Modeling the Transmission of Sentiment Across Different Markets: A Multivariate Dynamic Approach

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This paper examines how sentiments in one stock market affect others, particularly focusing on the role of news, social media, and economic indicators in this process. It discusses the increased interconnectedness of financial markets due to technology, which allows sentiments to spread quickly worldwide. The study looks at how news media, social media, and economic indicators can lead to investor optimism or pessimism, influencing stock prices. The main objective is to analyze how U.S. investor sentiment impacts the stock markets of G7 countries. The research uses data from the Global Finance database, including stock indices of G7 countries and two sentiment measures for the U.S. market: news sentiment and social media sentiment. A vector autoregression (VAR) model is used to model the sentiment transmission across markets, helping to understand the interconnectedness of these variables.

KEYWORDS: Investor Sentiment, Sentiment Transmission, G7, Multivariate Dynamic Analysis

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.

The purpose of this paper is to investigate the effects of U.S. investors' sentiment on other developed countries stock markets, G7 countries (Japan, the United Kingdom, France, Germany, Italy, and Canada).

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 firstday 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.

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

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.

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

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.

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

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.

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)

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.

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

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.

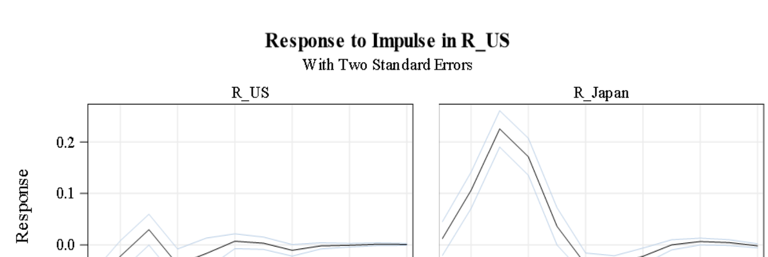
$$X_{1t} = \varepsilon_{1t} + a_1\varepsilon_{1t-1} + a_2\varepsilon_{1t-2+}a_3\varepsilon_{1t-3} + a_4\varepsilon_{2t-1+}a_5\varepsilon_{2t-2} + a_6\varepsilon_{2t-3} + \cdots$$

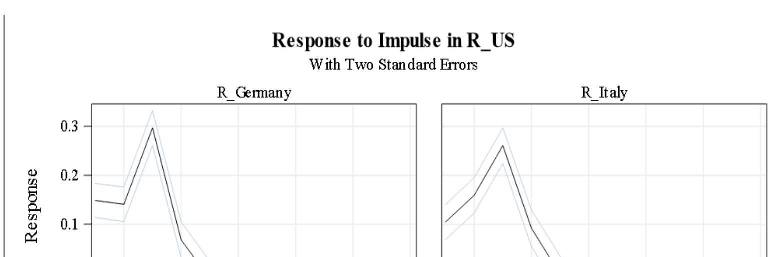
$$X_{2t} = \varepsilon_{2t} + b_1\varepsilon_{1t-1} + b_2\varepsilon_{1t-2+}b_3\varepsilon_{1t-3} + b_4\varepsilon_{2t-1+}b_5\varepsilon_{2t-2} + b_6\varepsilon_{2t-3} + \cdots$$

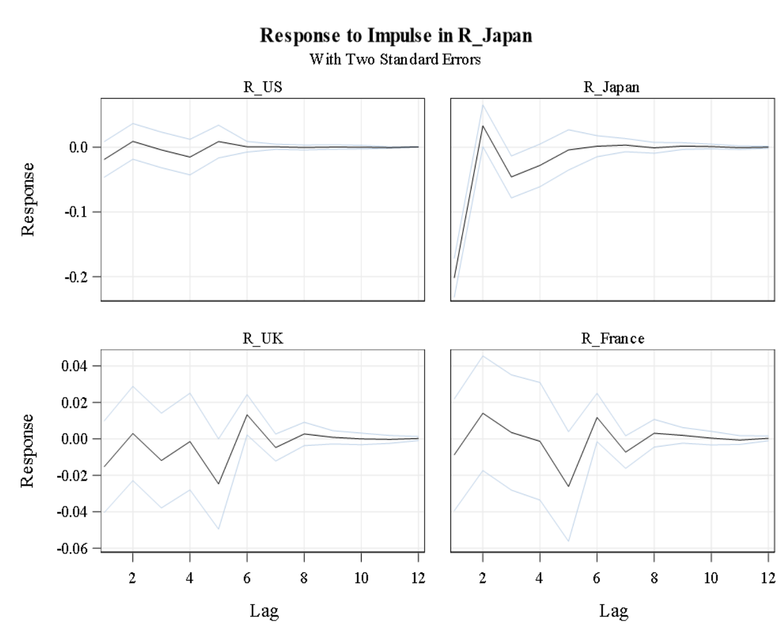
Take, for instance, a two-by-two matrix for lag representation from 1 to 3, expressed as two distinct equations. According to the model, an increase in X_{1t} for a single period, represented by ε_{1t} = .1 (approximating to a 10% rise), induces subsequent price hikes by a factor of a_1 × .1. Thus, a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

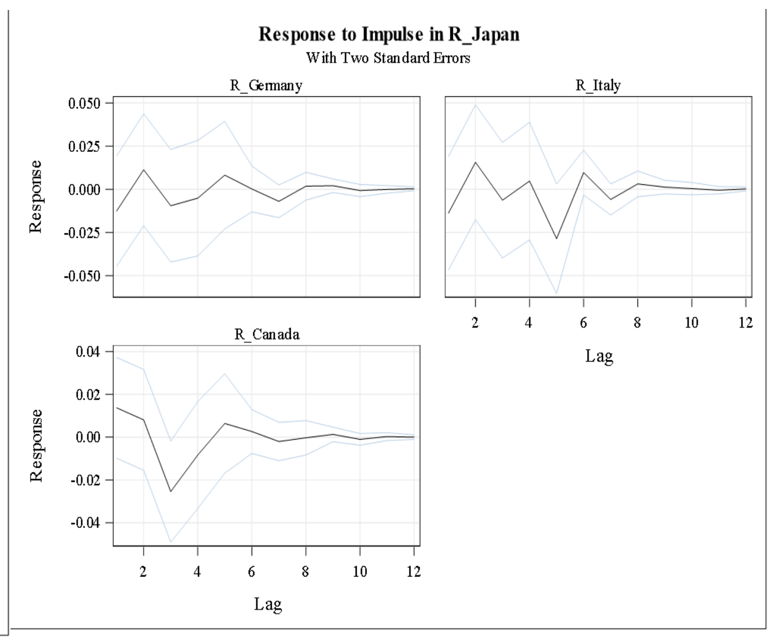
Simultaneously, X_{2t} experiences a rise by b_1 × .1 or $0.1b_1$% in the following period. Two periods later, it increases by b_2 × .1 or $0.1b_2$%. The direct effect of X_{1t}'s increase on X_{2t} is not explicitly observed through these parameters. The immediate period's impact is modeled by the correlation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

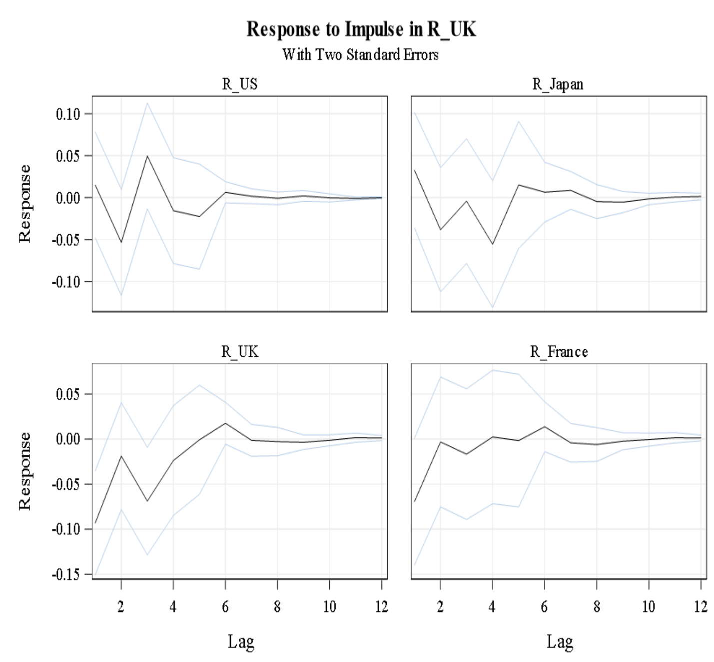
This model representation through an infinite series incorporates many coefficients in output tables. Yet, the structure becomes clearer when visualized through graphs, like those produced by PROC VARMAX, as opposed to scanning numerous figures in output tables. The impulse responses are plotted against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

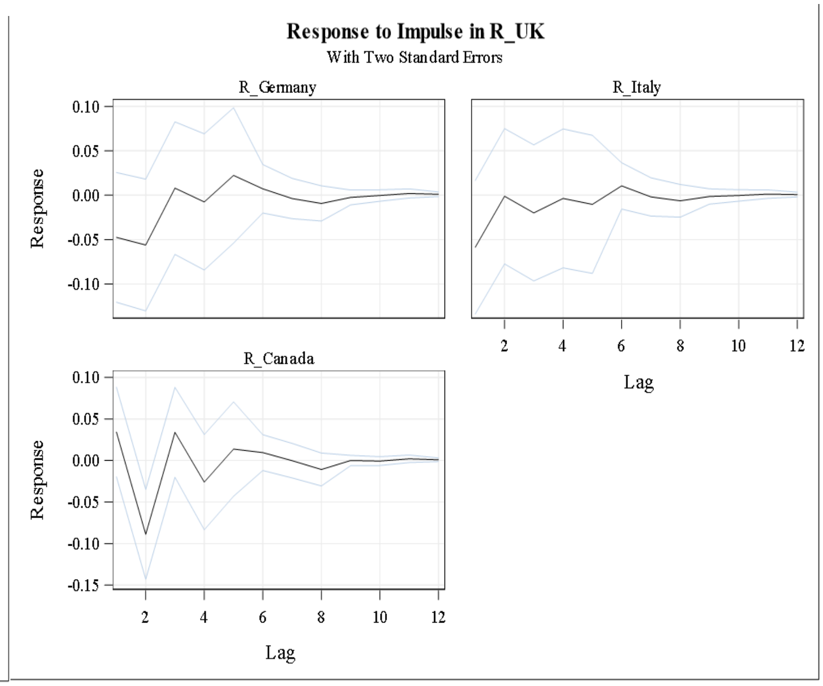


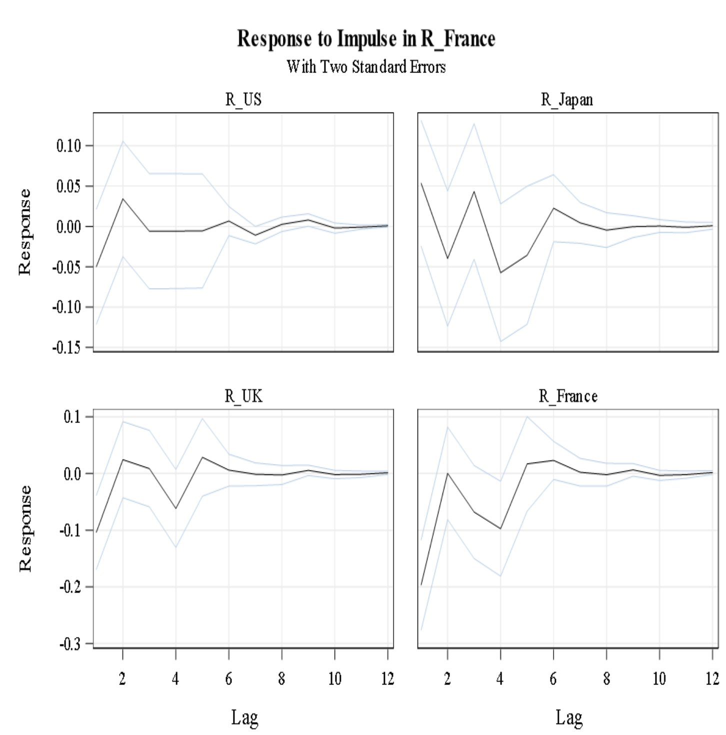


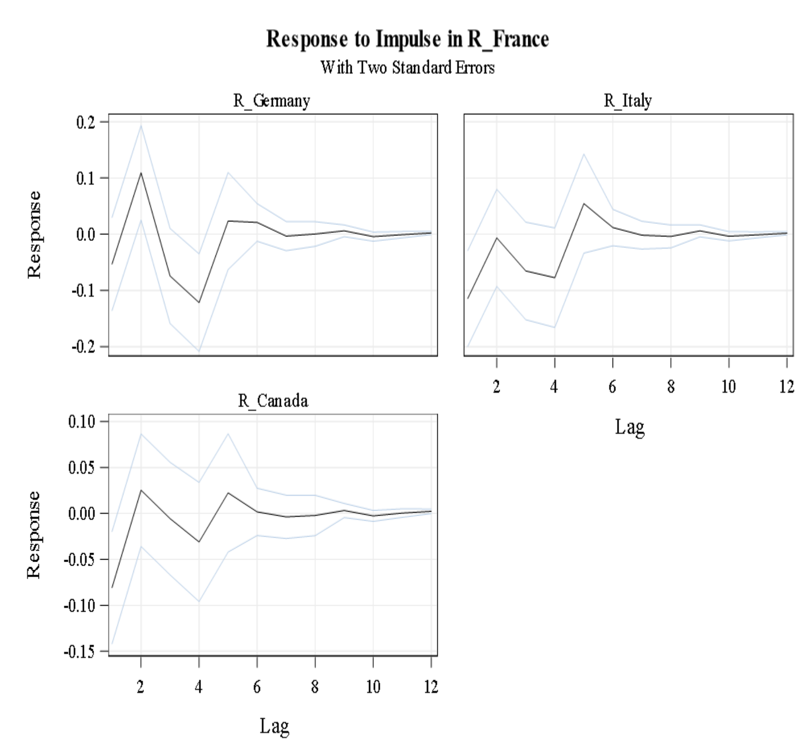

Response to Impulse in R_Japan
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag

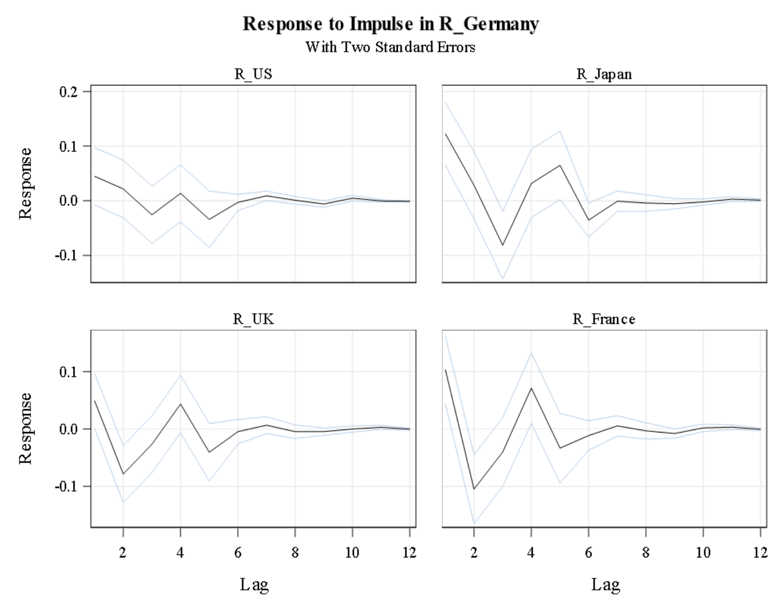

Response to Impulse in R_Japan
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag

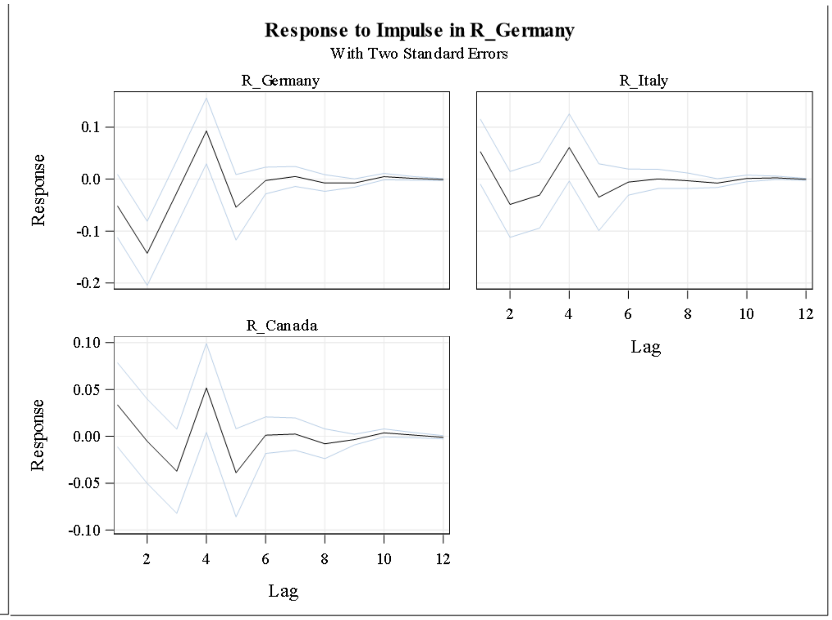

Response to Impulse in R_UK
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag

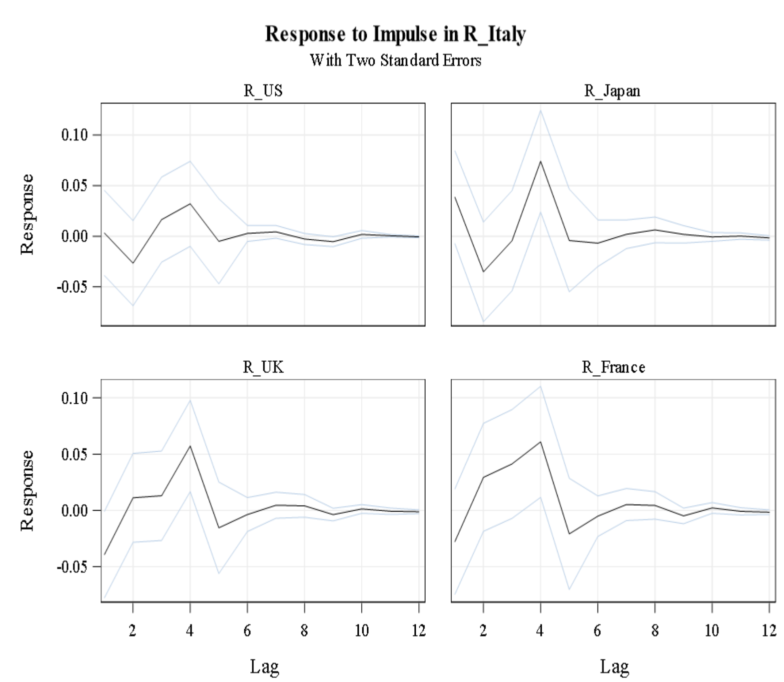

Response to Impulse in R_UK
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag

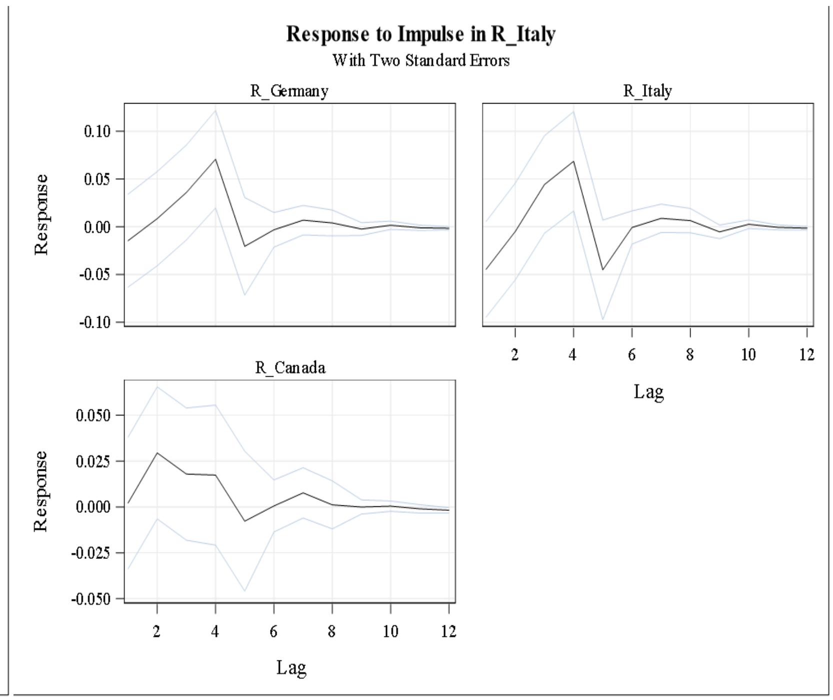

Response to Impulse in R_France
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag

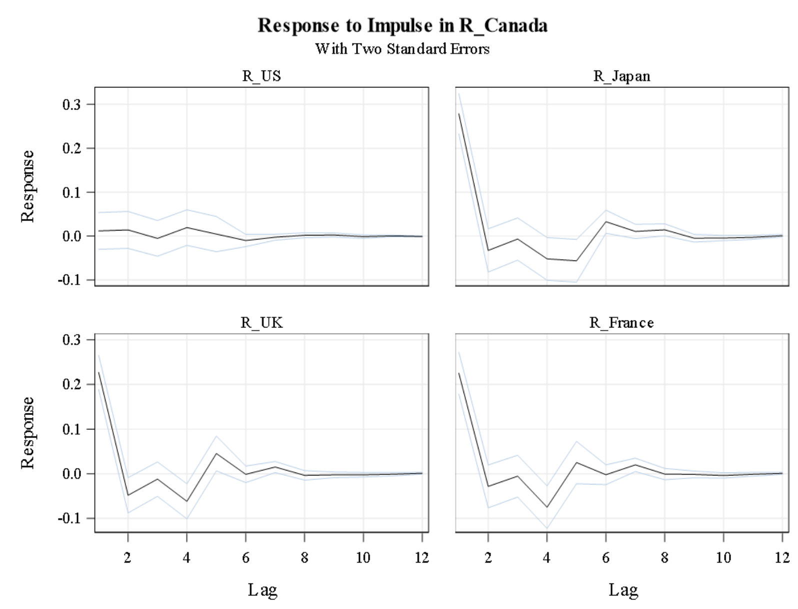

Response to Impulse in R_France
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag

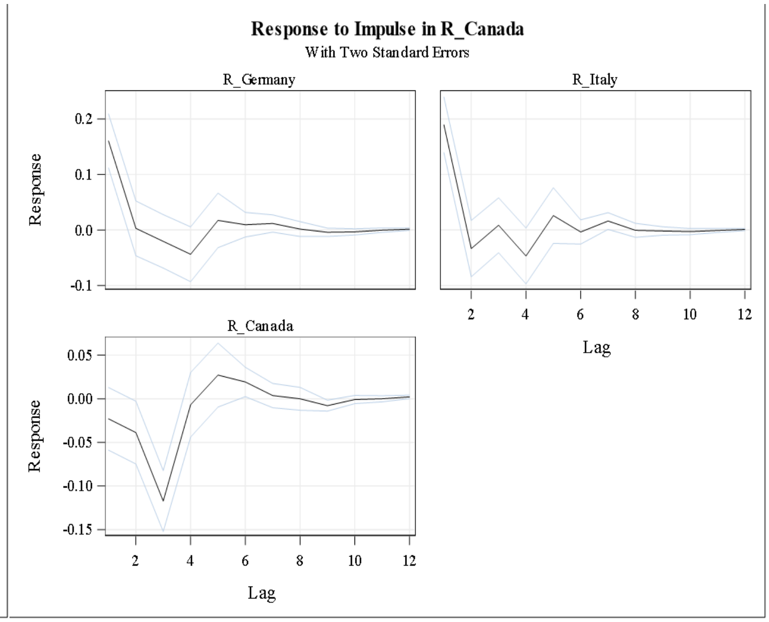

Response to Impulse in R_Germany
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag


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


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


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



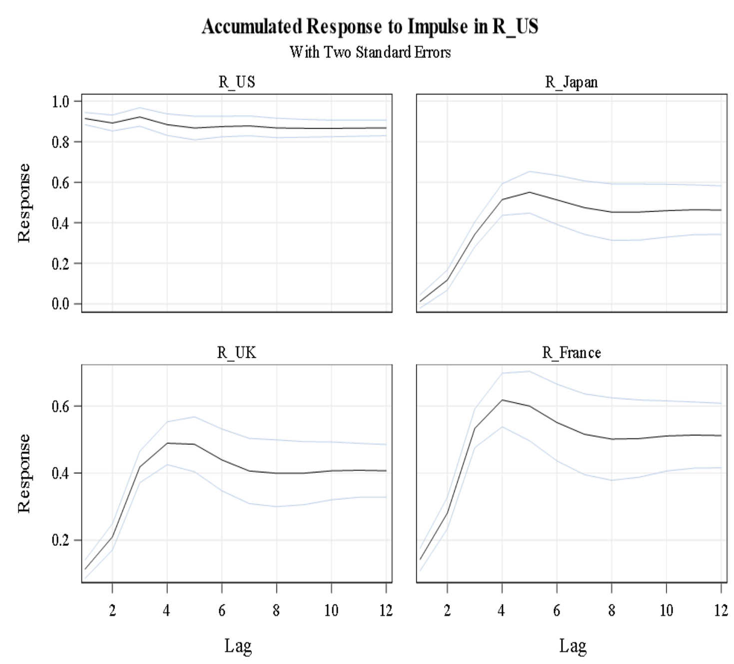


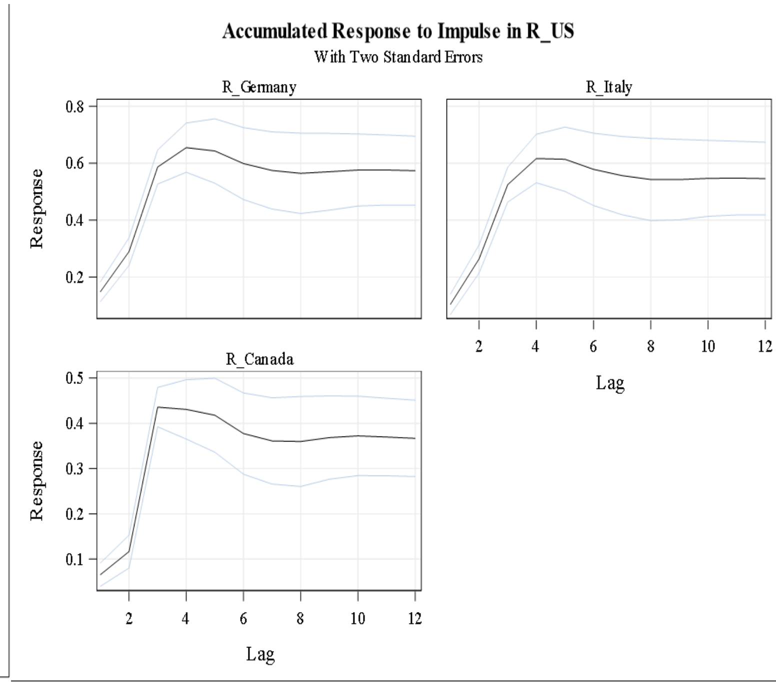
Cumulative Effects

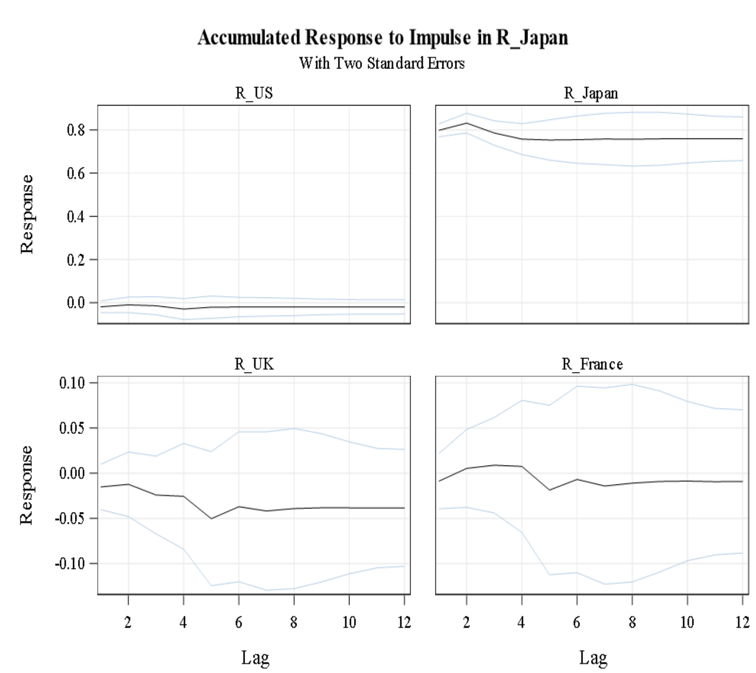
These effects are also cumulative, with the total impact on each series calculated as the sum of effects up to a specific lead value. In this study, these figures represent the aggregate impact on the series following a sudden shock to one of them.

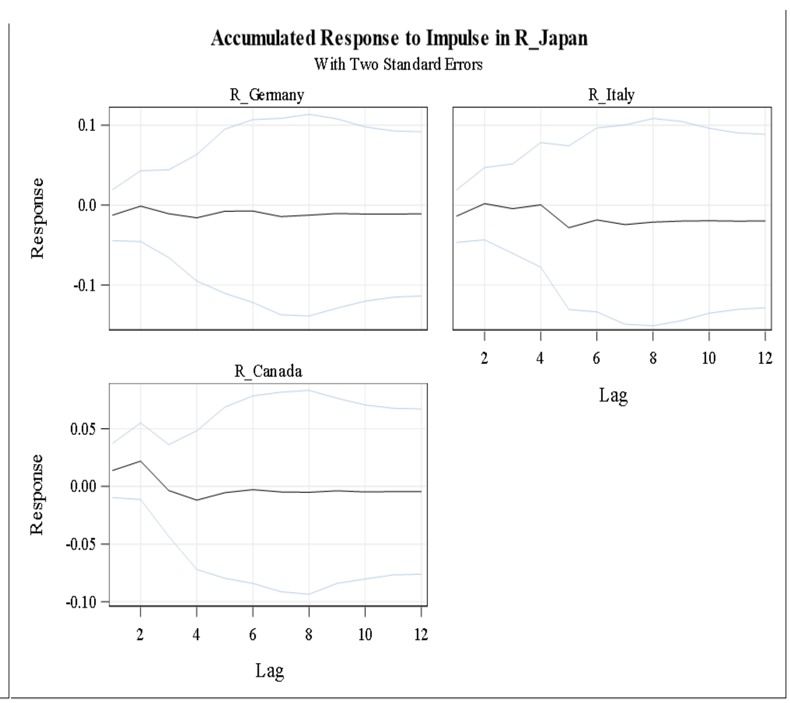
Below are plots for the cumulative effects. For instance, a shock to the R-US series (i.e., a large value of the error term ε_{1t}) results in a total effect of 0.85 times the immediate impact on the R_US series after four years. This corresponds to a multiplicative effect of 0.85, implying a 1% increase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

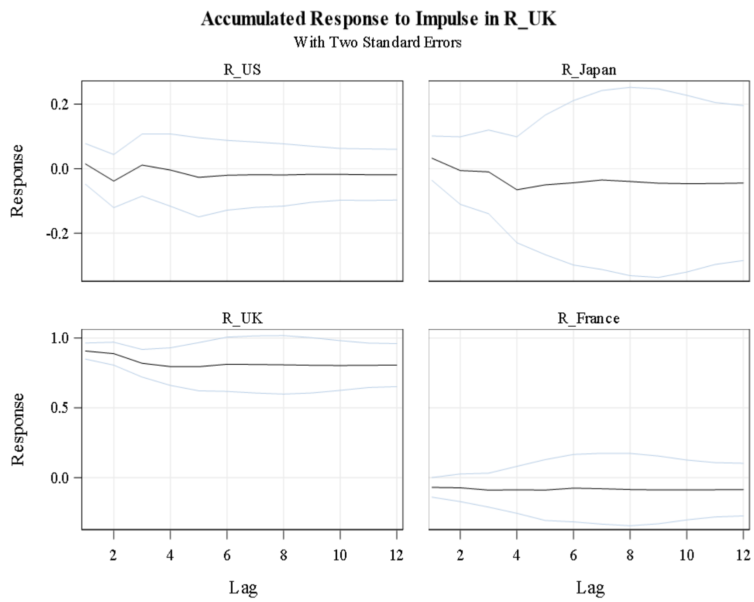
However, a shock to the US return series, ε1t, also influences the return series of other countries. For instance, the Japan return is affected by 0.5% after four years, as the graph for accumulated response to impulse in R_US at lag four displays a coefficient of nearly 0.5.

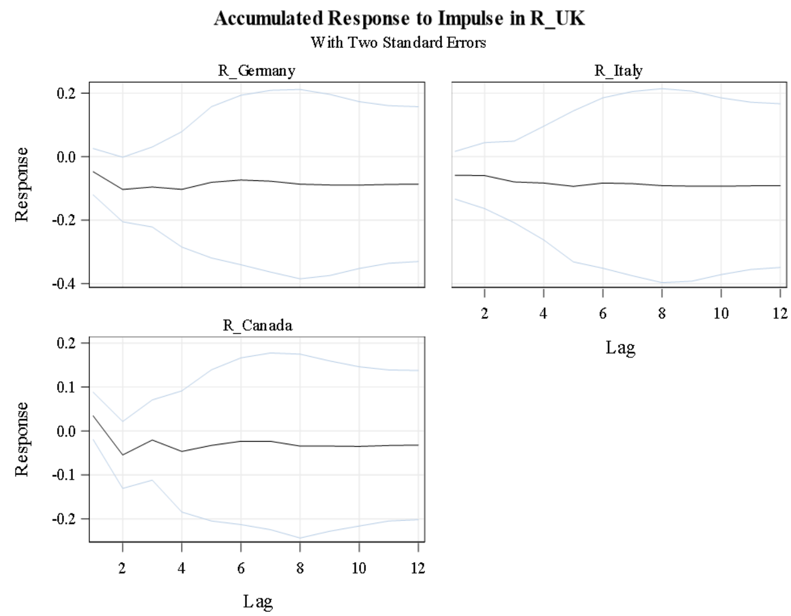

Accumulated Response to Impulse in R_US
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag

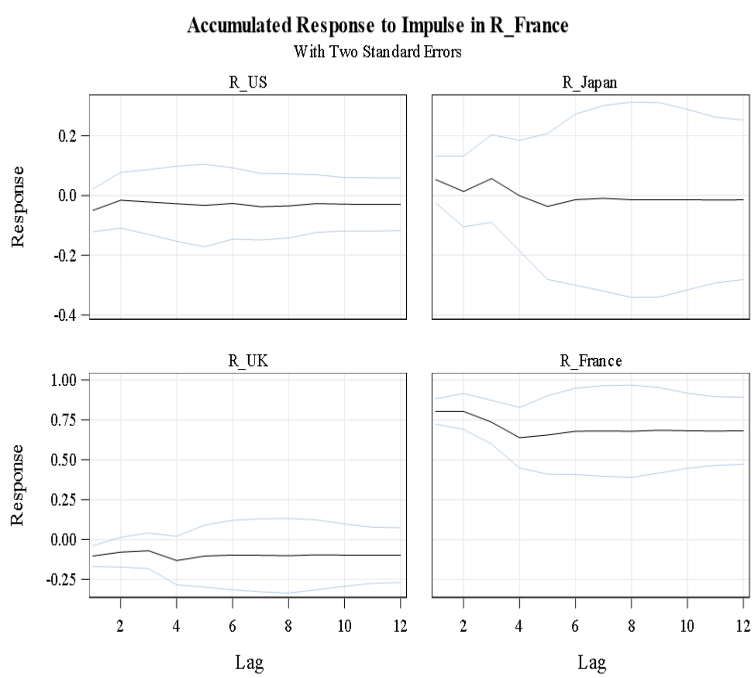

Accumulated Response to Impulse in R_US
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag

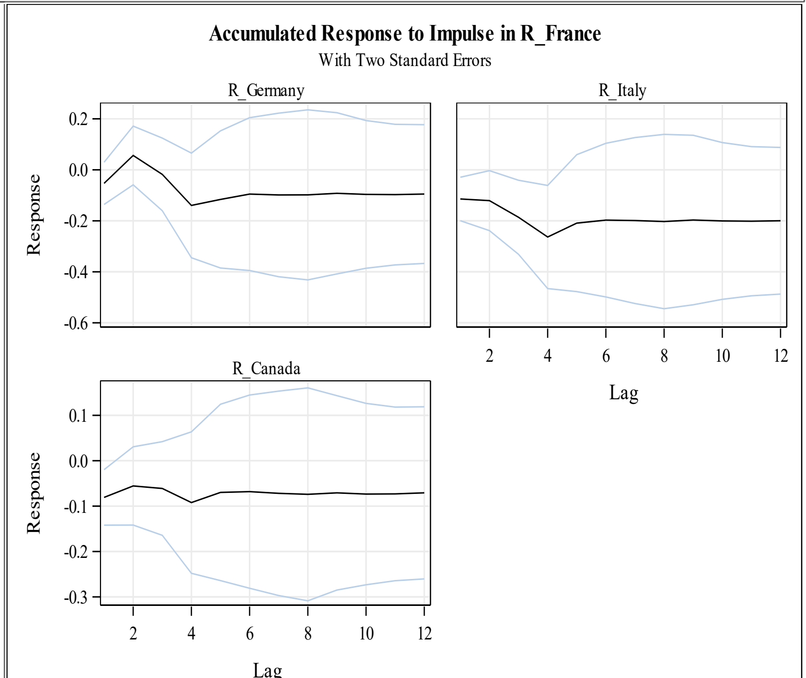

Accumulated Response to Impulse in R_Japan
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag

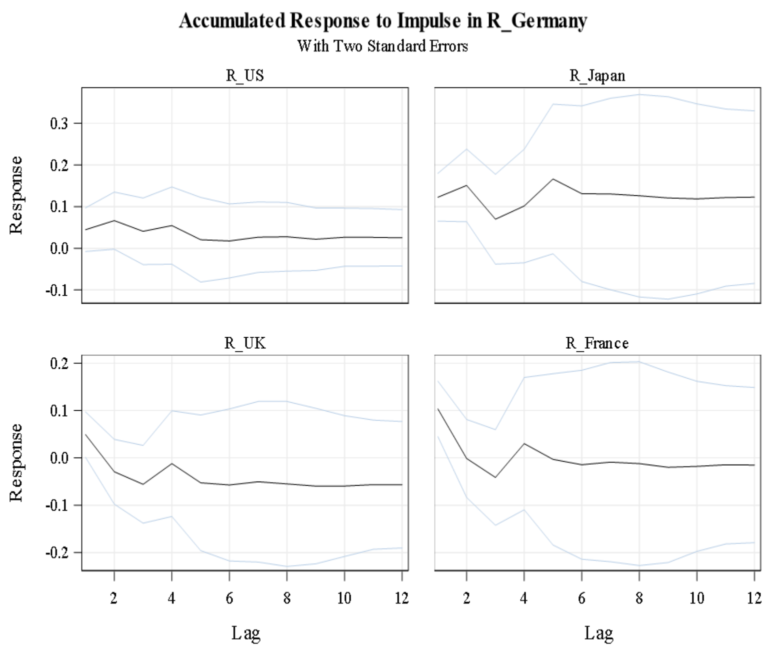

Accumulated Response to Impulse in R_Japan
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag

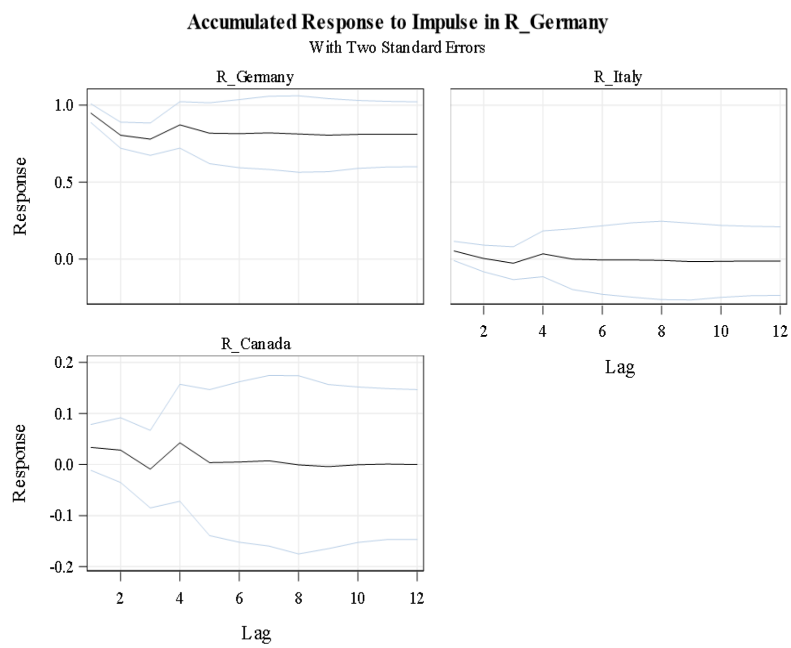

Accumulated Response to Impulse in R_UK
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag

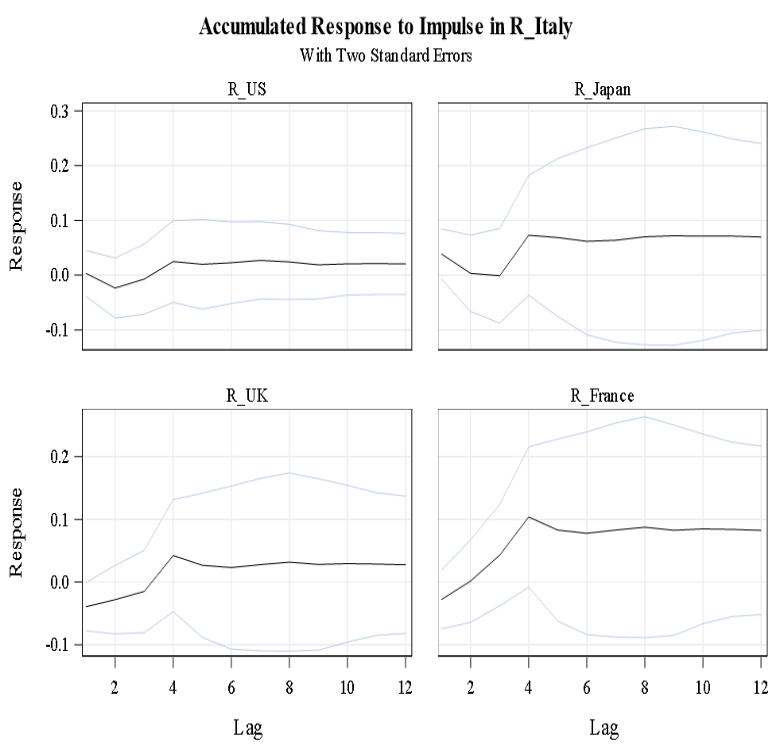

Accumulated Response to Impulse in R_UK
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag

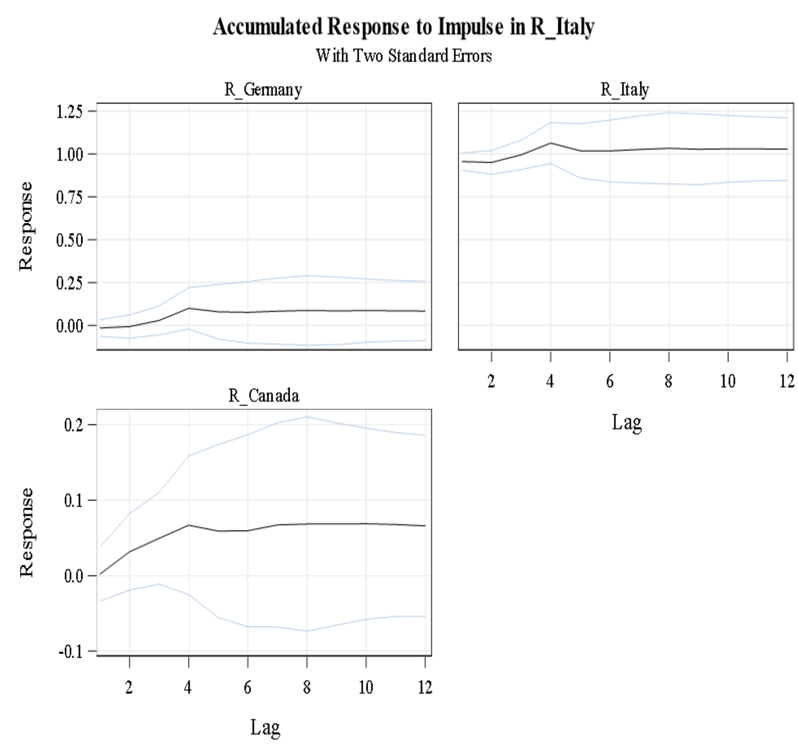

Accumulated Response to Impulse in R_France
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag

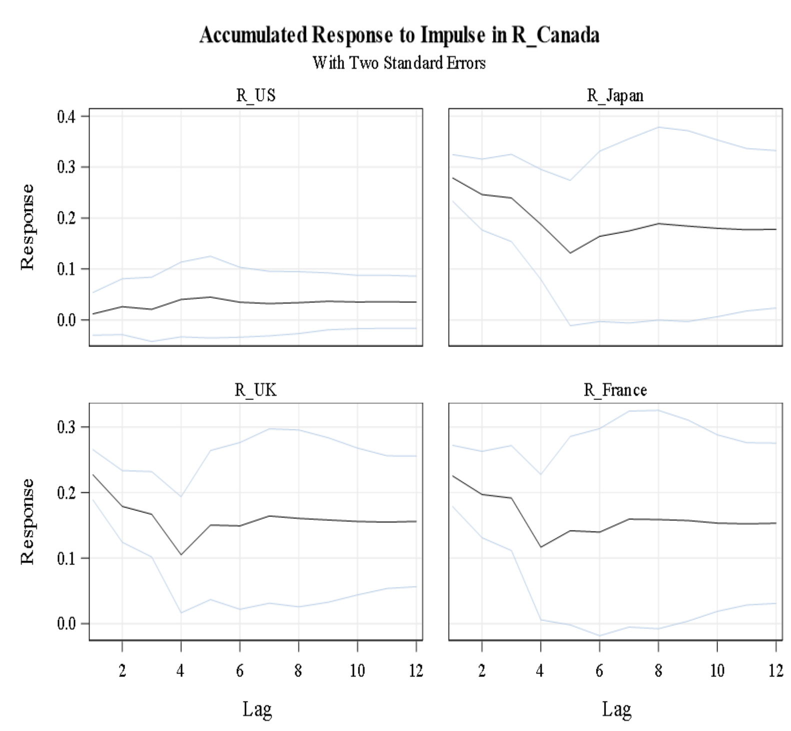

Accumulated Response to Impulse in R_France
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag

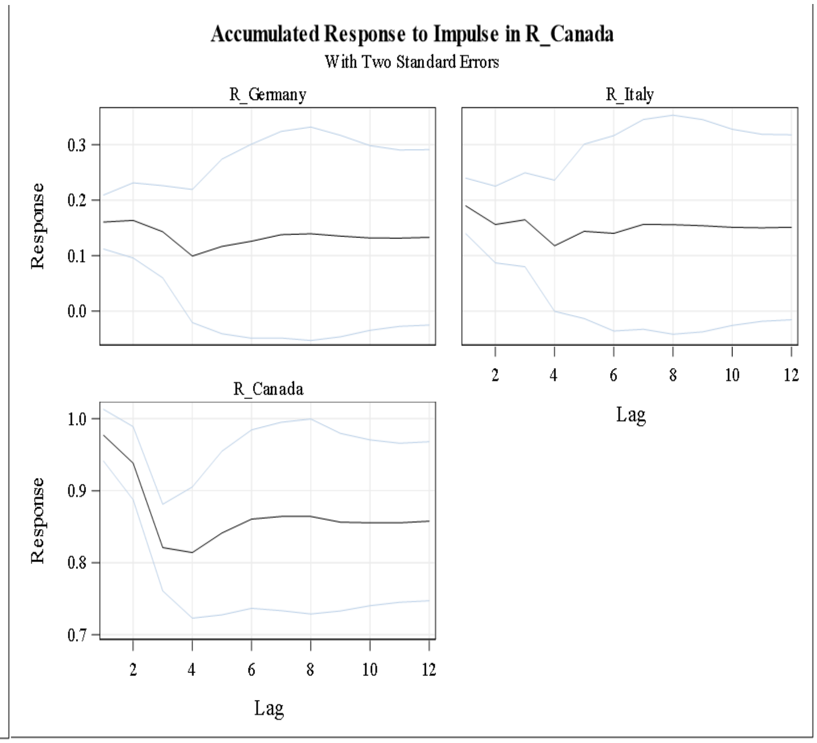

Accumulated Response to Impulse in R_Germany
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag


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


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

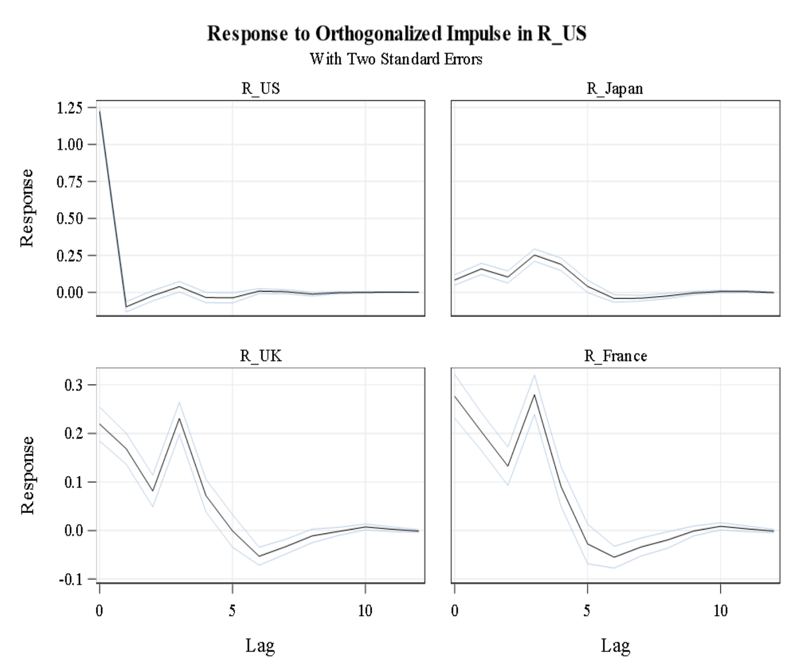


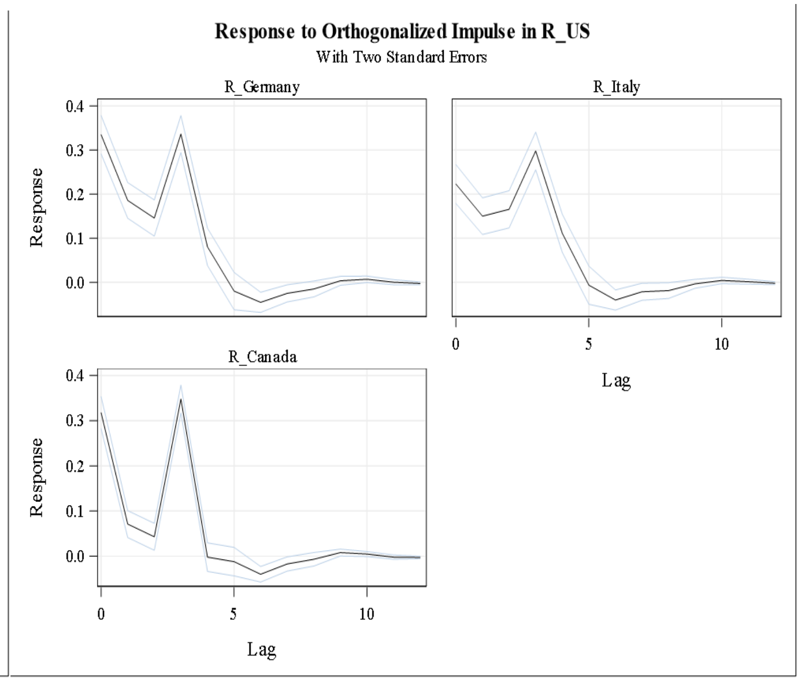


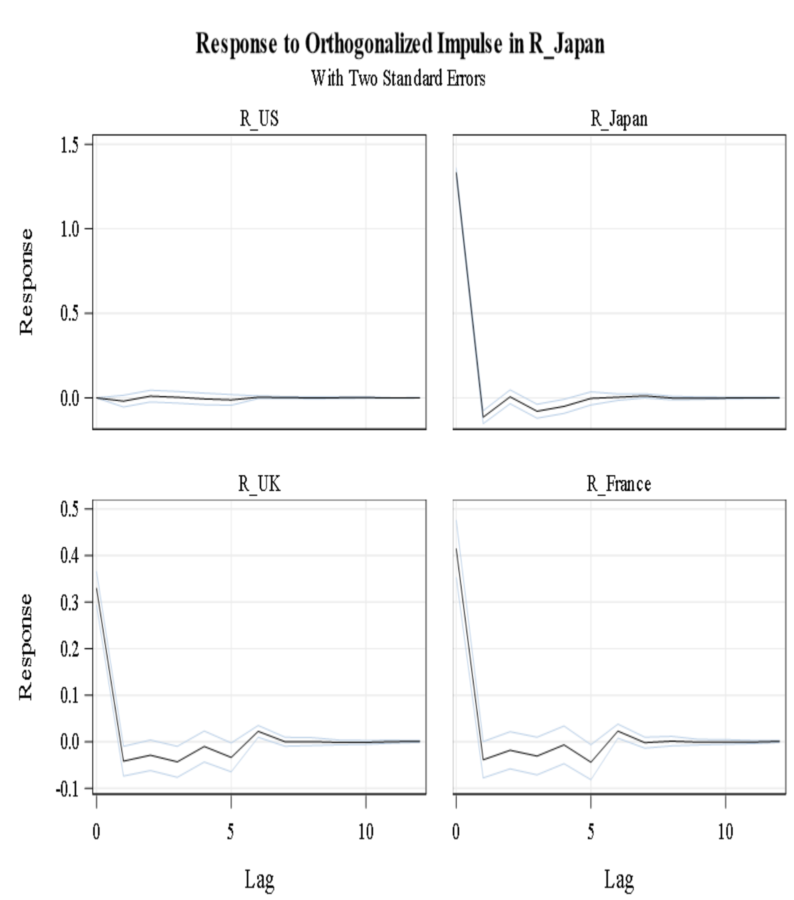
Effects of Orthogonal Shocks

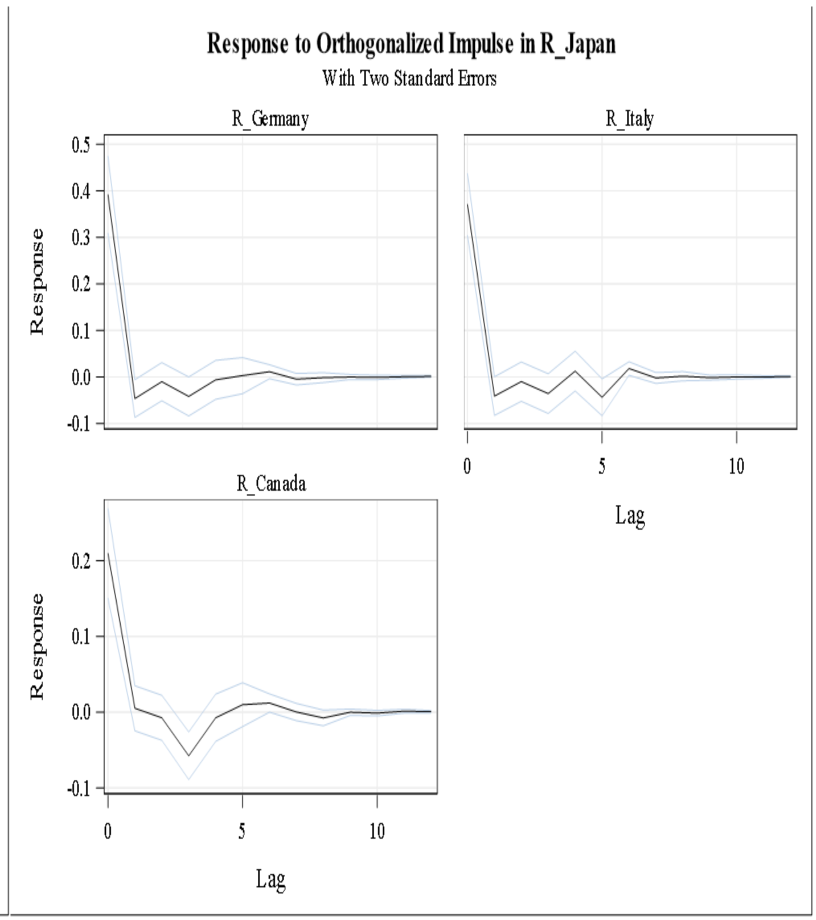
The output's third section highlights the impact of an orthogonal shock on one of the series. The concept rests on the premise that the error term exists solely in one series and does not contribute to the error in the other series due to the correlation of the error terms. These plots illustrate the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

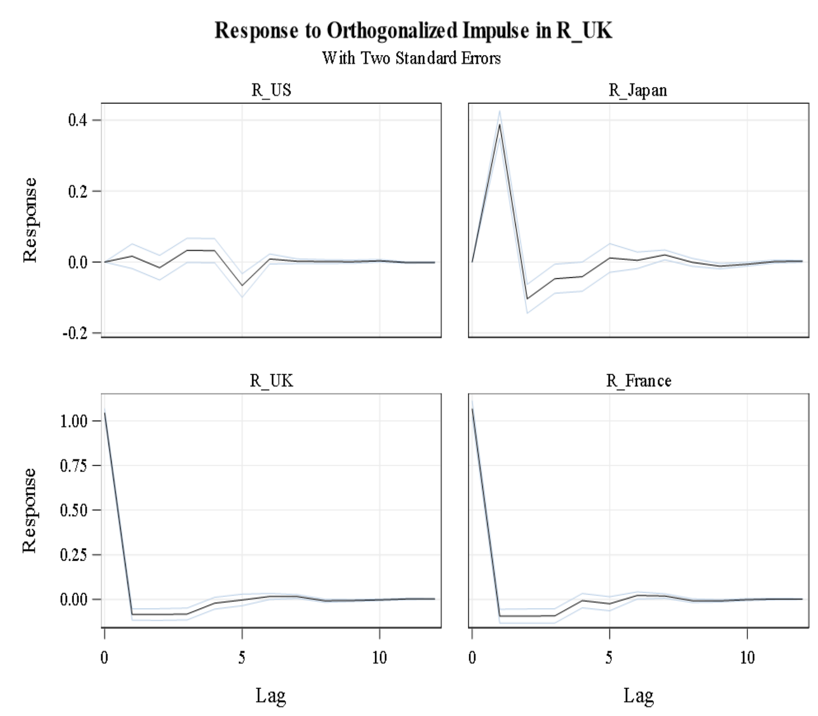
This effect is computed through an orthogonalization of the error terms' correlation matrix Σ. The covariance matrix is factored as Σ = PPT, where P can be interpreted as a lower triangular matrix. In this representation, the error processes are standardized to variance 1, and individual error processes 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.

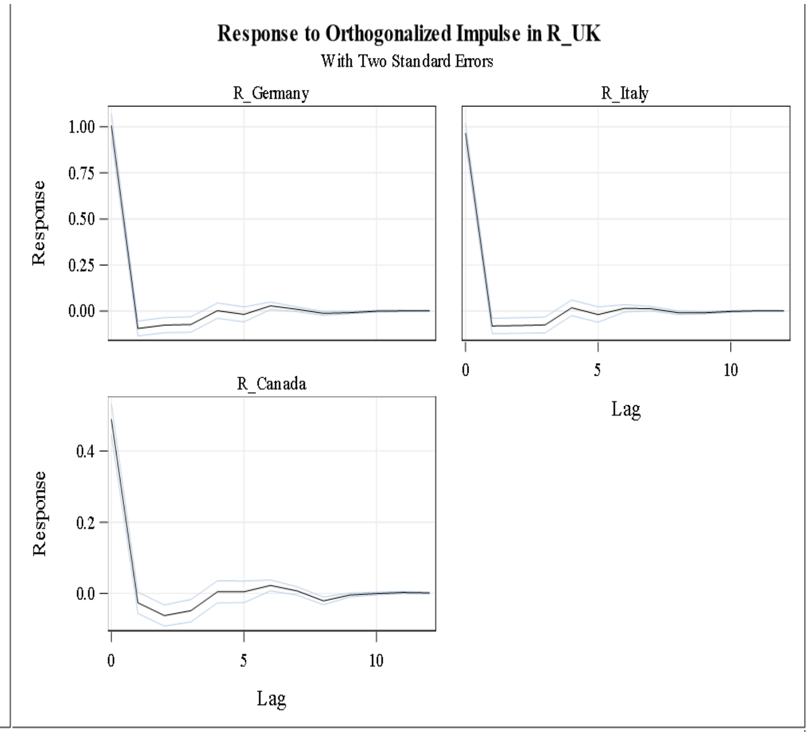

Response to Orthogonalized Impulse in R_US
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag

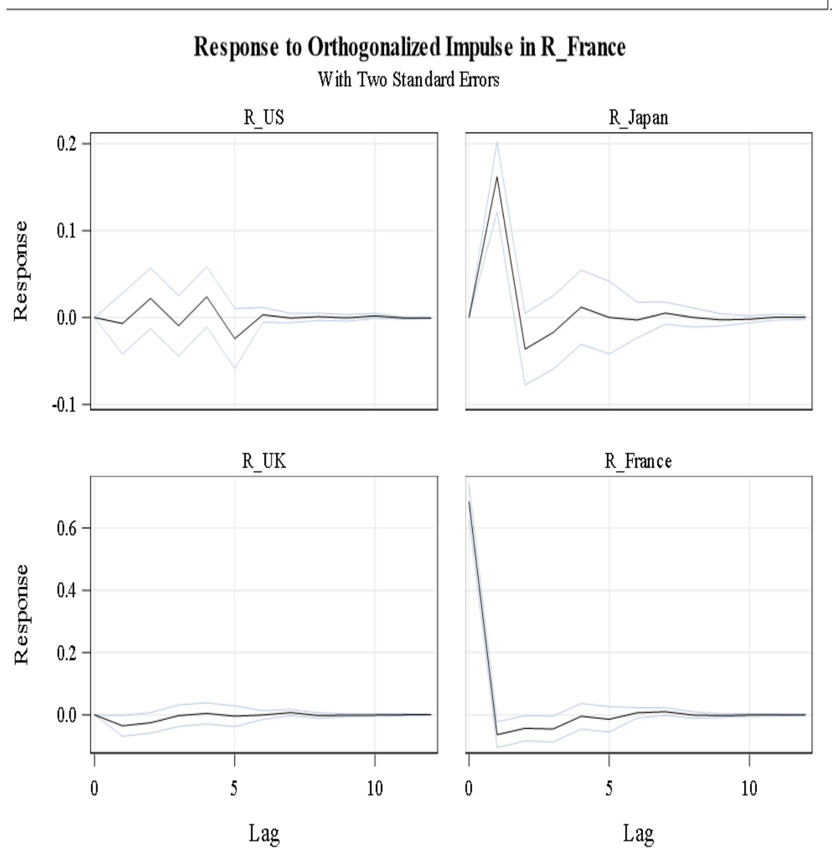

Response to Orthogonalized Impulse in R_US
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag

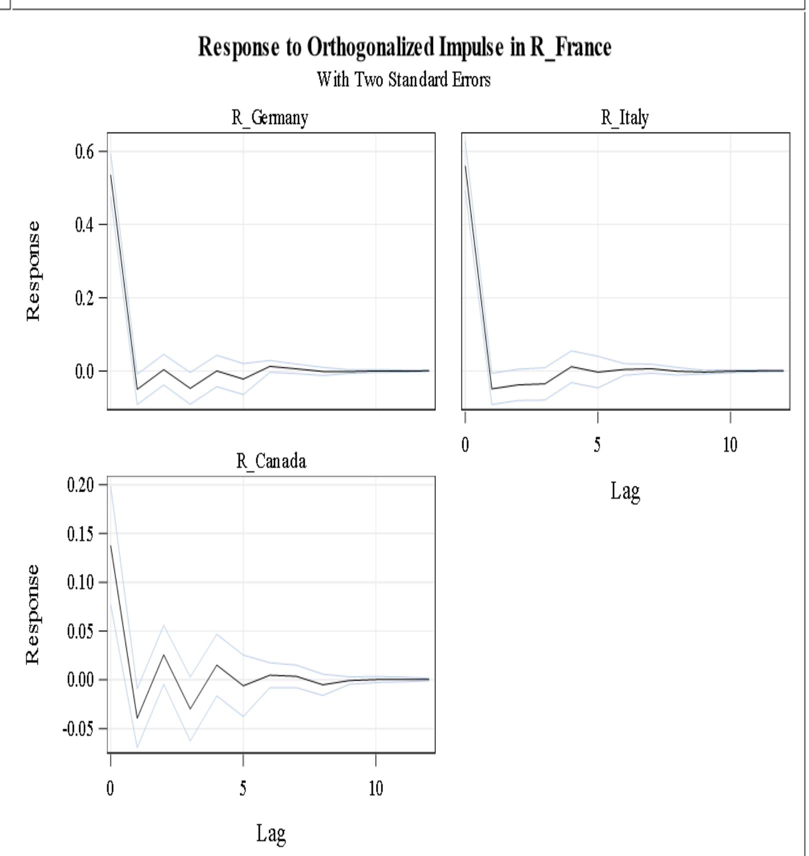

Response to Orthogonalized Impulse in R_Japan
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag

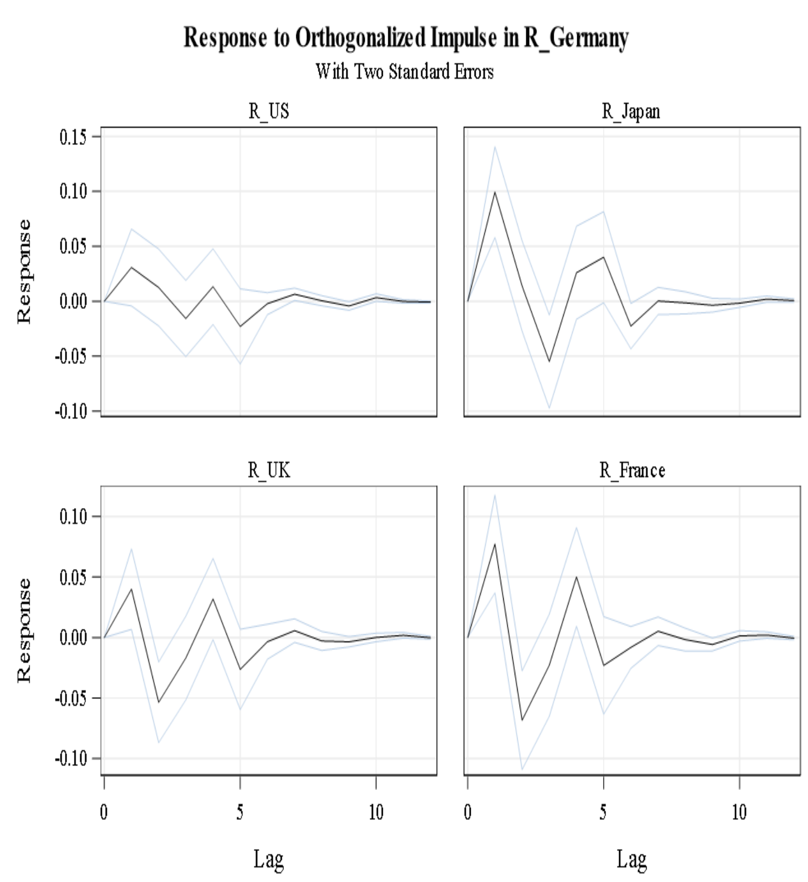

Response to Orthogonalized Impulse in R_Japan
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag

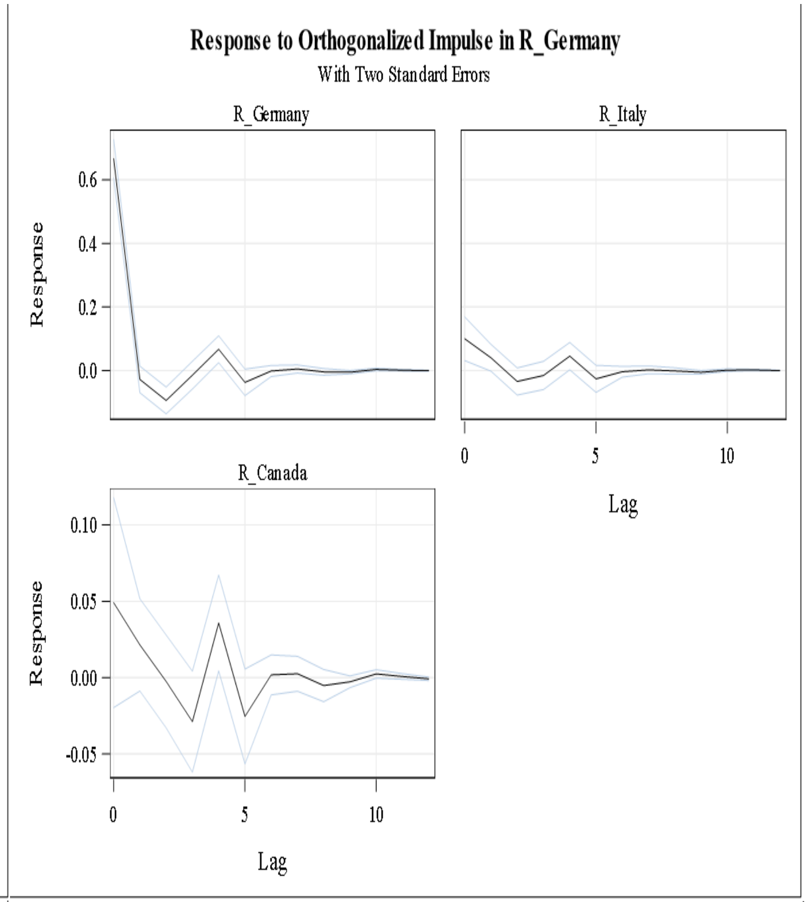

Response to Orthogonalized Impulse in R_UK
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag

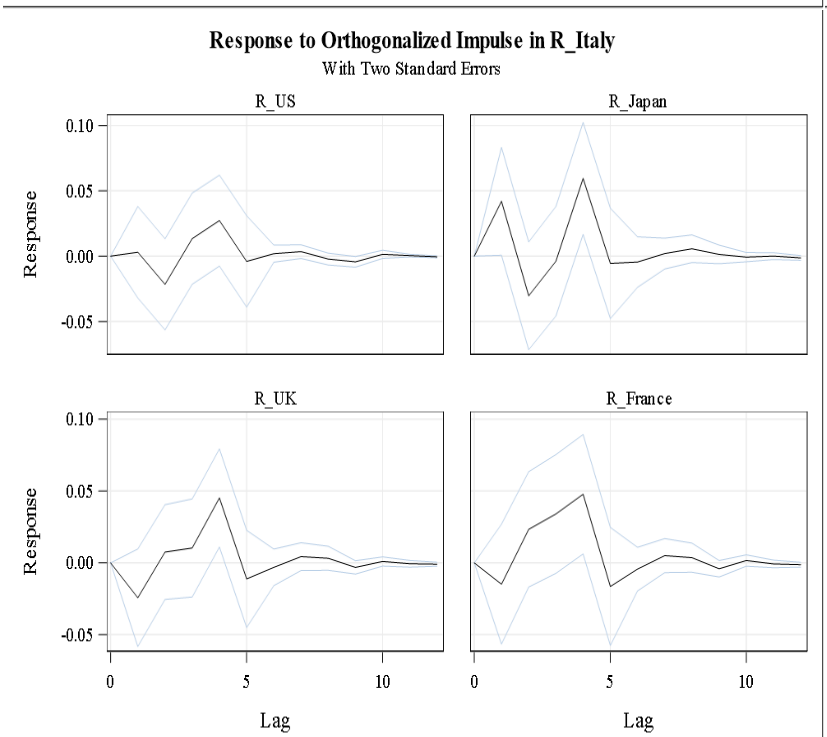

Response to Orthogonalized Impulse in R_UK
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag

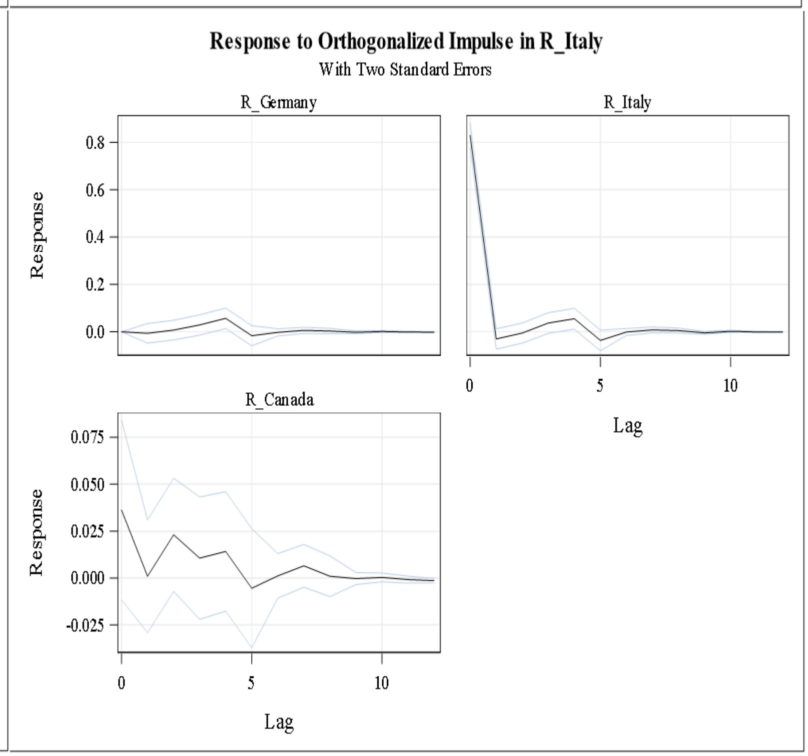

Response to Orthogonalized Impulse in R_France
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag

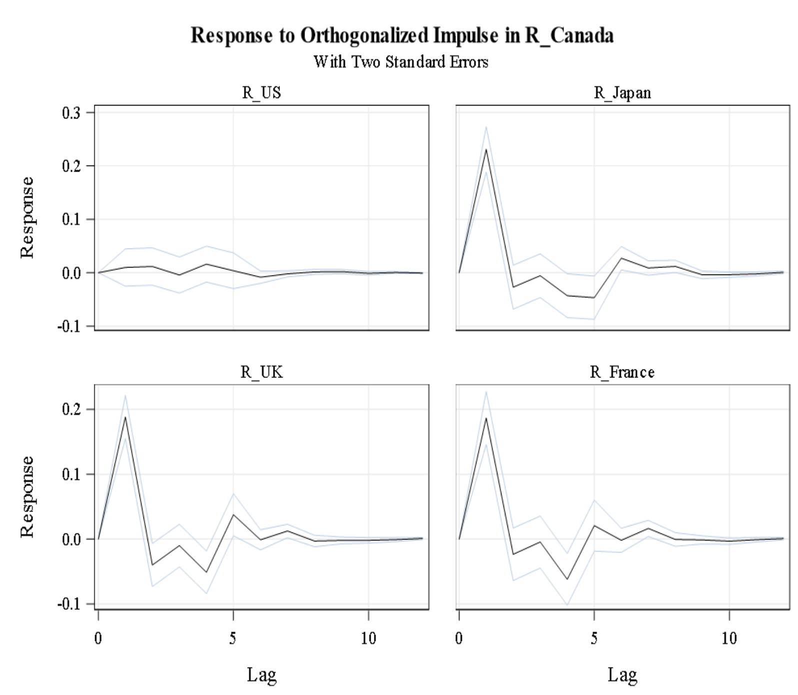

Response to Orthogonalized Impulse in R_France
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag

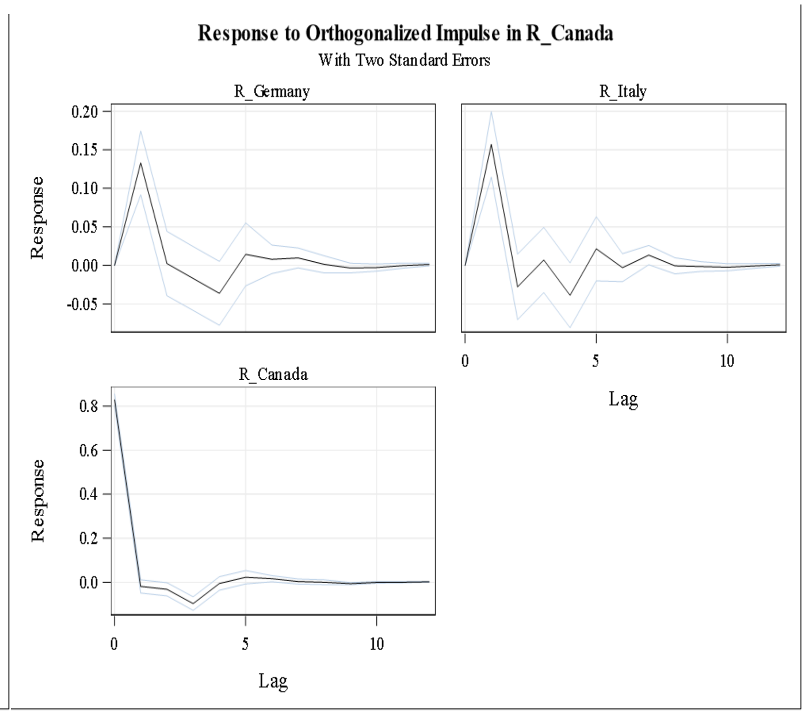

Response to Orthogonalized Impulse in R_Germany
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag
0
5
10


Response to Orthogonalized Impulse in R_Germany
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag
0
5
10


Response to Orthogonalized Impulse in R_Italy
With Two Standard Errors
R_US
R_Japan
R_UK
R_France
Response
Lag
0
5
10


Response to Orthogonalized Impulse in R_Italy
With Two Standard Errors
R_Germany
R_Italy
R_Canada
Response
Lag
0
5
10





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.

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)

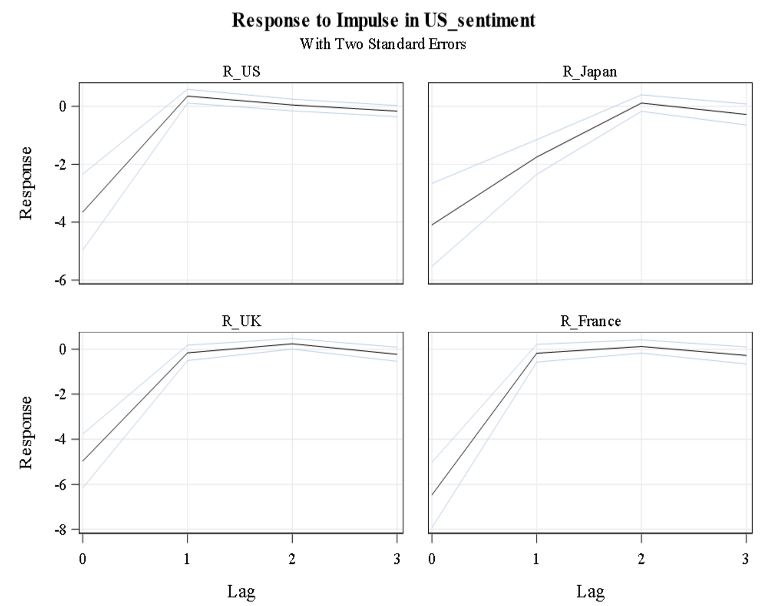
VARX(5,0)

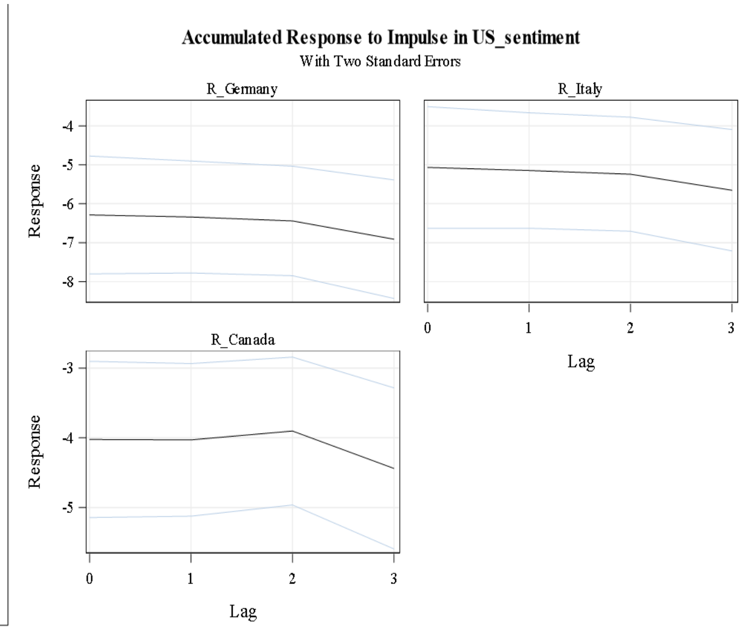
Equation	Estimate	t Value	Pr > |t|	Variable
R_Italy	0.1434	4.01	0.0001	1
	-5.06665	-6.48	0.0001	US_sentiment(t)
	0.10013	5.6	0.0001	R_US(t-1)
	-0.01377	-0.84	0.3998	R_Japan(t-1)
	-0.05709	-1.52	0.1274	R_UK(t-1)
	-0.11582	-2.73	0.0064	R_France(t-1)
	0.05029	1.61	0.1068	R_Germany(t-1)
	-0.04368	-1.75	0.08	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)

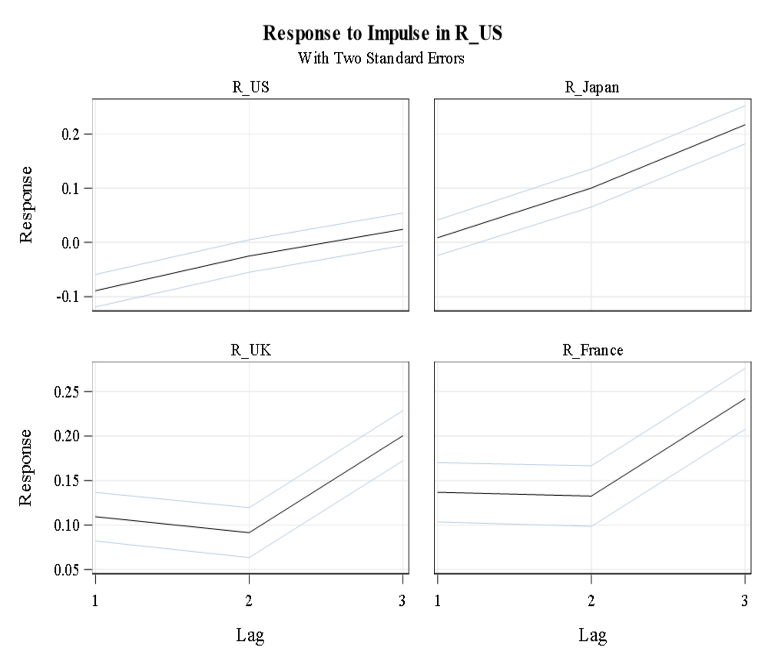
Table 16
Model Parameter Estimates (Least Square)
VARX(5,0)

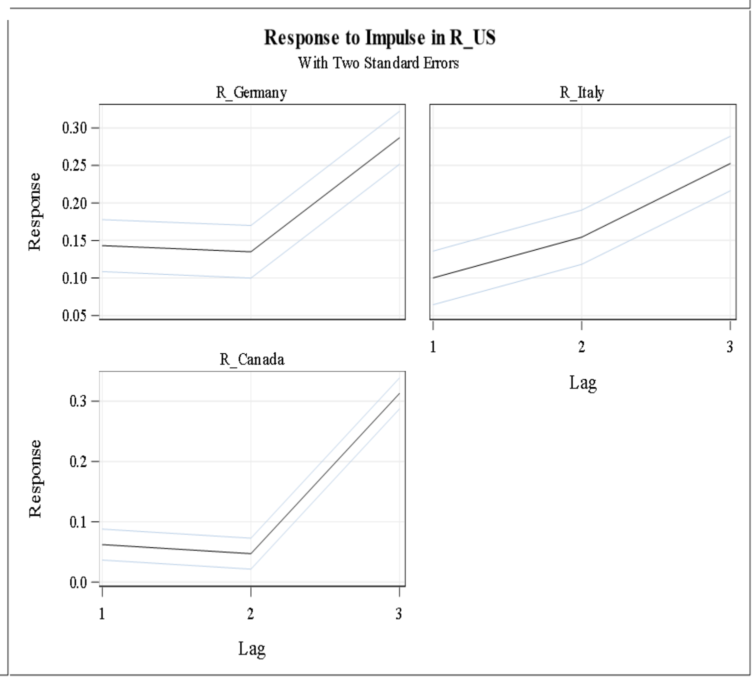
Equation	Estimate	t Value	Pr > |t|	Variable
R_Canada	0.14134	5.51	0.0001	1
	-4.02293	-7.19	0.0001	US_sentiment(t)
	0.0622	4.86	0.0001	R_US(t-1)
	0.01378	1.18	0.2395	R_Japan(t-1)
	0.03558	1.33	0.1848	R_UK(t-1)
	-0.08196	-2.7	0.0071	R_France(t-1)
	0.03151	1.41	0.1585	R_Germany(t-1)
	0.00281	0.16	0.8749	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)

Response Impulse in the US Sentiment









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.

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

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.

Results Interpretation

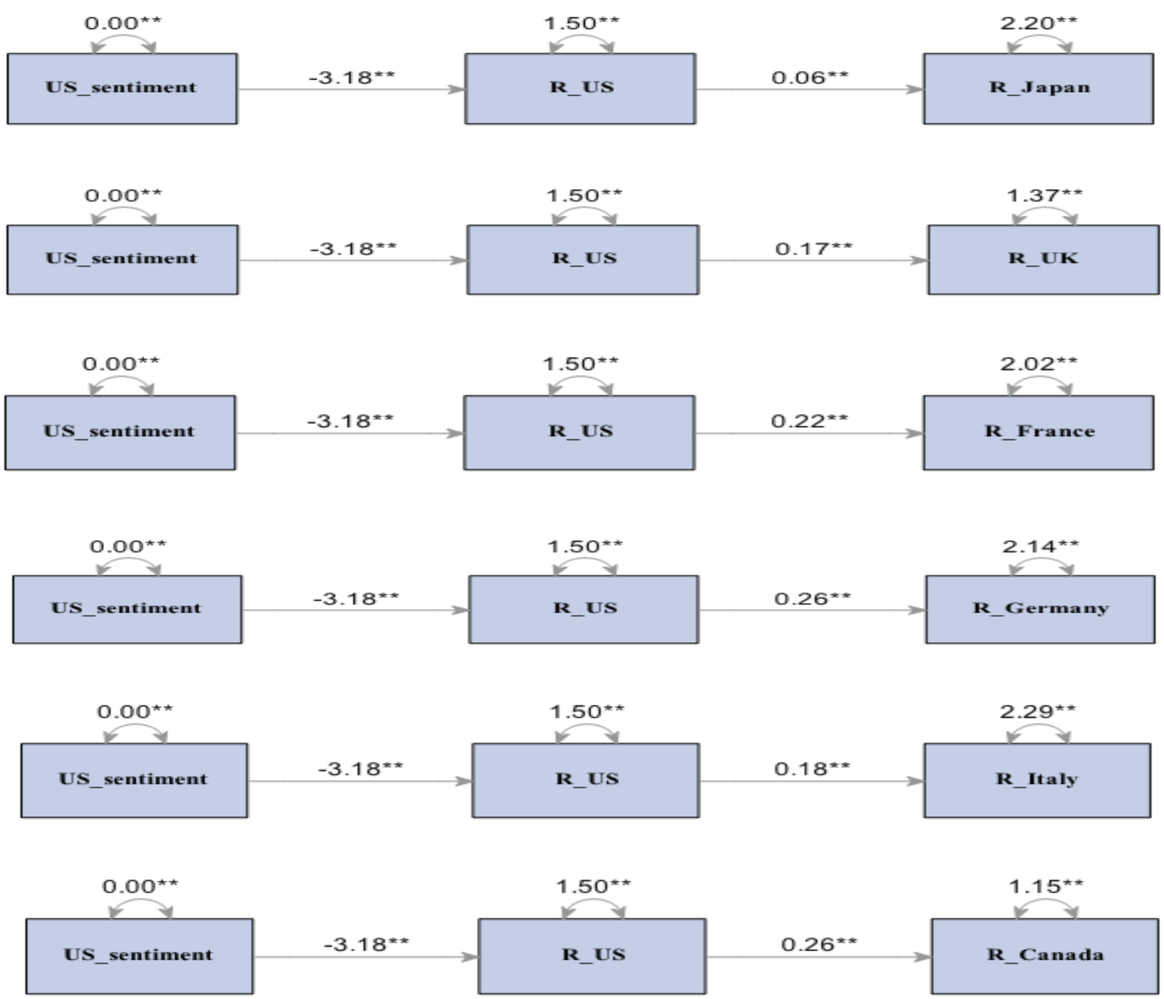
Table 18
PATH List

	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

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.



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.

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

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.

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