0.02045	-0.56	0.5741	R_UK(t-4)
	-0.11548	-2.79	0.0052	R_France(t-4)
	0.06222	2.05	0.0408	R_Germany(t-4)
	0.07007	2.91	0.0037	R_Italy(t-4)
	-0.02119	-0.87	0.3837	R_Canada(t-4)
	0.04695	2.5	0.0124	R_US(t-5)
	0.01101	0.75	0.4545	R_Japan(t-5)
	0.02413	0.67	0.5023	R_UK(t-5)
	-0.00272	-0.07	0.9472	R_France(t-5)
	-0.06276	-2.09	0.037	R_Germany(t-5)
	-0.00764	-0.32	0.7514	R_Italy(t-5)
	0.00575	0.24	0.8111	R_Canada(t-5)

Table 15
Model Parameter Estimates (Least Square)
VARX(5,0)

Equation	**Estimate**	**t Value**	**Pr > |t|**	**Variable**
R_Italy	0.1434	4.01	0.0001	1
	-5.06665	-6.48	0.0001	US_sentiment(t)
	0.10013	5.6	0.0001	R_US(t-1)
	-0.01377	-0.84	0.3998	R_Japan(t-1)
	-0.05709	-1.52	0.1274	R_UK(t-1)
	-0.11582	-2.73	0.0064	R_France(t-1)
	0.05029	1.61	0.1068	R_Germany(t-1)
	-0.04368	-1.75	0.08	R_Italy(t-1)
	0.17593	7.03	0.0001	R_Canada(t-1)
	0.17175	9.48	0.0001	R_US(t-2)
	0.01069	0.64	0.5208	R_Japan(t-2)
	-0.02263	-0.6	0.5464	R_UK(t-2)
	-0.01859	-0.44	0.6634	R_France(t-2)
	-0.03603	-1.14	0.2536	R_Germany(t-2)
	-0.01299	-0.52	0.6024	R_Italy(t-2)
	0.00964	0.37	0.7081	R_Canada(t-2)
	0.29475	16.16	0.0001	R_US(t-3)
	-0.00252	-0.15	0.8792	R_Japan(t-3)
	-0.00398	-0.11	0.9155	R_UK(t-3)
	-0.08279	-1.94	0.0527	R_France(t-3)
	-0.04716	-1.49	0.1352	R_Germany(t-3)
	0.03892	1.56	0.1187	R_Italy(t-3)
	0.01246	0.5	0.6191	R_Canada(t-3)
	0.11972	6.14	0.0001	R_US(t-4)
	0.01393	0.84	0.4012	R_Japan(t-4)
	-0.01811	-0.48	0.6297	R_UK(t-4)
	-0.08511	-1.99	0.0461	R_France(t-4)
	0.0385	1.23	0.22	R_Germany(t-4)
	0.07109	2.86	0.0043	R_Italy(t-4)
	-0.0166	-0.66	0.5084	R_Canada(t-4)
	0.05574	2.88	0.004	R_US(t-5)
	-0.02163	-1.42	0.1545	R_Japan(t-5)
	-0.00517	-0.14	0.8892	R_UK(t-5)
	0.03495	0.83	0.4089	R_France(t-5)
	-0.05477	-1.76	0.0779	R_Germany(t-5)
	-0.03136	-1.26	0.2078	R_Italy(t-5)
	0.00599	0.24	0.8092	R_Canada(t-5)

Table 16
Model Parameter Estimates (Least Square)
VARX(5,0)

Equation	Estimate	t Value	Pr > |t|	Variable
R_Canada	0.14134	5.51	0.0001	1
	-4.02293	-7.19	0.0001	US_sentiment(t)
	0.0622	4.86	0.0001	R_US(t-1)
	0.01378	1.18	0.2395	R_Japan(t-1)
	0.03558	1.33	0.1848	R_UK(t-1)
	-0.08196	-2.7	0.0071	R_France(t-1)
	0.03151	1.41	0.1585	R_Germany(t-1)
	0.00281	0.16	0.8749	R_Italy(t-1)
	-0.03384	-1.89	0.059	R_Canada(t-1)
	0.05728	4.42	0.0001	R_US(t-2)
	0.01292	1.08	0.279	R_Japan(t-2)
	-0.09056	-3.37	0.0008	R_UK(t-2)
	0.01365	0.45	0.6556	R_France(t-2)
	0.00087	0.04	0.9692	R_Germany(t-2)
	0.02753	1.54	0.1234	R_Italy(t-2)
	-0.04151	-2.25	0.0245	R_Canada(t-2)
	0.33025	25.28	0.0001	R_US(t-3)
	-0.02245	-1.89	0.059	R_Japan(t-3)
	0.03397	1.26	0.2061	R_UK(t-3)
	-0.01847	-0.6	0.5463	R_France(t-3)
	-0.03876	-1.71	0.0866	R_Germany(t-3)
	0.01848	1.03	0.3011	R_Italy(t-3)
	-0.11761	-6.55	0.0001	R_Canada(t-3)
	0.04136	2.96	0.0031	R_US(t-4)
	-0.00326	-0.27	0.7842	R_Japan(t-4)
	-0.02258	-0.84	0.4013	R_UK(t-4)
	-0.02744	-0.9	0.3695	R_France(t-4)
	0.03343	1.49	0.1371	R_Germany(t-4)
	0.02239	1.26	0.2095	R_Italy(t-4)
	-0.01967	-1.09	0.2741	R_Canada(t-4)
	0.02182	1.57	0.1162	R_US(t-5)
	0.00527	0.48	0.628	R_Japan(t-5)
	0.01347	0.51	0.6125	R_UK(t-5)
	0.01605	0.53	0.5964	R_France(t-5)
	-0.04703	-2.11	0.0346	R_Germany(t-5)
	0.00075	0.04	0.9666	R_Italy(t-5)
	0.01133	0.64	0.5241	R_Canada(t-5)

Table 17

Granger-Causality Wald Test

Group 1 Variables: US Sentiment

Group 2 Variables: Japan, UK, France, Germany, Italy, Canada

DF	Chi-Square	Pr > ChiSq
30	113.4	<.0001

Table 18
PATH List

	Path		Estimate	t Value	Pr > |t|
US_sentiment	===>	**R_US**	-3.18075	-4.9391	<.0001
R_US	===>	**R_Japan**	0.06452	3.7734	0.0002
R_US	===>	**R_UK**	0.16961	12.5457	<.0001
R_US	===>	**R_France**	0.21596	13.1612	<.0001
R_US	===>	**R_Germany**	0.26457	15.6857	<.0001
R_US	===>	**R_Italy**	0.17584	10.0814	<.0001
R_US	===>	**R_Canada**	0.26175	21.2093	<.0001

Table 19
CCC-GARCH (1,1) Model Parameter
US Sentiment & US Return

Parameter	Estimate	t Value	Pr > |t|
CCC1_2	-0.0697	-4.92	0.0001
GCHC1_1	0.00003	4.29	0.0001
GCHC2_2	0.02785	7.38	0.0001
ACH1_1_1	0.16089	7.67	0.0001
ACH1_2_2	0.12431	11.91	0.0001
GCH1_1_1	0.79145	26.63	0.0001
GCH1_2_2	0.85588	77.53	0.0001

Table 20
CCC-GARCH (1,1) Model Parameter
US Sentiment & Japan Return

Parameter	Estimate	t Value	Pr > |t|
CCC1_2	-0.11139	-7.92	0.0001
GCHC1_1	0.00003	4.25	0.0001
GCHC2_2	0.0517	5.84	0.0001
ACH1_1_1	0.16107	7.54	0.0001
ACH1_2_2	0.11035	11.73	0.0001
GCH1_1_1	0.7892	25.71	0.0001
GCH1_2_2	0.86907	80.99	0.0001

Table 21
CCC-GARCH (1,1) Model Parameter
US Sentiment & UK Return

Parameter	Estimate	t Value	Pr > |t|
CCC1_2	-0.12766	-9.1	0.0001
GCHC1_1	0.00003	4.3	0.0001
GCHC2_2	0.02592	5.94	0.0001
ACH1_1_1	0.16581	7.66	0.0001
ACH1_2_2	0.12156	10.92	0.0001
GCH1_1_1	0.7833	25.23	0.0001
GCH1_2_2	0.86008	69.71	0.0001

Table 22
CCC-GARCH (1,1) Model Parameter
US Sentiment & France Return

Parameter	Estimate	t Value	Pr > |t|
CCC1_2	-0.13302	-9.49	0.0001
GCHC1_1	0.00004	4.36	0.0001
GCHC2_2	0.04244	6.38	0.0001
ACH1_1_1	0.16925	7.69	0.0001
ACH1_2_2	0.11086	10.87	0.0001
GCH1_1_1	0.77746	24.52	0.0001
GCH1_2_2	0.86871	74.3	0.0001

Table 23
CCC-GARCH (1,1) Model Parameter
US Sentiment & Germany Return

Parameter	Estimate	t Value	Pr > |t|
CCC1_2	-0.12177	-8.67	0.0001
GCHC1_1	0.00003	4.33	0.0001
GCHC2_2	0.03945	6.32	0.0001
ACH1_1_1	0.16695	7.66	0.0001
ACH1_2_2	0.10054	10.91	0.0001
GCH1_1_1	0.78079	24.88	0.0001
GCH1_2_2	0.88087	83.49	0.0001

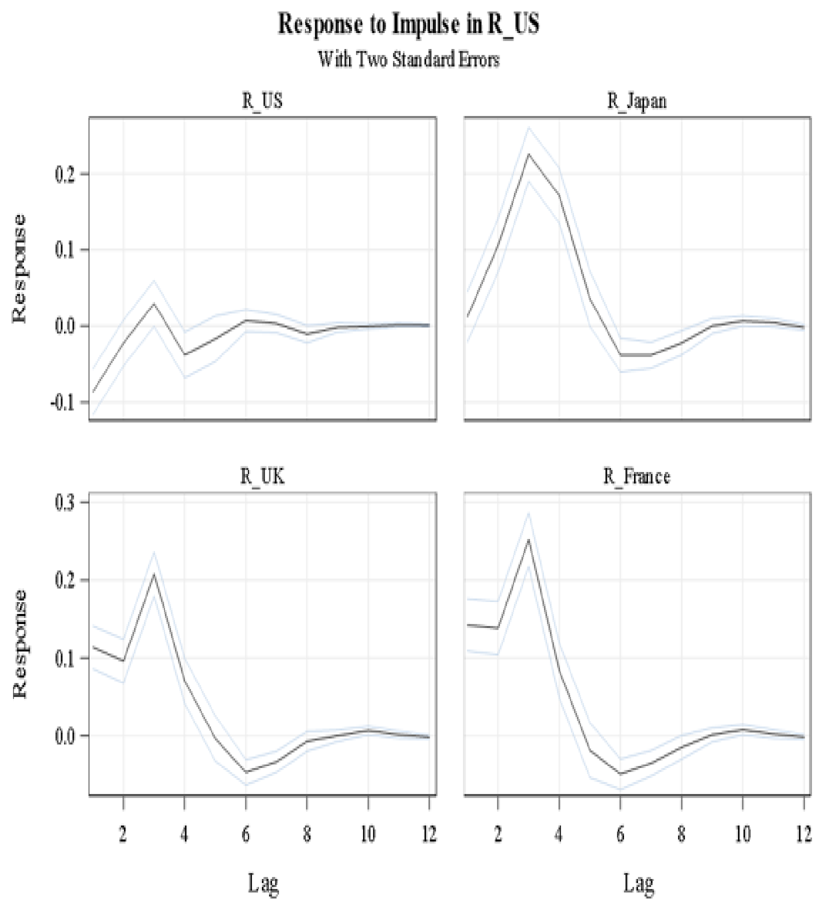
Table 24
CCC-GARCH (1,1) Model Parameter
US Sentiment & Italy Return

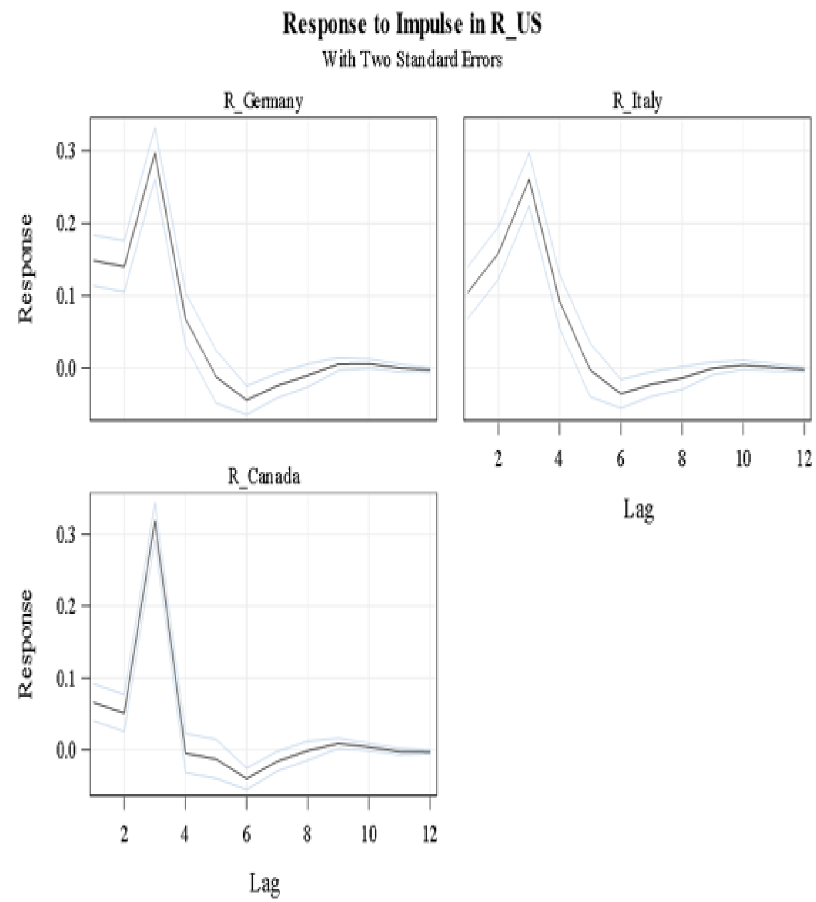
Parameter	Estimate	t Value	Pr > |t|
CCC1_2	-0.10393	-7.34	0.0001
GCHC1_1	0.00003	4.31	0.0001
GCHC2_2	0.02963	5.25	0.0001
ACH1_1_1	0.16393	7.64	0.0001
ACH1_2_2	0.11317	11.59	0.0001
GCH1_1_1	0.78505	25.46	0.0001
GCH1_2_2	0.88897	99.41	0.0001

Table 25
CCC-GARCH (1,1) Model Parameter
US Sentiment & Canada Return

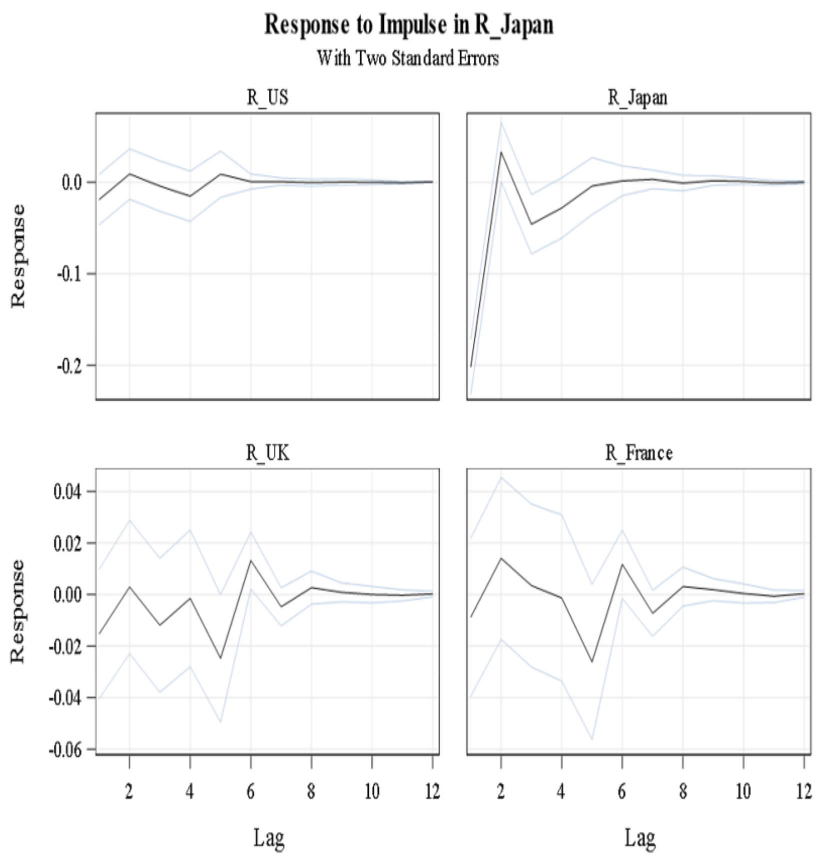
Parameter	Estimate	t Value	Pr > |t|
CCC1_2	-0.10118	-7.17	0.0001
GCHC1_1	0.00003	4.34	0.0001
GCHC2_2	0.01231	5.47	0.0001
ACH1_1_1	0.16482	7.71	0.0001
ACH1_2_2	0.10976	12.24	0.0001
GCH1_1_1	0.78529	25.82	0.0001
GCH1_2_2	0.88224	96.96	0.0001

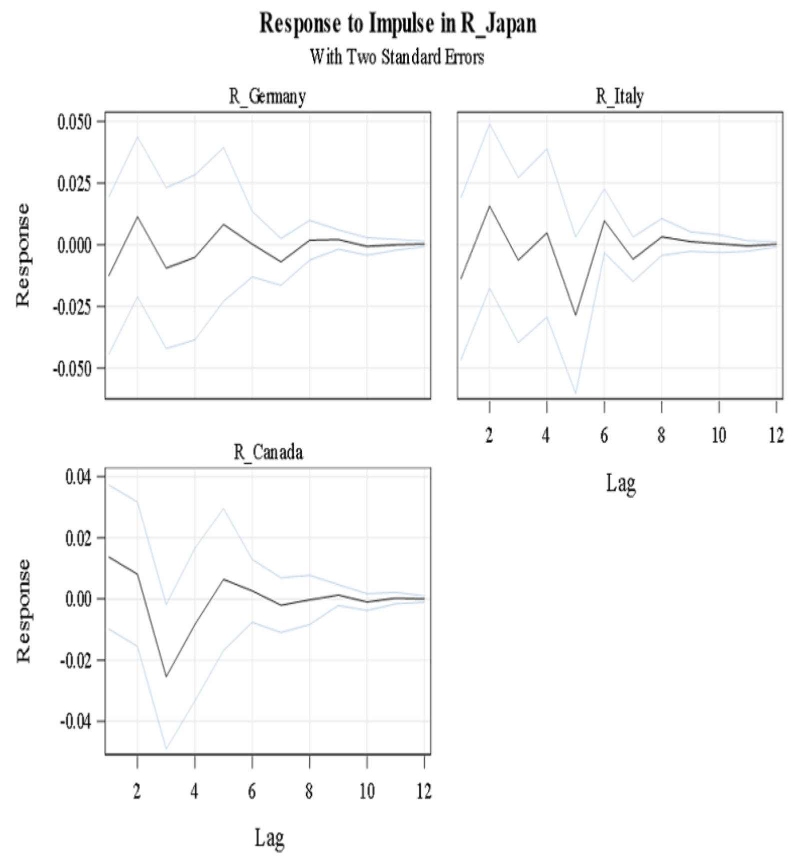
Graph 1


Response to Impulse in R_US
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag

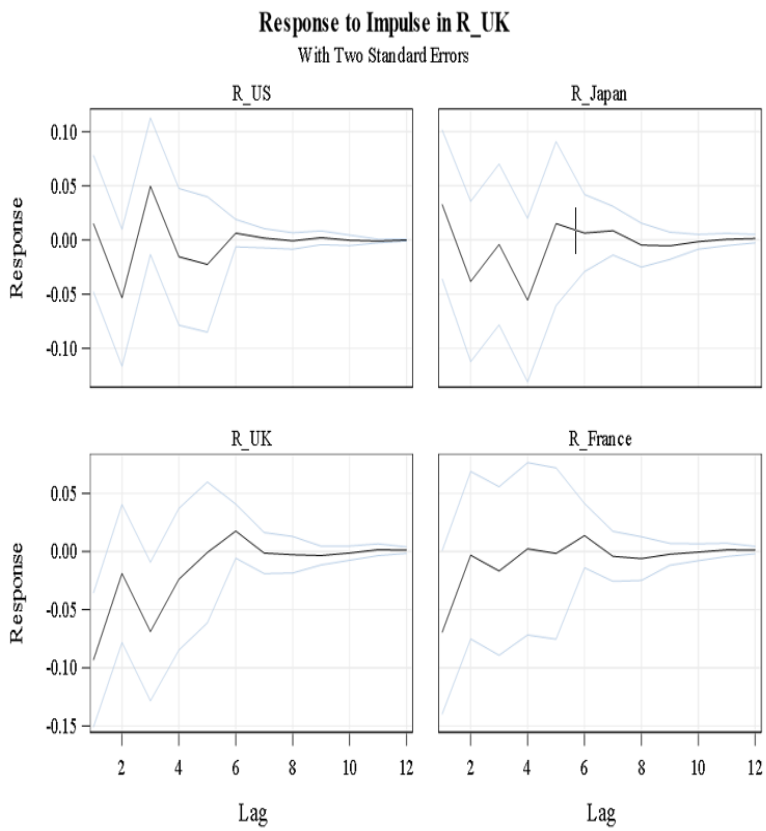

Response to Impulse in R_US
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag

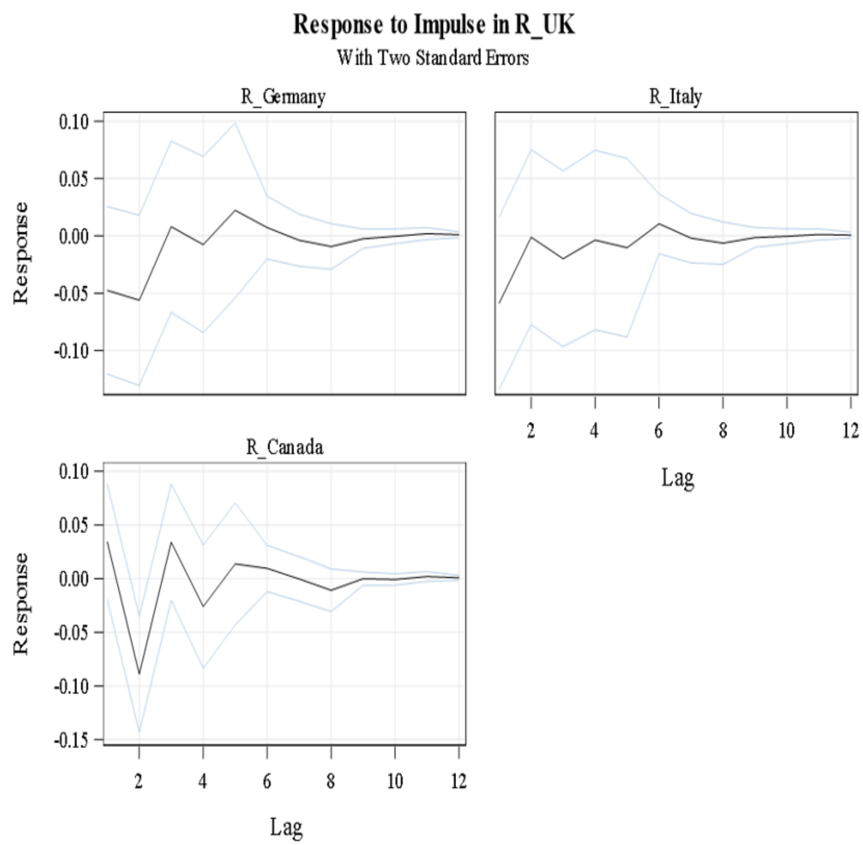
Graph 2


Response to Impulse in R_Japan
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag
0.0
-0.1
-0.2
0.04
0.02
0.00
-0.02
-0.04
-0.06
2
4
6
8
10
12

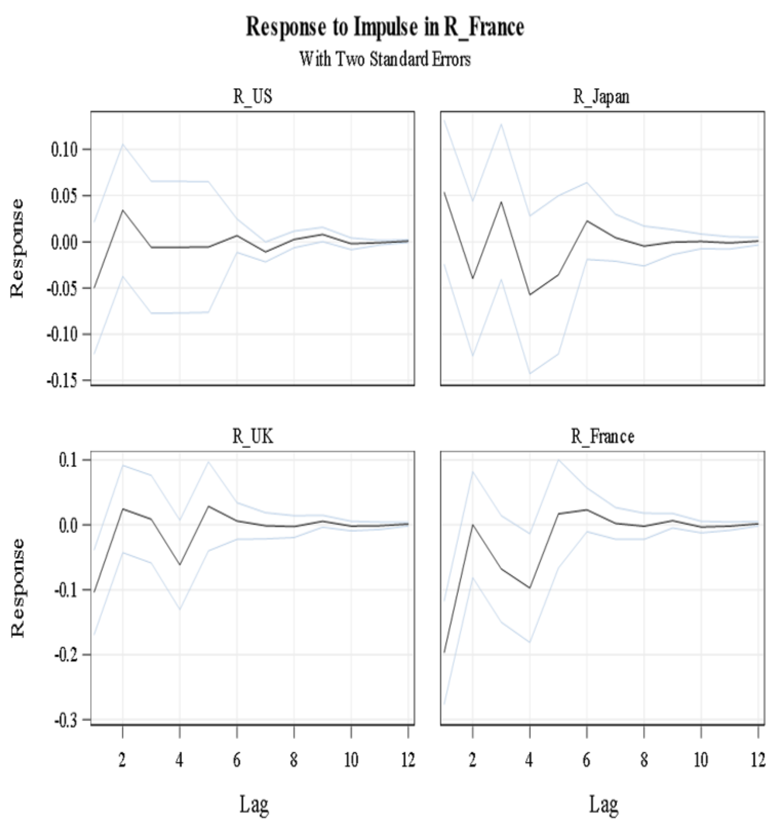

Response to Impulse in R_Japan
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag
0.050
0.025
0.000
-0.025
-0.050
0.04
0.02
0.00
-0.02
-0.04
2
4
6
8
10
12

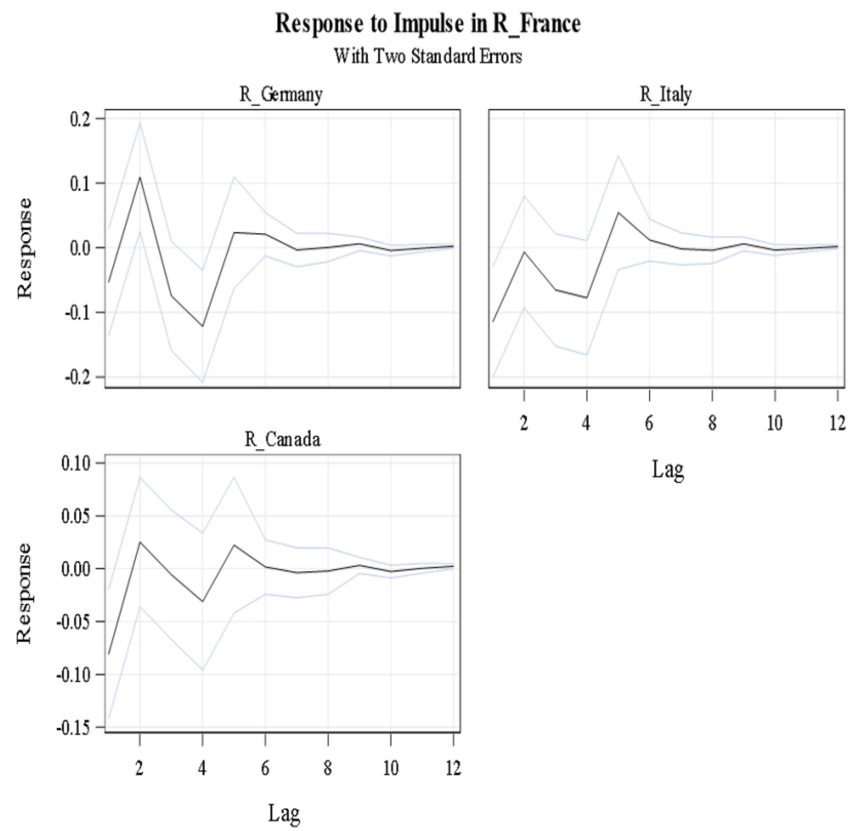
Graph 3


Response to Impulse in R_UK
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag

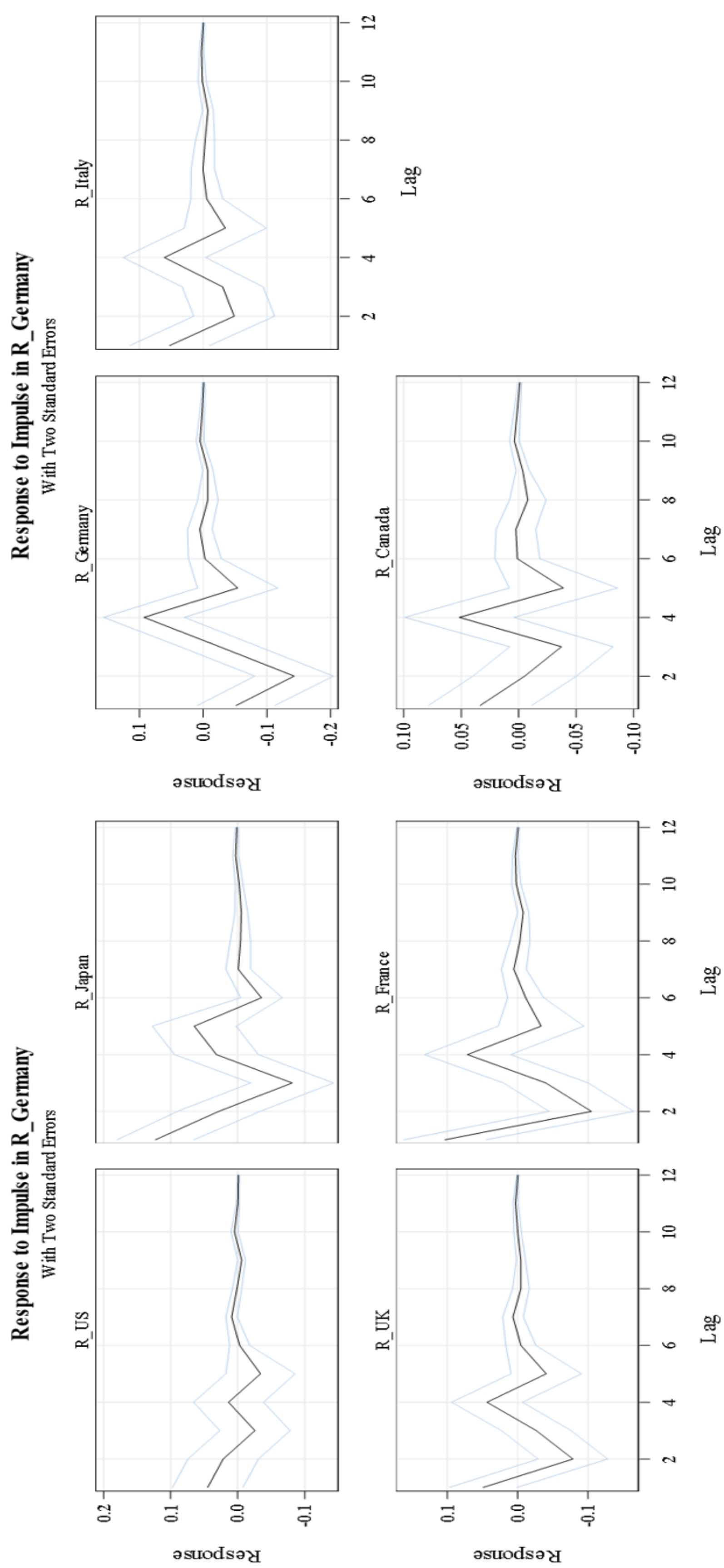

Response to Impulse in R_UK
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag

Graph 4

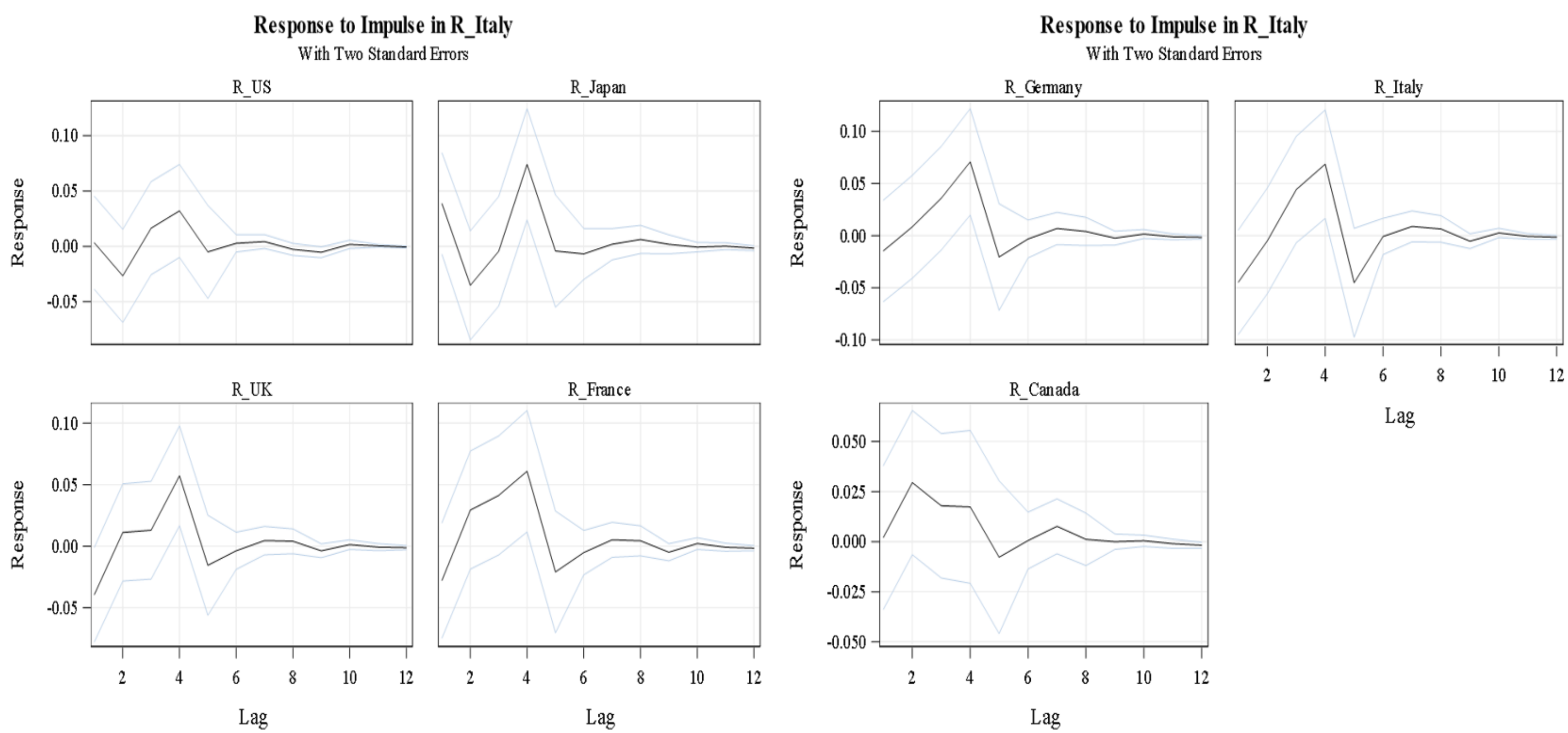

Response to Impulse in R_France
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag


Response to Impulse in R_France
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag

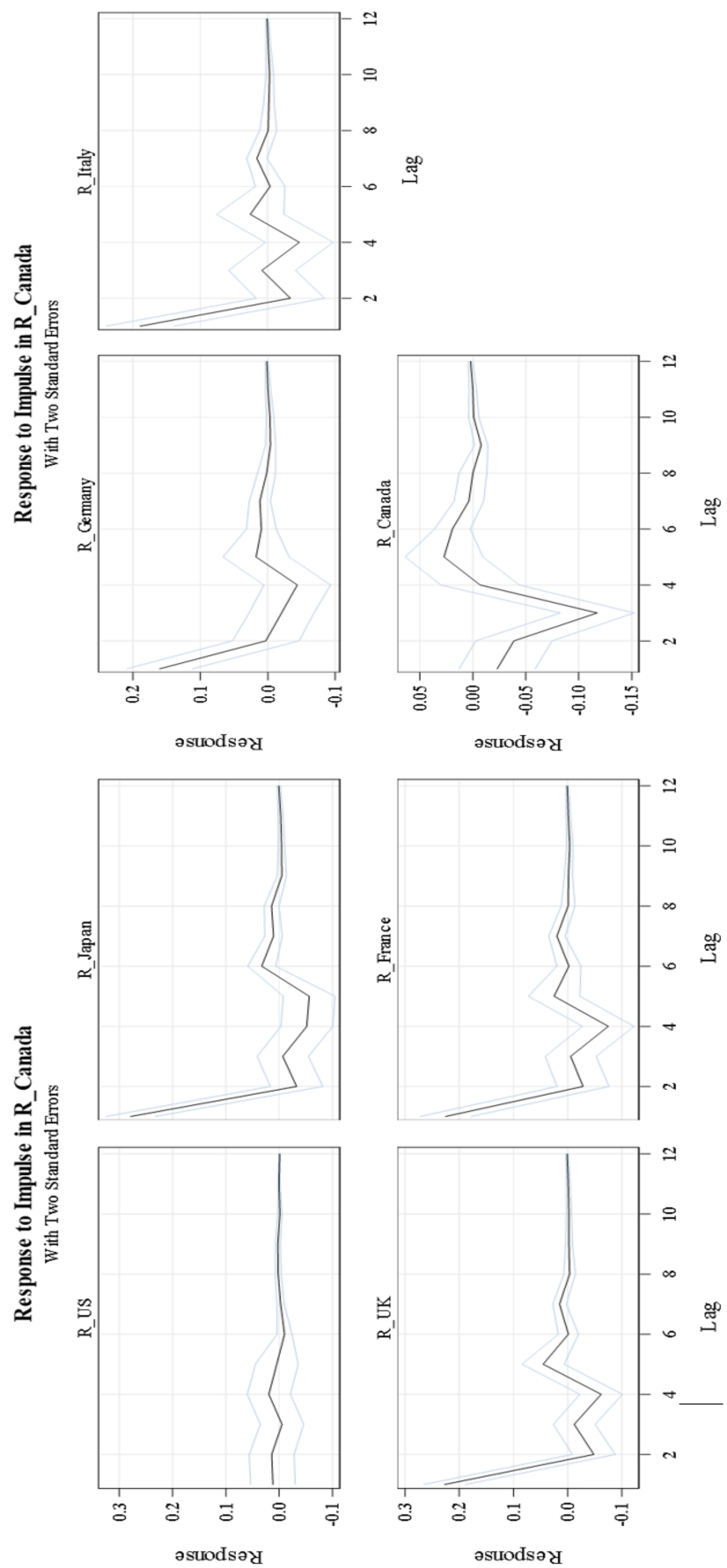
Graph 5


Response to Impulse in R_Germany
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response to Impulse in R_Germany
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag

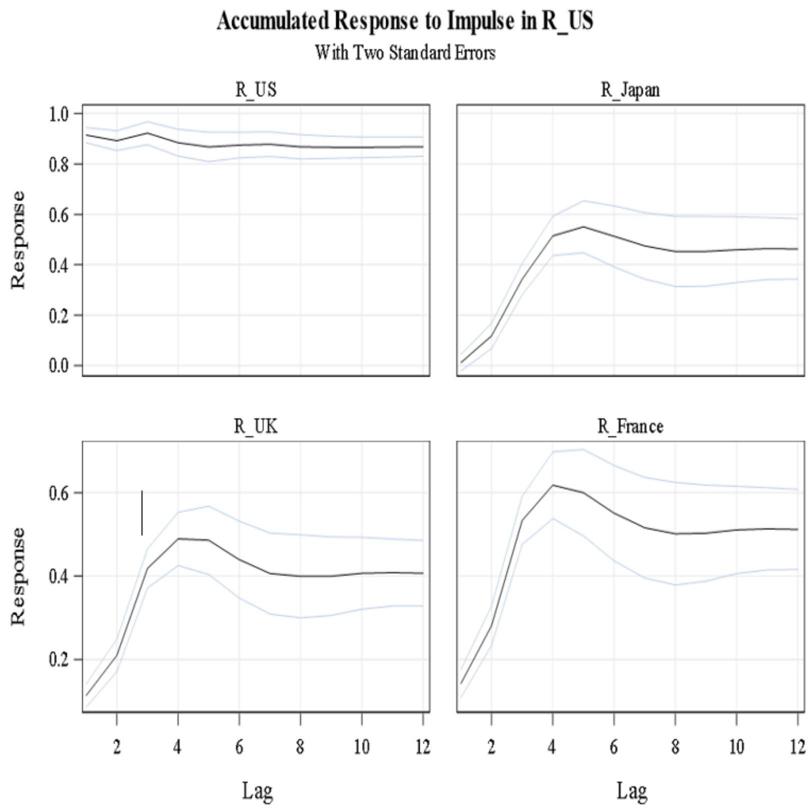
Graph 6

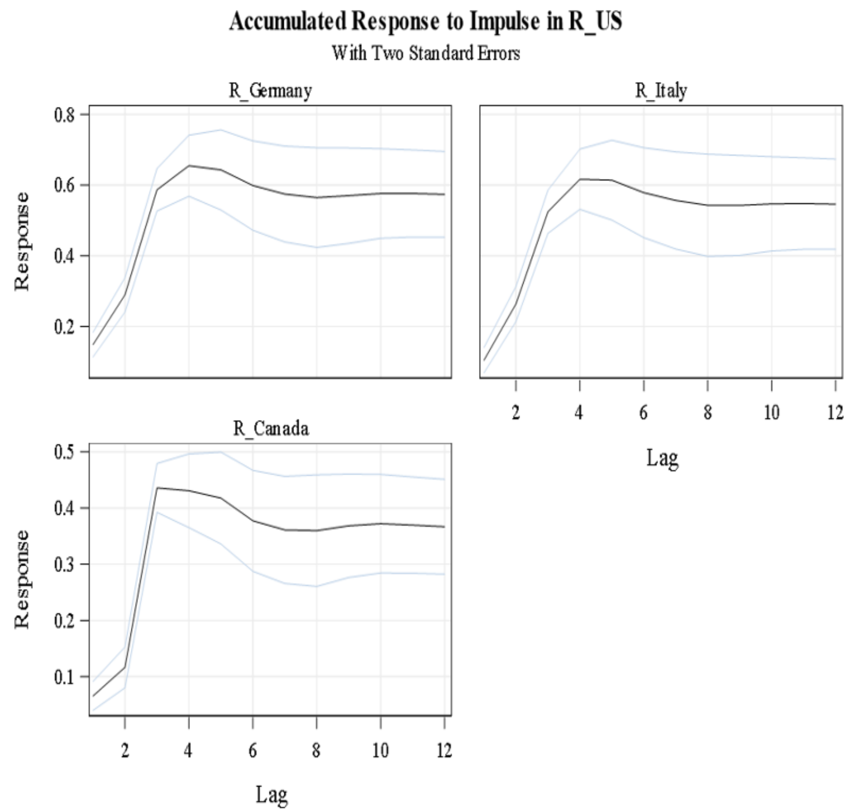

Response to Impulse in R_Italy
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag
0.10
0.05
0.00
-0.05
2
4
6
8
10
12
Response to Impulse in R_Italy
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag
0.10
0.05
0.00
-0.05
-0.10
0.050
0.025
0.000
-0.025
-0.050

Graph 7

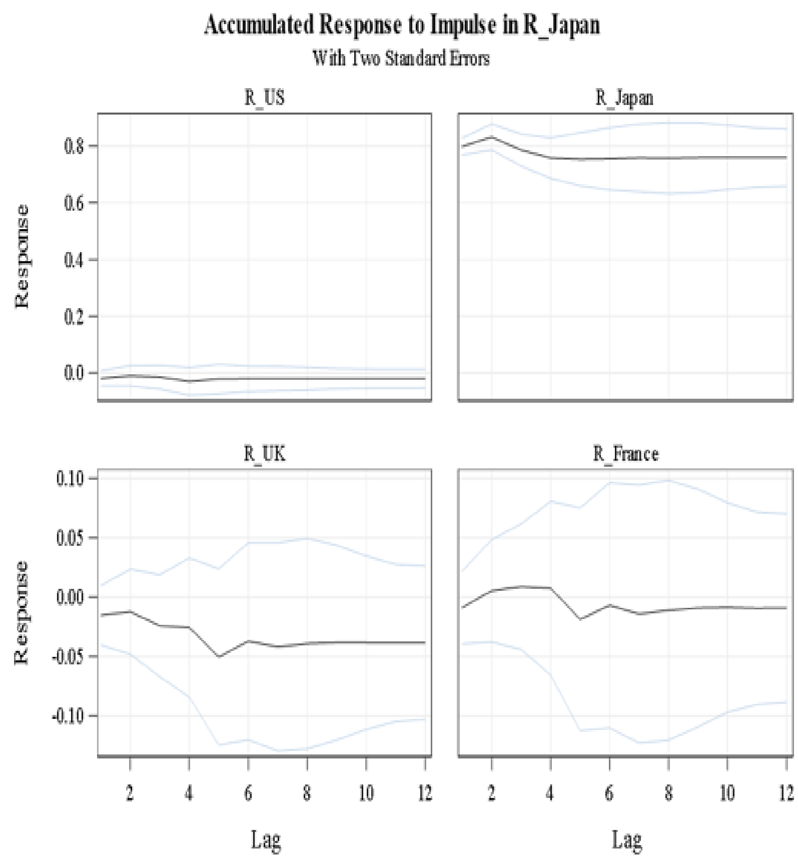

Response to Impulse in R_Canada
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response to Impulse in R_Canada
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag

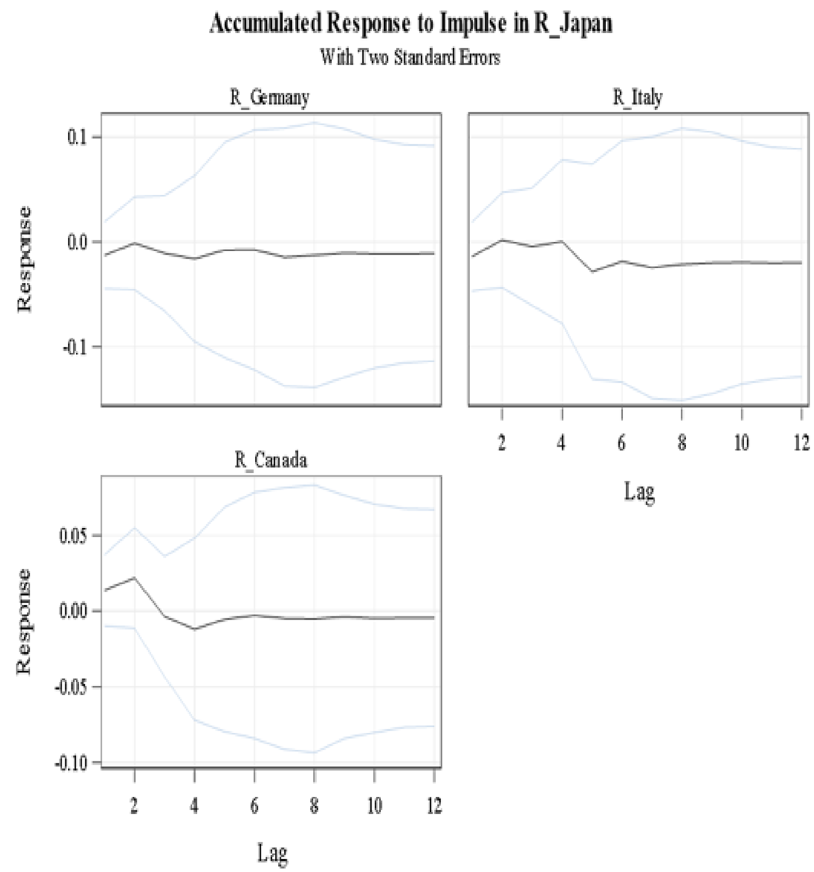
Graph 8


Accumulated Response to Impulse in R_US
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag
1.0
0.8
0.6
0.4
0.2
0.0
2
4
6
8
10
12

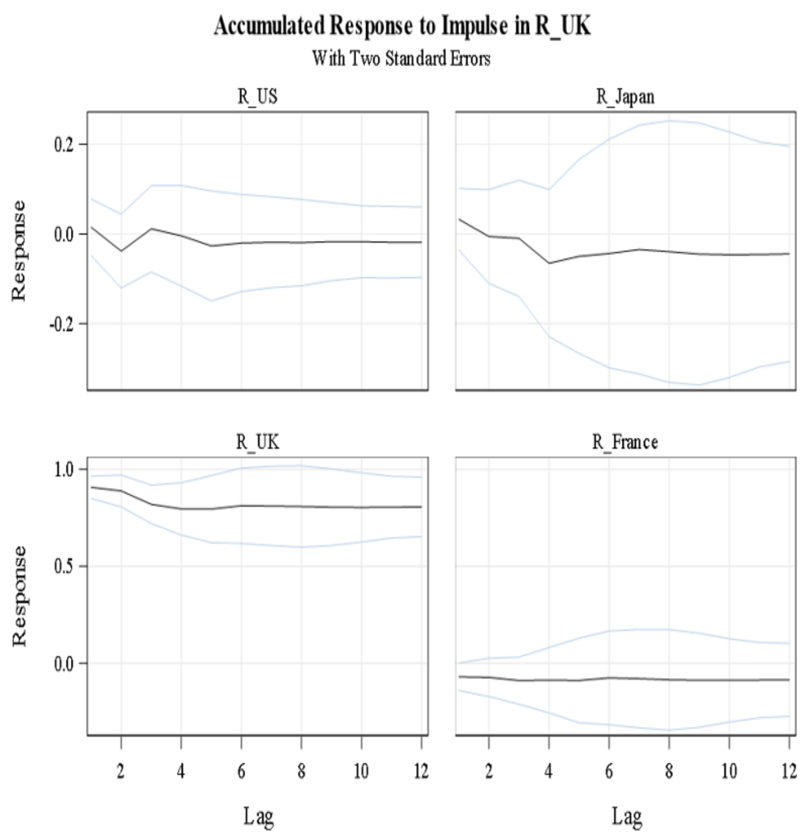

Accumulated Response to Impulse in R_US
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag
0.8
0.6
0.4
0.2
0.5
0.3
0.1
2
4
6
8
10
12

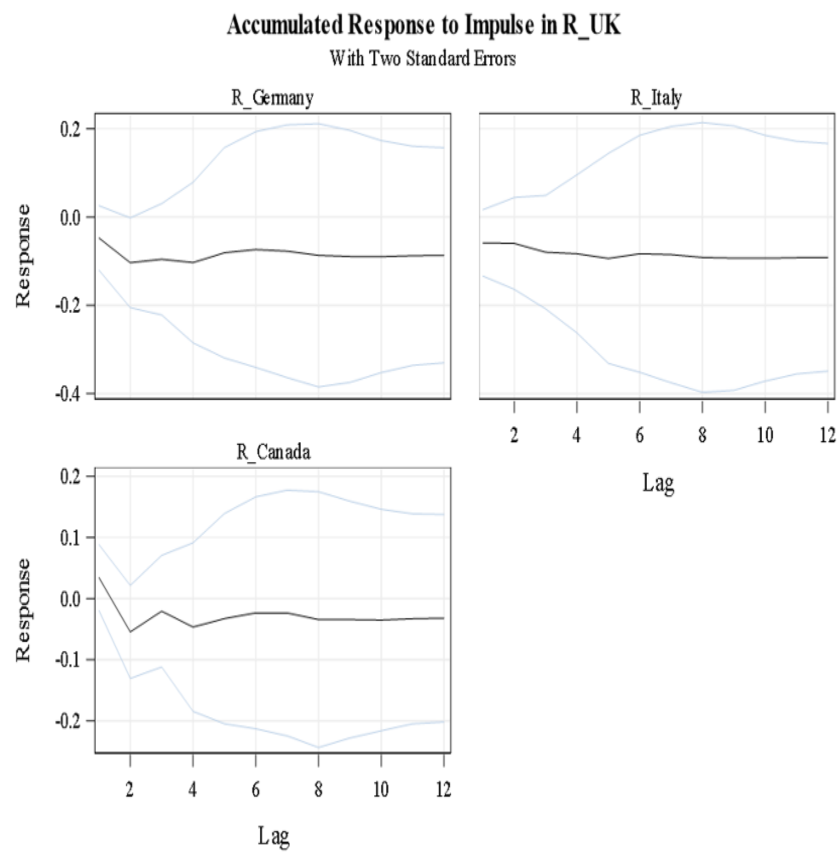
Graph 9


Accumulated Response to Impulse in R_Japan
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag
0.8
0.6
0.4
0.2
0.0
0.10
0.05
0.00
-0.05
-0.10
2
4
6
8
10
12

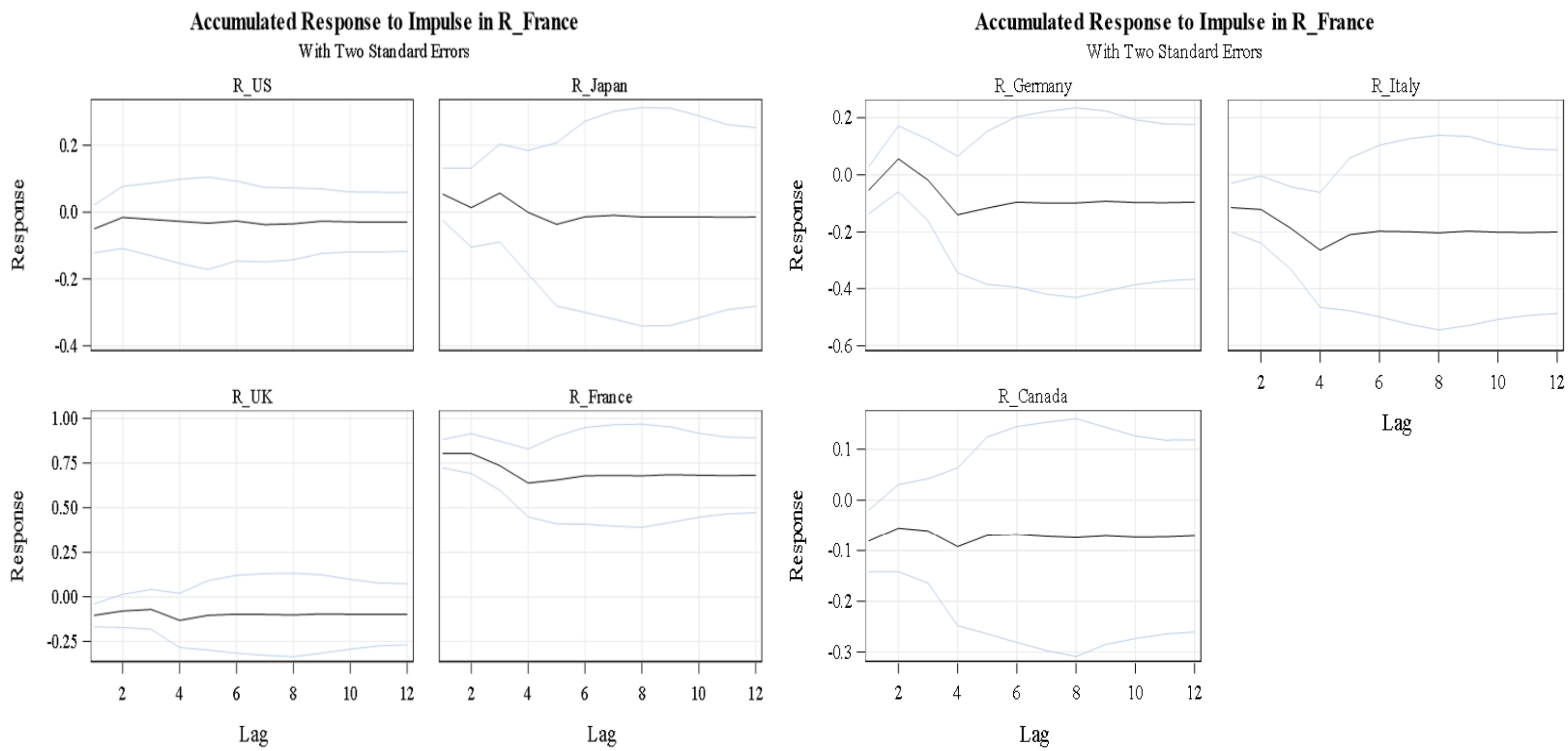

Accumulated Response to Impulse in R_Japan
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag
0.1
0.0
-0.1
0.05
0.00
-0.05
-0.10
2
4
6
8
10
12

Graph 10

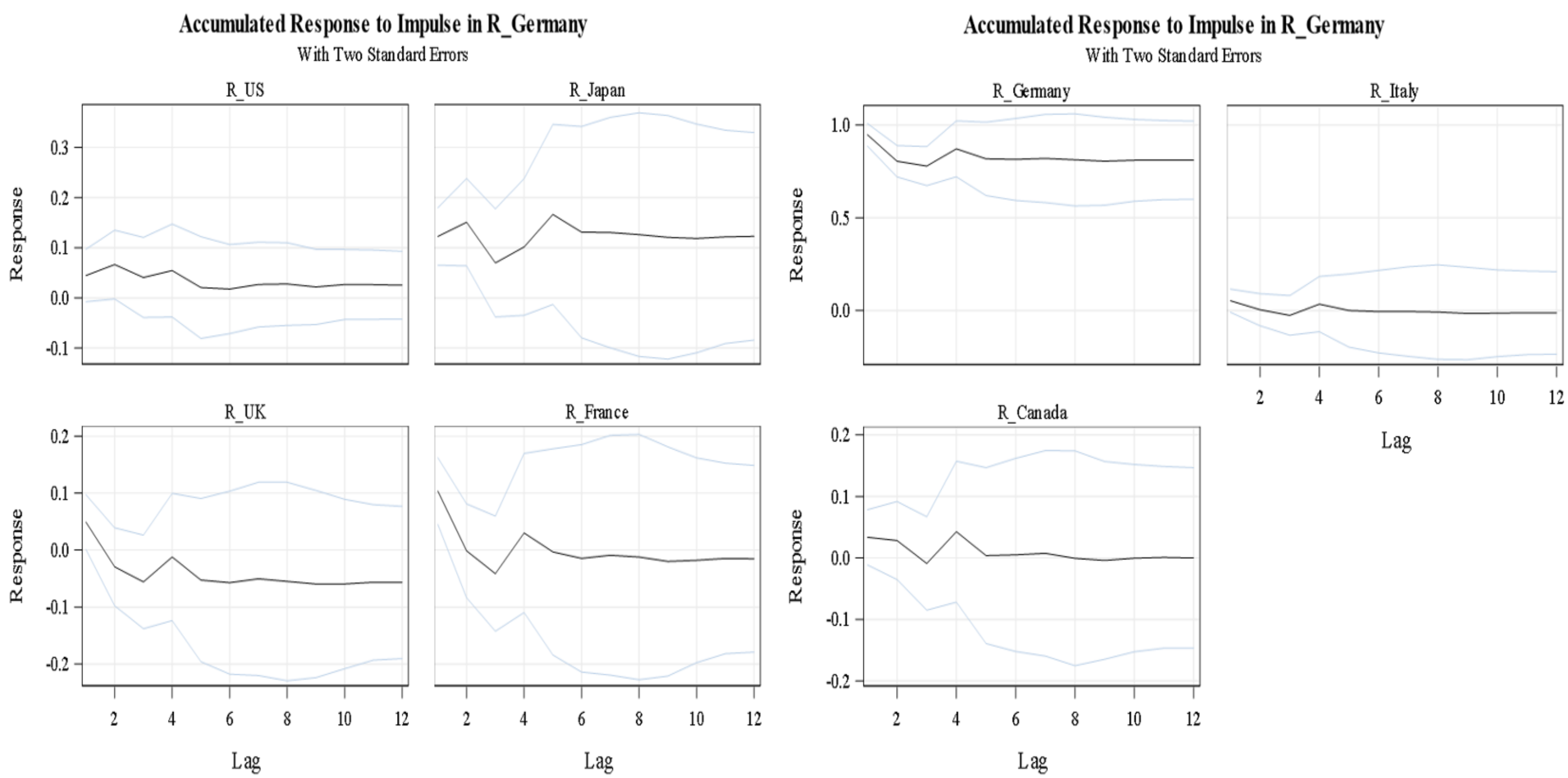

Accumulated Response to Impulse in R_UK
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Response
0.2
0.0
-0.2
1.0
0.5
0.0
2
4
6
8
10
12
Lag
Lag


Accumulated Response to Impulse in R_UK
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Response
0.2
0.0
-0.2
-0.4
0.1
-0.1
2
4
6
8
10
12
Lag
Lag

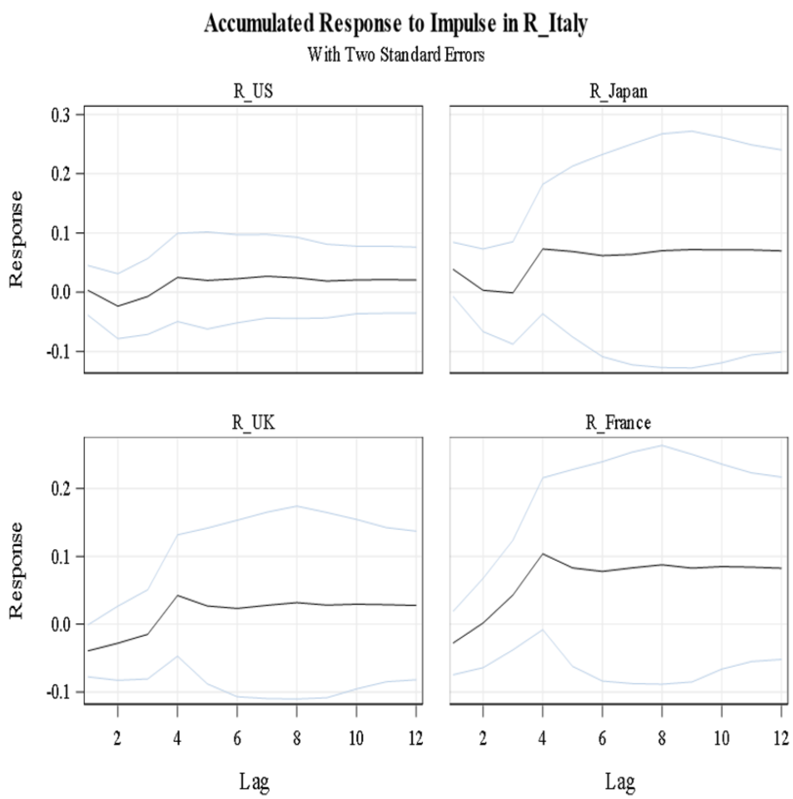
Graph 11


Accumulated Response to Impulse in R_France
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag
Accumulated Response to Impulse in R_France
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag

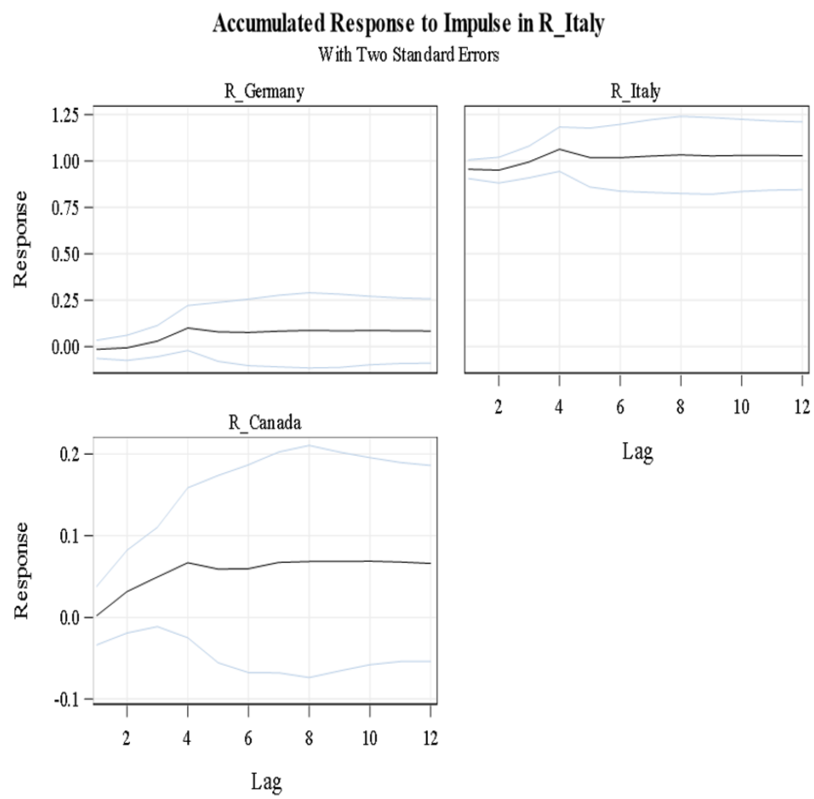
Graph 12


Accumulated Response to Impulse in R_Germany
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag
Accumulated Response to Impulse in R_Germany
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag

Graph 13

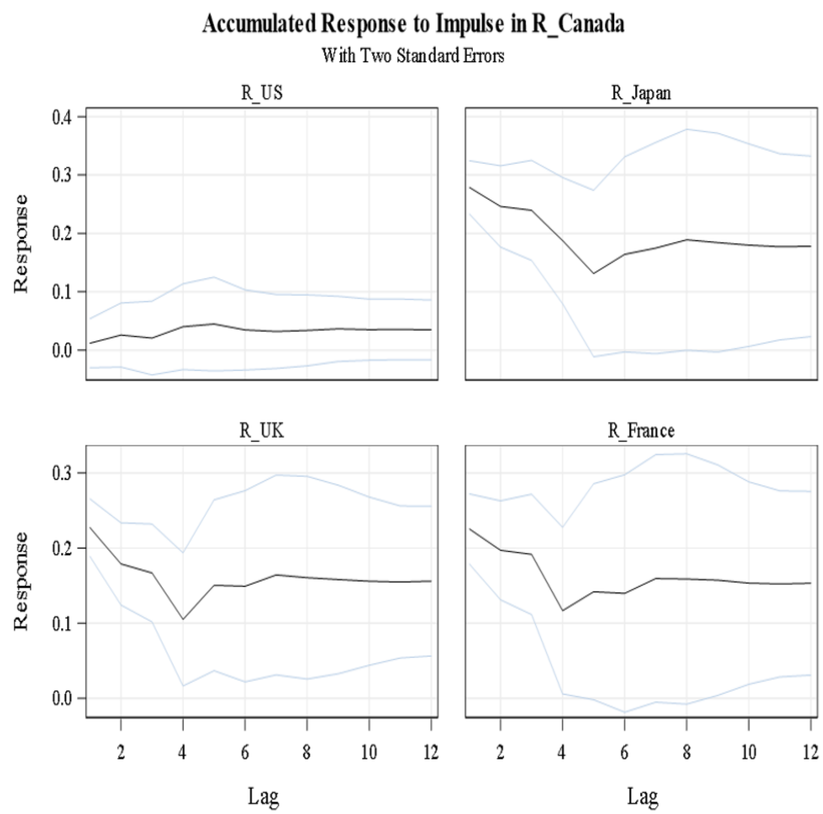


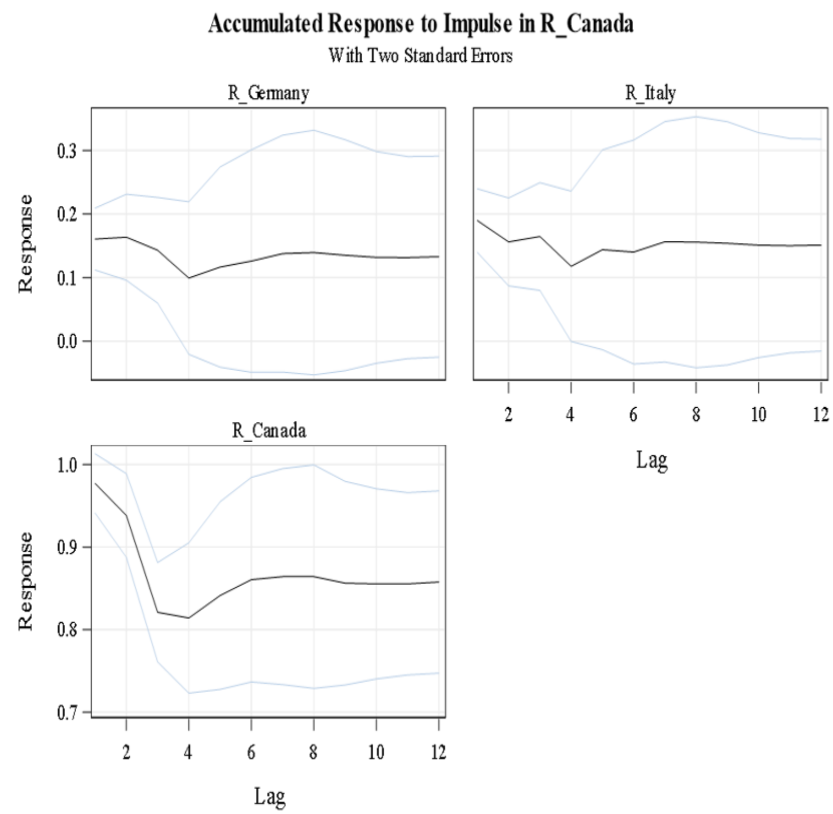
Accumulated Response to Impulse in R_Italy
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag



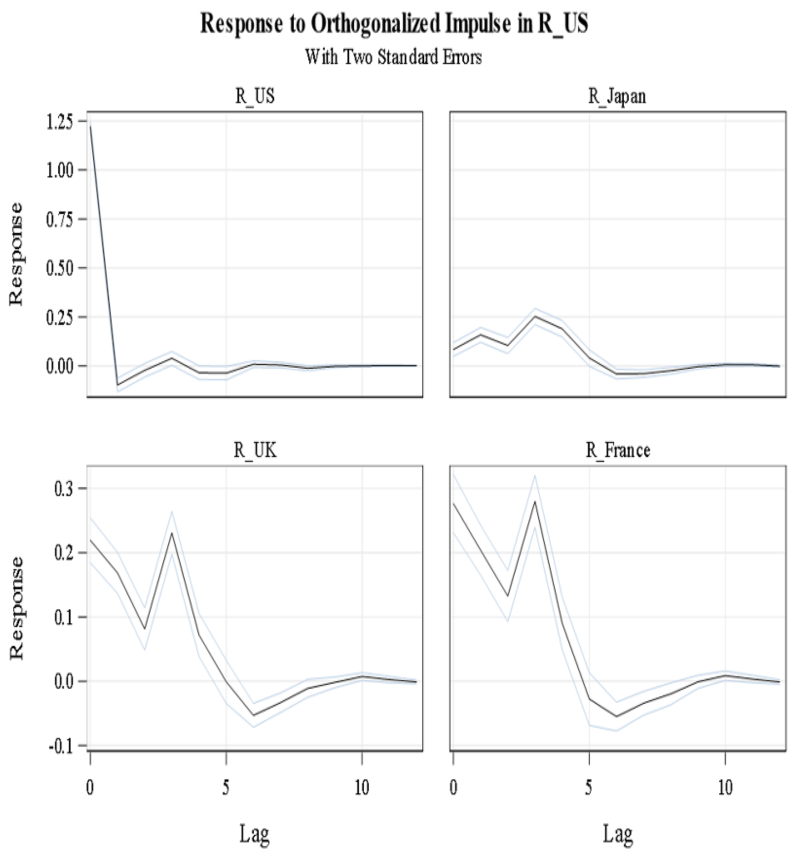
Accumulated Response to Impulse in R_Italy
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag

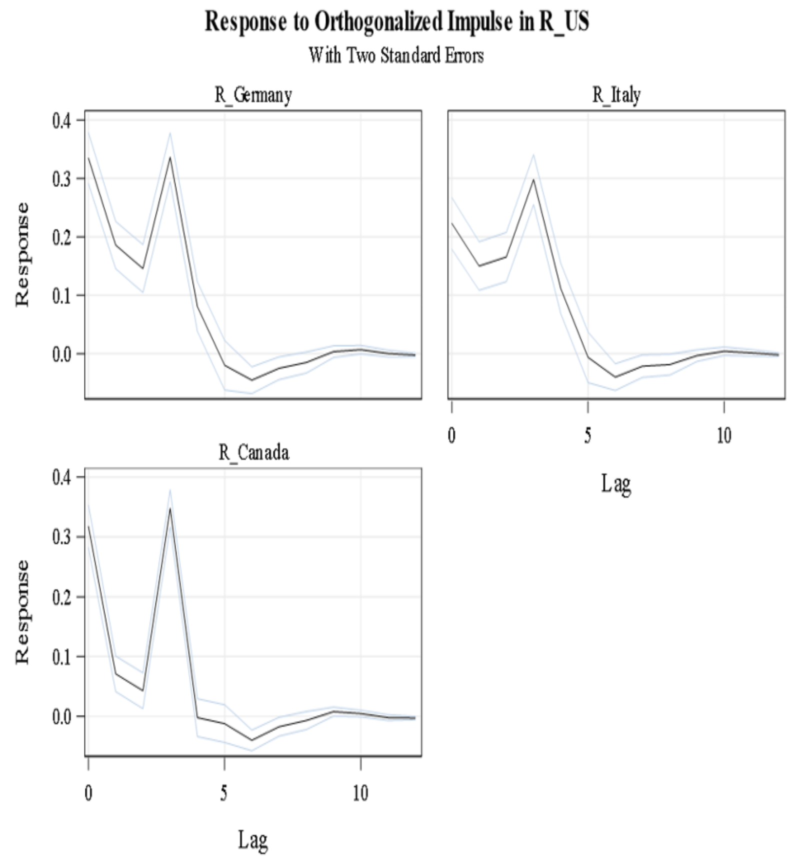
Graph 14


Accumulated Response to Impulse in R_Canada
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag

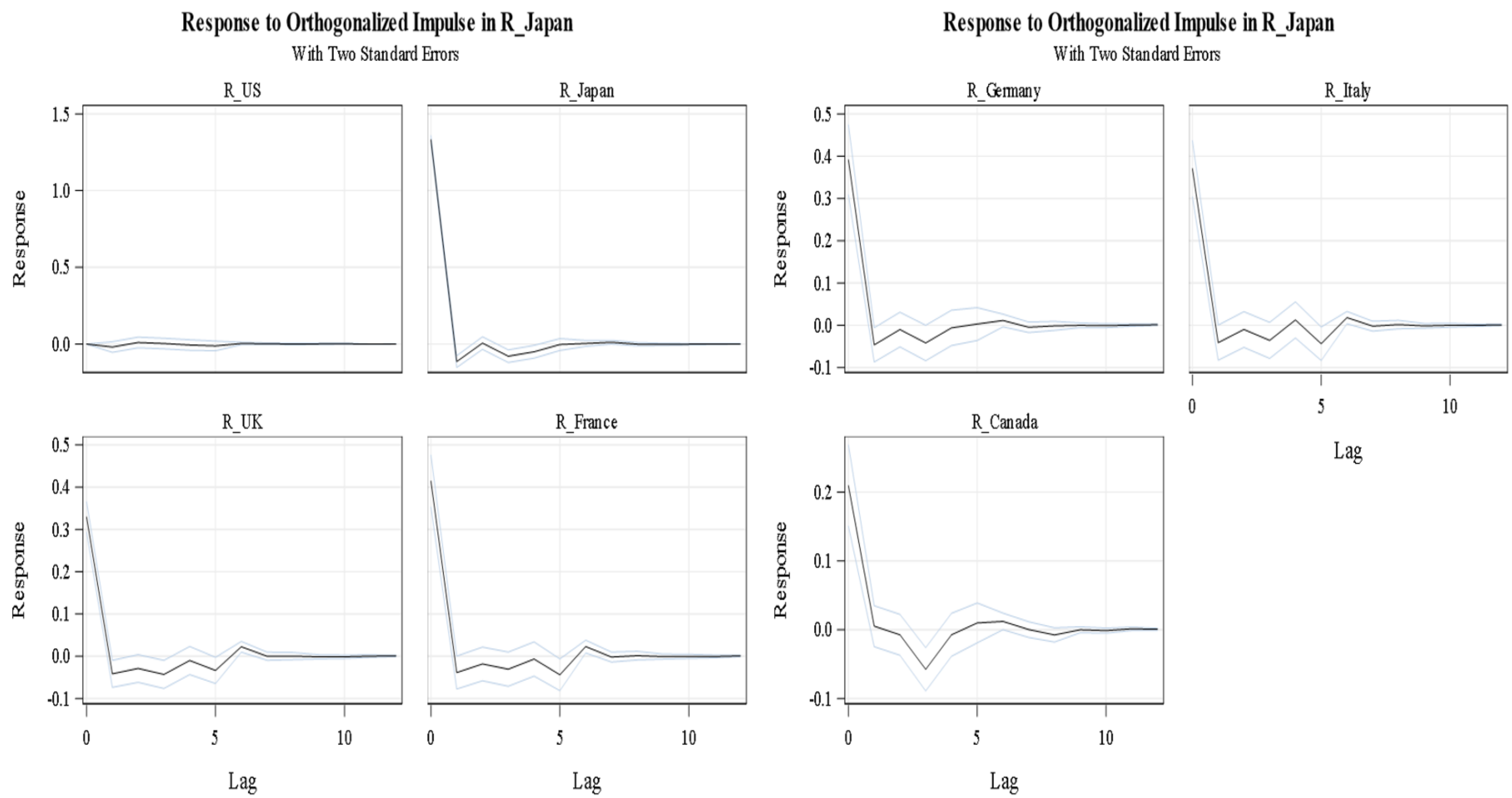

Accumulated Response to Impulse in R_Canada
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag

Graph 15

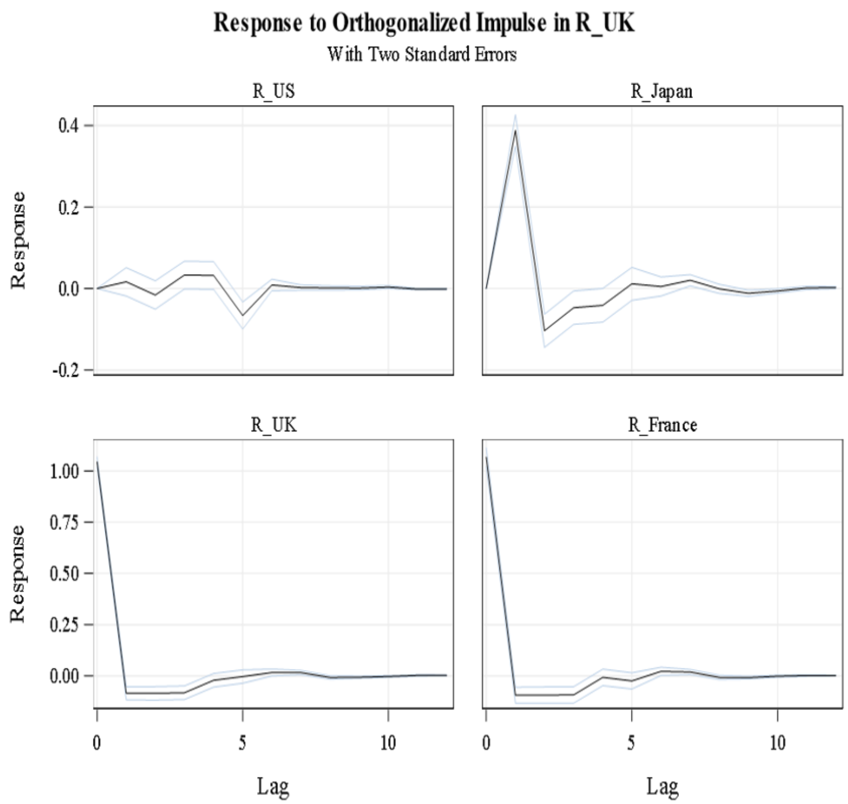

Response to Orthogonalized Impulse in R_US
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag
1.25
1.00
0.75
0.50
0.25
0.00
0.3
0.2
0.1
0.0
-0.1
0
5
10

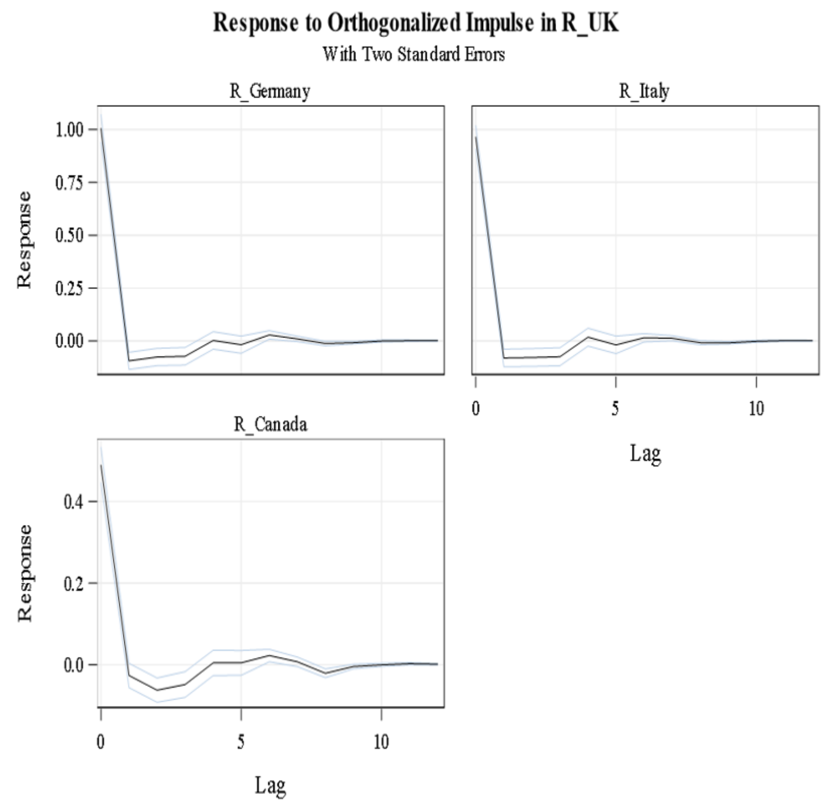

Response to Orthogonalized Impulse in R_US
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag
0.4
0.3
0.2
0.1
0.0
0
5
10

Graph 16

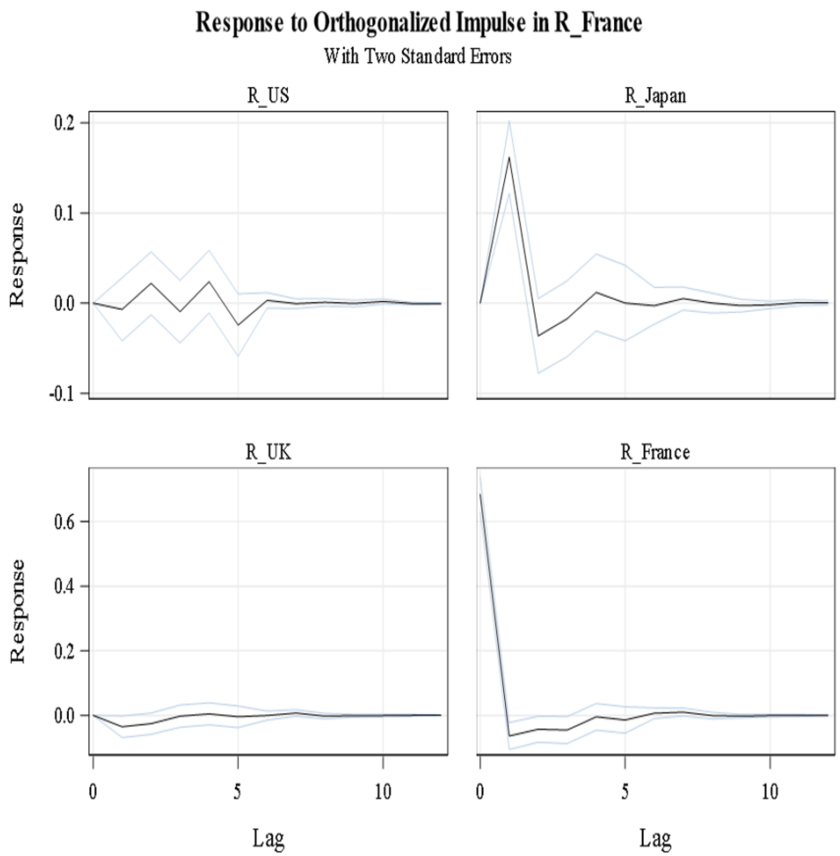

Response to Orthogonalized Impulse in R_Japan
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag
Response to Orthogonalized Impulse in R_Japan
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag

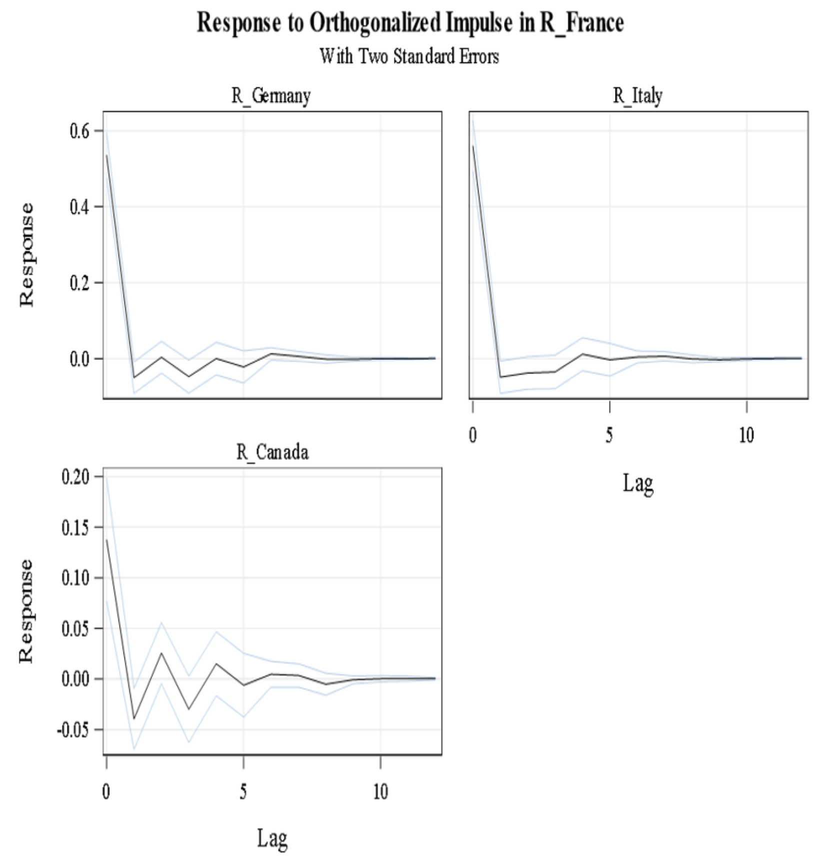
Graph 17


Response to Orthogonalized Impulse in R_UK
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag
0.4
0.2
0.0
-0.2
1.00
0.75
0.50
0.25
0.00
0
5
10

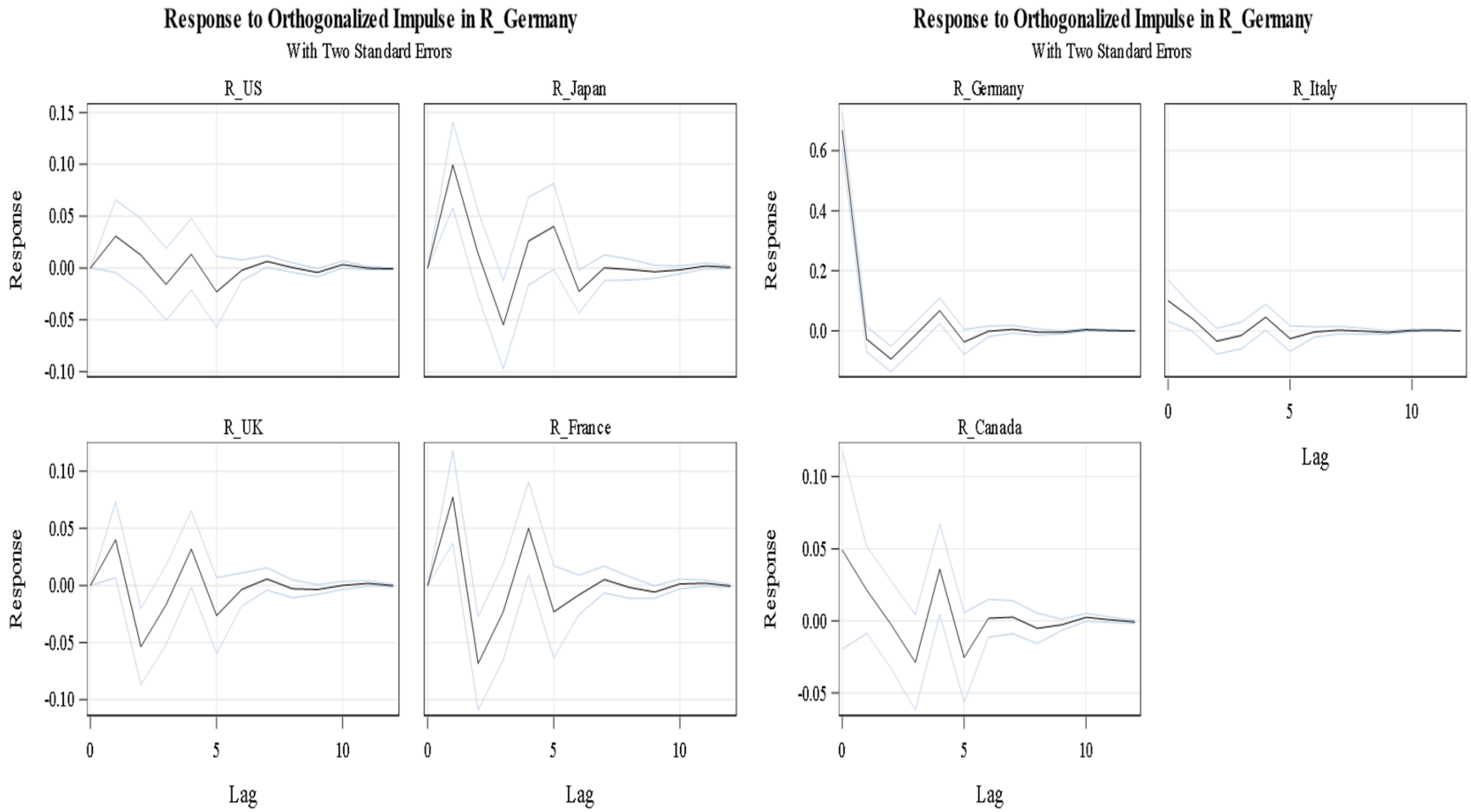

Response to Orthogonalized Impulse in R_UK
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag
1.00
0.75
0.50
0.25
0.00
0.4
0.2
0.0
0
5
10

Graph 18


Response to Orthogonalized Impulse in R_France
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag
0
5
10
0.2
0.1
0.0
-0.1
0.6
0.4

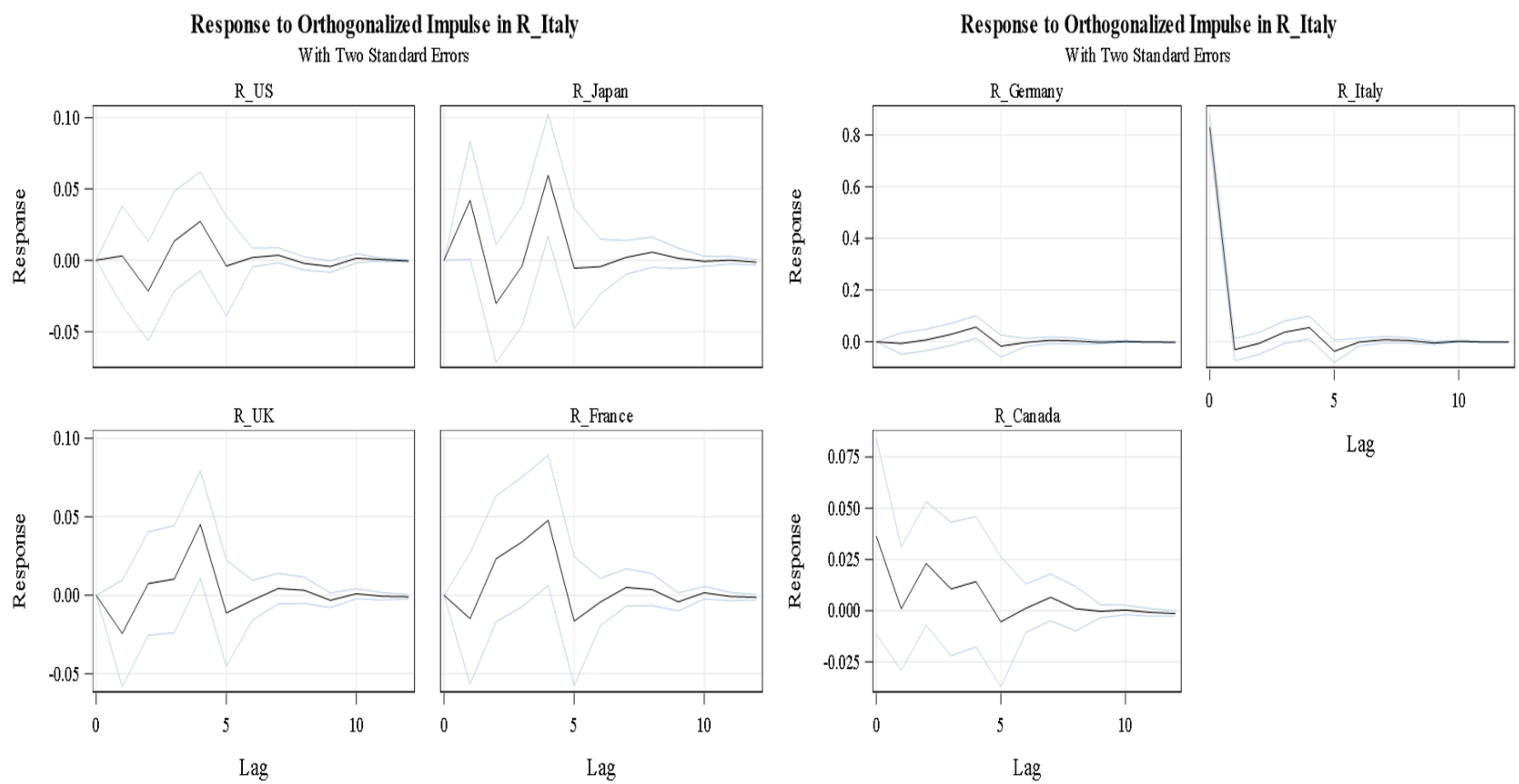

Response to Orthogonalized Impulse in R_France
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag
0
5
10
0.6
0.4
0.2
0.0
0.20
0.15
0.10
0.05
0.00
-0.05

Graph 19

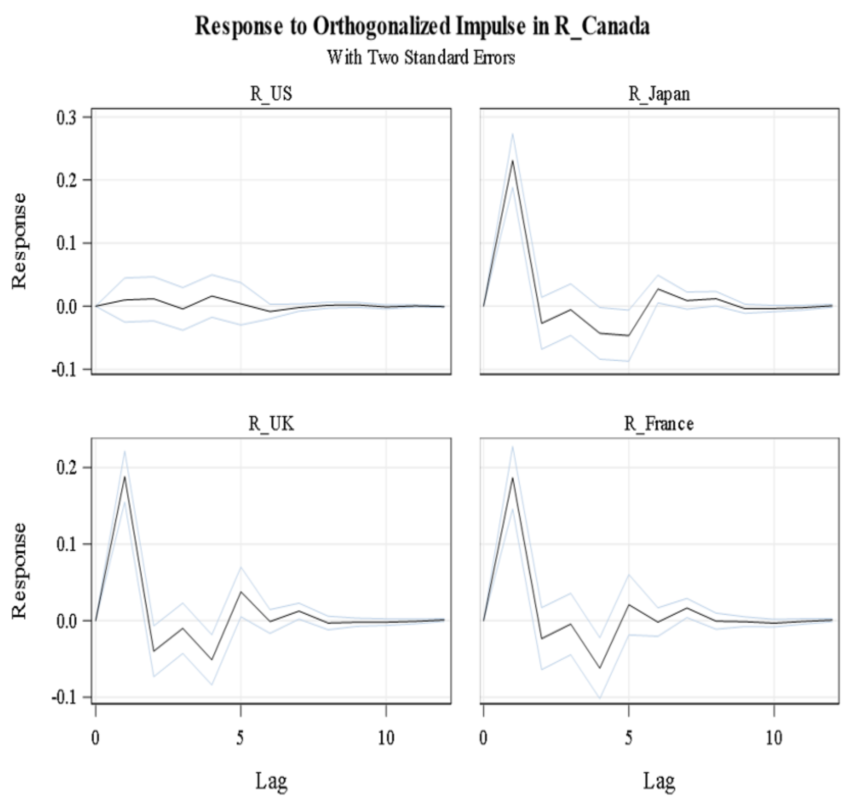


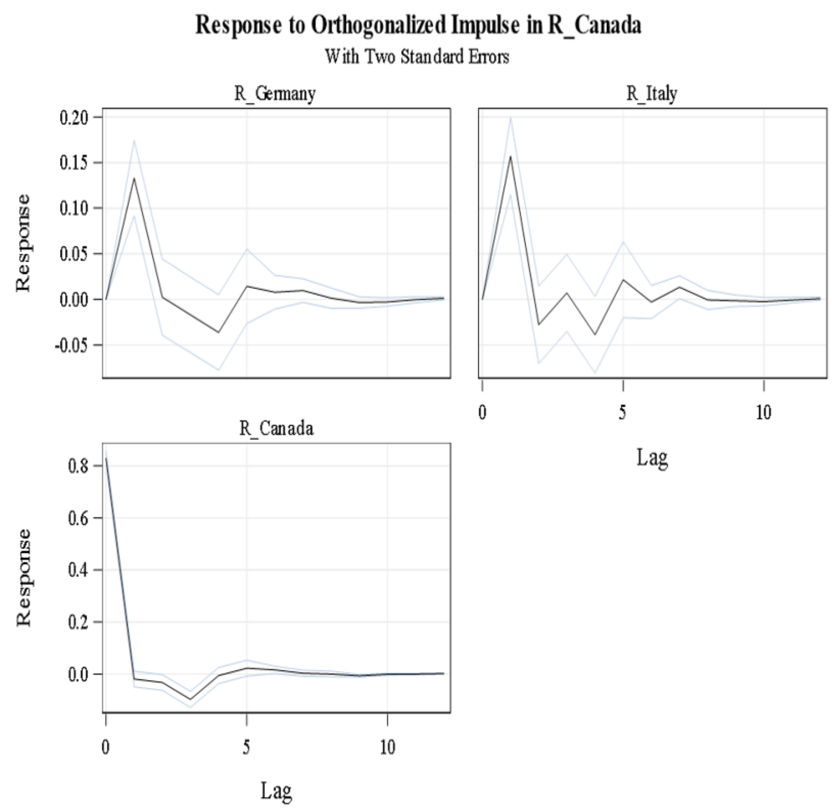
Response to Orthogonalized Impulse in R_Germany
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response to Orthogonalized Impulse in R_Germany
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag

Graph 20


Response to Orthogonalized Impulse in R_Italy
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag
0.10
0.05
0.00
-0.05
0
5
10
Response to Orthogonalized Impulse in R_Italy
With Two Standard Errors
R_Germany
R_Italy
R_Canada
0.8
0.6
0.4
0.2
0.0
0.075
0.050
0.025
0.000
-0.025

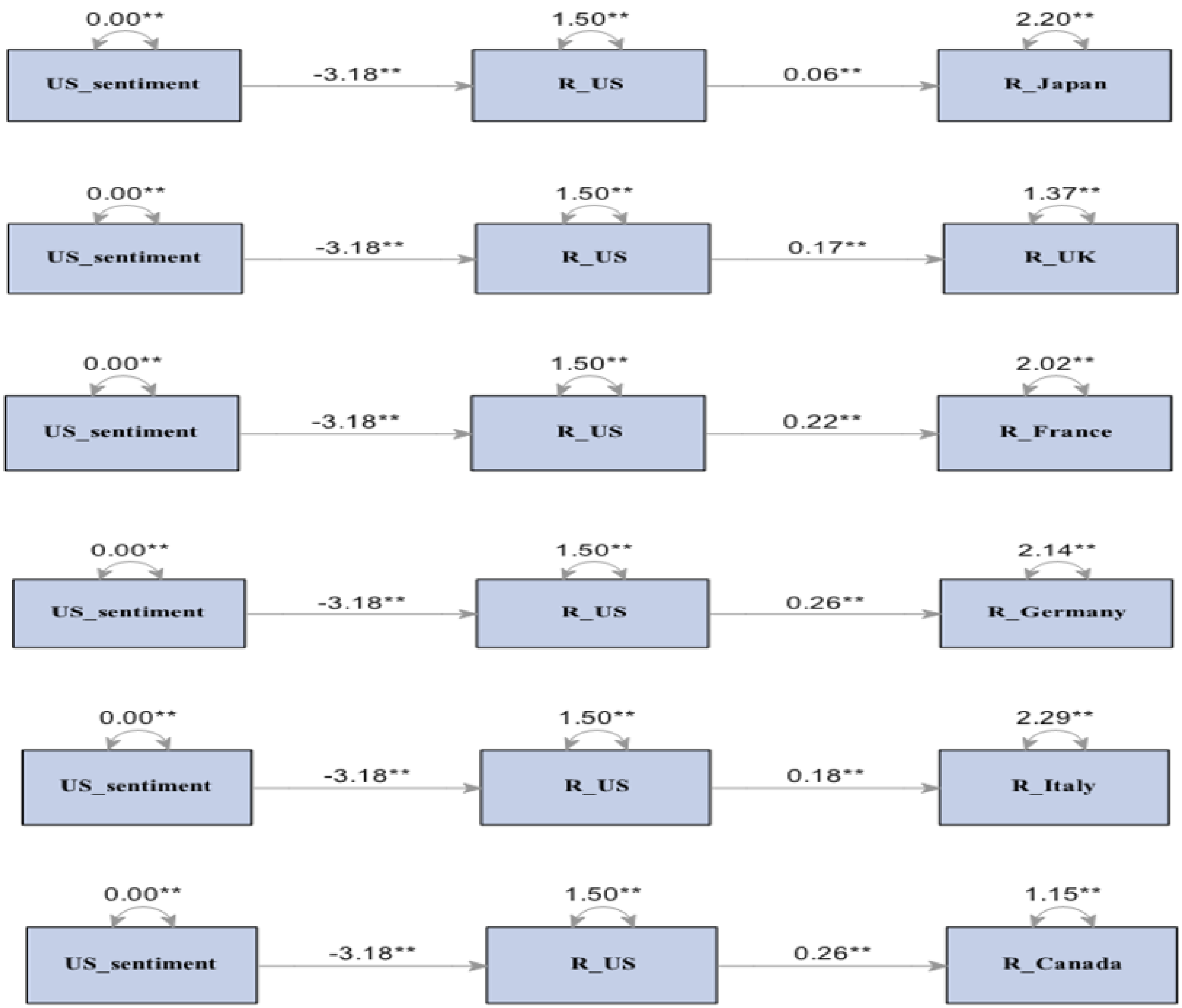
Graph 21


Response to Orthogonalized Impulse in R_Canada
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag
0.3
0.2
0.1
0.0
-0.1
0
5
10


Response to Orthogonalized Impulse in R_Canada
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag
0.20
0.15
0.10
0.05
0.00
-0.05
0.8
0.6
0.4
0.2
0.0
0
5
10

Graph 22

PATH Analysis



VITA

Amin Amoulashkarian

Department of Finance

Education

Ph.D.	2023	Finance, Old Dominion University
MBA	2017	Sharif University
B.Sc.	2014	Aerospace Engineering, Sharif University