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An Econometric Analysis on Influential Power Across Global Stock Markets

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Abstract

Global stock markets are considered to be more integrated than ever and having impacts on each other. By utilizing the VAR model and the corresponding impulse response functions (IRFs), this research paper constructs the "Influence Index" to quantify and order the influential power for major stock markets across the globe. Statistical evidences show that the U.S. stock market dominates the global markets by achieving the highest influence index of 3.18, followed by Australia (1.85) and Britain (1.12). However, stock markets housed in developing economies show very weak influential power, which could be due to the lack of international recognitions and market establishment. Stock markets in China and Argentina possess the lowest and the second lowest market power with influence index of only 0.26 and 0.28 respectively. Corresponding evidences also offer an important indication that established markets are much less sensitive to impacts generated from other markets, while developing markets are more prone to outside influences.

JEL classification numbers: G12; G14; G17
Keywords: Global Stock Markets, Market Power, Influence Index

1 Introduction

Global stock markets across different countries and regions are now more integrated than ever. A financial tsunami in the U.S. stock market could trigger chain reactions that may cause huge impacts on the European and the Asian markets. Likewise, unexpected good news from the U.S. stock market is expected to have positive spillover effects on other major financial markets. Then, the interesting questions are: which market has more influential power over other markets? How can we quantify the influential power for each major stock market all over the world? The purpose of this research paper is to conduct econometric and statistical analysis for global major stock markets to identify their market power. More importantly, by inventing the "Influence Index", which is derived from the impulse response functions (IRFs) of the VAR(P) model, this research enables us to quantify and rank the market influential power for each major stock market across the globe.

A handful of past literatures made efforts trying to explain the general correlation relationships and the spillover effects among international financial markets. Hamao and

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Masulis (1990) utilized an ARCH model and discovered that stock price volatility spilled over from New York stock market to Tokyo stock market and from New York stock market to London stock market. But no price volatility spillover effect was found in other directions. Their research provides valuable implication to this research, since they implied that the New York stock market should have more influential power than other stock markets for the fact that the spillover effect was only single-direction. On the other side, Ramchand and Susmel (1998), by using a SWARCH model, found that the correlations between the U.S. stock market and other stock markets are higher when the U.S. market itself is in a state of high volatility. The result suggests that the correlation relationships are time-dependent.

By using simulated return data, Bartram and Wang (2005) claimed that the "contagion effect" indeed existed during period of financial crisis, making the benefit of portfolio diversification negligible. Khan and Park (2009) confirmed the "contagion effect" in stock markets across different countries during the 1997 Asian financial crisis. Their findings are based on their model evidences that regression residual correlations are increased significantly during the crisis period when compared to non-crisis period. Nevertheless, these literatures built on market correlation analysis were criticized by others. For example, Forbes and Rigobon (2002) argued that the existence of heteroskedasticity would bias the testing results for the "contagion effect" which is based on market correlations. The authors discovered that stock market co-movements are stable and in high level over time, which are said to be interdependence. The insight from Forbes and Rigobon (2002) suggests that alternative econometric method is needed to improve the statistical integrity for investigating the contagion effect.

2 Data and Methodology

2.1 Data

In order to capture the general sentiment of global stock markets, 10 major stock market indices from 10 different countries and regions are selected. As shown in Table 1, these indices contain both major developed economies and emerging economies. Each index covers daily level data for a sample period from July 1st, 1998 to June 30th, 2018 (a total of twenty years)

Table I: Sample Index Composition

Index	Country/Region	Sample Period
S&P500	United States	Daily data from July 1st, 1998 to June 30th, 2018
S&P/TSX	Canada	
FTSE100	Britain	
DAX	Germany	
EURO STOXX50	Europe	
Nikkei 225	Japan	
HangSeng	Hong Kong	
ASX200	Australia	
Merval	Argentina	
Shanghai Composite	China	

2.2 Testing for Stationarity Condition

Augmented Dickey-Fuller Unit Root Test is the statistical procedure for testing the stationarity condition. A typical test equation with trend and drift can be expressed as equation (1). The associated testing hypotheses are H_0: $\alpha_1 = 0$ (non-stationary) versus H_a: $\alpha_1 < 0$ (stationary).

$$\Delta y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 t + \delta_1 \Delta y_{t-1} + \varepsilon_t \tag{1}$$

2.3 The Vector Autoregression Model

A vector autoregression model with P-lags [VAR(P)] can be expressed as equation (2). The advantage of a VAR(P) model is that we can get more information from the underlying time series variables than a single-equation setup. Moreover, the VAR(P) model can provide with the impulse response functions (IRFs) [defined in section 2.5] that are very crucial and valuable for us to analyze the behaviors of the underlying variables for potential economic and market shocks.

$$\mathbf{Z_t = \Pi_1 Z_{t-1} + \Pi_2 Z_{t-2} + \Pi_3 Z_{t-3} + \ldots + \Pi_p Z_{t-p} + \varepsilon_t} \tag{2}$$

i. Matrix $\mathbf{Z_{t-p}}$ contains p-period time-lagged independent variables, where p can take 1, 2, …, P.
ii. Matrix $\mathbf{\Pi_p}$ contains coefficients of $\mathbf{Z_{t-p}}$, where p can take 1, 2, …, P.

2.4 Testing for Long-Run Cointegration in a Multiple-Equation Framework

Since the sample contains ten major stock market indices across the globe, it is necessary to set up a multiple-equation framework for detecting the cointegration relationships. Johansen Rank Test is the best choice for testing purposes, because it can identify up to G-1 number of cointegration relationships. The test is based on a G-Variable VAR(P) model [equation (2)]. The model is then undergone a process called "cointegration transformation", which yields a form of equation (3). The rank of $\mathbf{\Pi}$ contains information about the number of cointegration relationships. The minimum rank of $\mathbf{\Pi}$ is 0 and the maximum rank of $\mathbf{\Pi}$ is G. Both rank (0) and rank (G) suggest that there is no cointegration relationship within the underlying equation framework. For a rank of $\mathbf{\Pi}$ that is greater than 0 and smaller than G, the number of the rank equates to the number of cointegration relationships.

$$\mathbf{\Delta Z_t = \Gamma_1 \Delta Z_{t-1} + \Gamma_2 \Delta Z_{t-2} + \Gamma_3 \Delta Z_{t-3} + \ldots + \Gamma_{p-1} \Delta Z_{t-(p-1)} + \Pi\, Z_{t-p} + \varepsilon_t} \tag{3}$$

i. Matrix $\mathbf{\Delta Z_{t-(p-1)}}$ refers to the differenced variables of $\mathbf{Z_{t-(p-1)}}$, where p can take 1, 2, …, P.
ii. Matrix $\mathbf{\Gamma_{p-1}}$ refers to the coefficients of $\mathbf{\Delta Z_{t-(p-1)}}$, where p can take 1, 2, …, P.
iii. Matrix $\mathbf{\Pi}$ refers to $(\mathbf{I - \Pi_1 - \Pi_2 - \Pi_3 - \ldots - \Pi_P})$.

2.5 Impulse Response Functions (IRFs)

The impulse response functions of one particular time series variable can track the variable future movement path, after the variable is experienced a hypothetical one-standard-deviation economic or market shock by some other variable within the G-variable system. As shown in expression (4), mathematically, IRFs are the partial derivatives of variable Y with respect to shock "ε" to variable "g" at time "t" for "s" periods into the future.

$$\frac{\partial Y(t+s)}{\partial \varepsilon g(t)} \quad \text{[IRF for variable Y at time "t" with "s" periods into the future]} \tag{4}$$

i. Y refers to one time series variable of the G-variable system
ii. εg(t) refers to one-standard-deviation shock to variable “g” at time “t”,
iii. “g” can take 1, 2, …, G; “t” can take 1, 2, …, T; “s” can take 1,2, …, S.

3 Empirical Results

This section contains three subsections. The first subsection reports statistics that describe the time series behaviors of global major stock market indices. The second subsection reports statistics from the VAR model and the corresponding impulse response functions for each market index. The third subsection shows the construction and interpretation of “Influence Index” for each stock market in the sample. Furthermore, numeric values of the “Influence Index” are reported to offer the comparison of influential power across different markets.

3.1 Time-series Behaviors of Global Major Stock Market Indices

Table 1 shows the summary statistics and the Shapiro-Wilk normality test for ten major stock market indices across the globe. As we can see, Merval (Argentina) has the largest standard deviation of 1.26, which is much higher than any other indices’ in the sample. On the other hand, Shanghai Composite (China) has the second largest standard deviation of 0.38. This provides an implication that developing economies might have higher market risk in terms of its own long-run volatility. Developed economies, such as U.S. and Britain, have lower standard deviations of 0.29 and 0.17 respectively. This is also consistent with the argument that developed economies are typically more stable and have less market fluctuations than developing economies. More interestingly, the Shapiro-Wilk test for normality rejects the null hypothesis that the data is normal for every single index. Because the indices are in the logged form, the rejection of the null hypothesis yields significant statistical evidence that all market indices within the sample are not lognormal.

Table 2 displays correlation coefficients for each pair of stock market indices. Bonferroni adjustments are implemented in performing the correlation significance test to circumvent the potential multiple comparison problem. The correlation testing results are very impressive, because, as we can see, all pairs of stock market indices are correlated at 1% significance level. This builds an empirical ground that stock markets in different geographic locations are interconnected and influenced by each other. As a supplement, Graph 1 illustrates the time series plots of all stock market indices in the sample. The graph shows a very interesting pattern that indices form a visual of “co-movements” over time. In other words, all indices share the similar ups and downs during the sample period, although they are completely different markets in different countries or regions.

A natural and essential follow-up to Table 2 and Graph 1 would be the unit root test to further investigate the time-series behaviors of those stock market indices. Table 3 does this job by conducting the Augmented Dickey-Fuller Unit Root Tests. The testing equation contains both drift and trend, and one augmentation term is also incorporated to ensure uncorrelated errors. The initial testing results on the level data provide evidences that all stock market indices in the sample are non-stationary (null hypothesis is FTR for every individual index). This suggests that market index level by itself could continue drifting away from its long-run mean, which is consistent with the observation in the real world that bull market and bear market are not symmetric in terms of length and magnitudes. The sequential unit root testing results on the first-differenced data show that all the variables are stationary (null hypothesis is rejected for every individual index). As a major implication of table 3, there are enough statistical evidences to conclude that all indices in the sample are I(1). This finding is so exciting, since I(1) is the necessary condition to form long-run cointegration relationships.

Table 1: Summary Statistics and Shapiro-Wilk Test for Normality

The upper part of this table shows the summary statistics for ten major stock market indices across the globe. The index data is in the logged scale [i.e. ln(index)] and covers a sample period from July 1st, 1998 to June 30th, 2018. The lower part of this table shows the Shapiro-Wilk normality test for each individual index. "W" is the Shapiro-Wilk test statistic. "V" is the scale index that measures the degree of departure from normality. "Z" is the corresponding Z-score. "***" denotes significant at 1% level.

Index	**Mean**	**Std. Dev.**	**Min**	**25%**	**50%**	**75%**	**Max**
SP500	7.24	0.29	6.52	7.04	7.18	7.41	7.96
ASX	8.37	0.25	7.77	8.12	8.42	8.58	8.83
FTSE100	8.65	0.17	8.10	8.56	8.68	8.77	8.97
DAX	8.77	0.38	7.70	8.52	8.76	9.02	9.51
TSX	9.29	0.28	8.58	9.05	9.38	9.52	9.71
Hangseng	9.77	0.33	8.80	9.51	9.87	10.04	10.41
Merval	7.66	1.26	5.30	6.57	7.63	8.20	10.47
Nikkei	9.49	0.29	8.86	9.24	9.53	9.73	10.09
Eurostoxx50	8.07	0.21	7.50	7.92	8.05	8.20	8.61
Shanghai	7.68	0.38	6.92	7.37	8.01	8.01	8.71

			Shapiro-Wilk Test for Normality			
Index	**Skewness**	**Kurtosis**	**W**	**V**	**Z**	**P-Value**
SP500	0.52	2.66	0.96	129.46	12.81	0.00***
ASX	-0.31	1.84	0.94	175.31	13.61	0.00***
FTSE100	-0.67	2.80	0.95	137.93	12.98	0.00***
DAX	-0.04	2.51	0.99	42.40	9.87	0.00***
TSX	-0.51	1.99	0.92	228.03	14.30	0.00***
Hangseng	-0.47	2.26	0.95	143.42	13.08	0.00***
Merval	0.41	2.34	0.95	140.51	13.02	0.00***
Nikkei	-0.03	1.83	0.96	120.81	12.63	0.00***
Eurostoxx50	0.26	2.66	0.99	32.71	9.19	0.00***
Shanghai	0.10	2.29	0.98	63.58	10.94	0.00***

Table 2: Testing for Correlations

This table shows the correlation coefficients for each pair of stock market indices in the sample, along with their statistical significance. The index data is in the logged scale [i.e. ln(index)] and covers a sample period from July 1st, 1998 to June 30th, 2018. The single asterisk "*" in this table denotes that the correlation is significant at 1% level. The Bonferroni Adjustment is implemented to counteract the potential problem of multiple comparisons.

	SP500	ASX	FTSE100	DAX	TSX
SP500	1				
ASX	0.6839*	1			
FTSE100	0.8798*	0.6061*	1		
DAX	0.9323*	0.7459*	0.9063*	1	
TSX	0.7506*	0.9446*	0.6867*	0.8368*	1
Hangseng	0.7349*	0.8903*	0.7122*	0.8453*	0.9527*
Merval	0.8292*	0.8351*	0.6066*	0.8185*	0.8766*
Nikkei	0.7953*	0.4323*	0.8011*	0.7101*	0.4361*
Eurostoxx50	0.3483*	0.1137*	0.5747*	0.3545*	0.1114*
Shanghai	0.5264*	0.7319*	0.4833*	0.6814*	0.7436*
	Hangseng	**Merval**	**Nikkei**	**Eurostoxx50**	**Shanghai**
Hangseng	1				
Merval	0.8330*	1			
Nikkei	0.4301*	0.4730*	1		
Eurostoxx50	0.1377*	-0.1000*	0.7077*	1	
Shanghai	0.8055*	0.6483*	0.2922*	0.1141*	1

Graph 1: Time Series Plots of Global Major Stock Market Indices

This graph displays time series plots of ten major stock market indices across the globe. The index data is in the logged scale [i.e. ln(index)] and covers a sample period from July 1st, 1998 to June 30th, 2018. The horizontal axis represents time. "0" refers to the 1st data point (July 1st, 1998). "500" refers to the 501st data point of the sample (April 5th, 2000). Other time points follow the same logic of ordering.

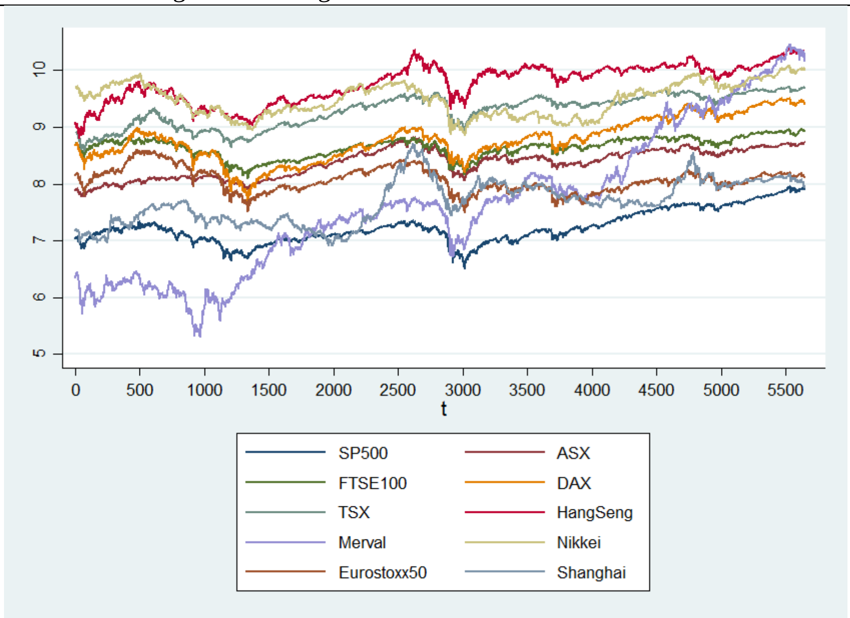

Table 3: Augmented Dickey-Fuller Unit Root Test for Major Stock Market Indices

This table shows the results for testing the stationarity condition for each individual stock market index. The index data is in the logged scale [i.e. ln(index)] and covers a sample period from July 1st, 1998 to June 30th, 2018. The Augmented Dickey-Fuller Unit Root Testing equation includes both drift and trend. One augmentation term is included to ensure uncorrelated testing equation errors. The null hypothesis: the time series contains unit root. The 1% critical value is -3.96. The notation "R***" indicates that the null hypothesis is rejected at 1% significance level. "FTR" indicates that the null hypothesis is "fail to reject" at 1% significance level. For the reason of determining total number of unit roots, the testing procedure follows a sequential process until the null hypothesis is rejected. If the null hypothesis is "FTR" for the level data, then the follow-up unit root test on first-differenced data is necessary. If the null hypothesis is "R***", then no further unit root test is needed.

	Testing on Level Data		**Testing on First-differenced Data**		
Company	**Test Statistic**	**Hypothesis**	**Test Statistic**	**Hypothesis**	**Stationarity**
SP500	-1.74	FTR	-55.67	R***	I(1)
ASX	-2.39	FTR	-52.78	R***	I(1)
FTSE100	-2.80	FTR	-55.16	R***	I(1)
DAX	-2.42	FTR	-53.30	R***	I(1)
TSX	-2.78	FTR	-53.39	R***	I(1)
Hangseng	-3.00	FTR	-50.14	R***	I(1)
Merval	-2.43	FTR	-50.04	R***	I(1)
Nikkei	-1.74	FTR	-52.01	R***	I(1)
Eurostoxx50	-2.49	FTR	-54.20	R***	I(1)
Shanghai	-1.94	FTR	-52.25	R***	I(1)

Table 4: Johansen Rank Test for Cointegrations

This table presents the Johansen Rank Test for cointegrations. The number of cointegration relationships is determined by the rank of the Π matrix (detailed in section 2.4). Since there are 10 indices in the sample, a 10-variable testing equation framework is needed. Both rank (0) and rank (10) suggests no cointegration relationship. Rank (r), where $0 < r < 10$, indicates r # of cointegration relationships. The testing procedure follows a sequential testing process until the first time that the null hypothesis is fail-to-reject. The testing results are based on 5% significance level. The star symbol "★" indicates the correctly specified rank.

Rank	**Parameters**	**LL**	**Eigenvalue**	**Trace Statistic**	**5% Critical Value**
0	110	185313.31	.	279.67	233.13
1	129	185346.17	0.01158	213.95	192.89
2	146	185377.88	0.01118	150.53★	156.00
3	161	185397.52	0.00693	111.26	124.24
4	174	185414.34	0.00594	77.61	94.15
5	185	185429.59	0.00539	47.11	68.52
6	194	185437.86	0.00292	30.58	47.21
7	201	185444.56	0.00237	17.18	29.68
8	206	185450.49	0.00210	5.31	15.41
9	209	185453.07	0.00091	0.15	3.76
10	210	185453.15	0.00003		

Table 4 conducts the formal Johansen Rank Test for cointegrations. It serves as the statistical proof to the visual clue as displayed in graph 1, which shows the "co-movements" pattern of indices over time. The testing procedure follows a sequential testing process until the first time that the null hypothesis is not rejected. The number of cointegration relationships is determined by the rank of **Π** matrix (detailed in section 2.4). As shown in table 4, the first time that the null hypothesis is not rejected is for testing rank(**Π**) = 2. Consequently, the evidences are significant to conclude that there are 2 long-run cointegration relationships within the 10 major stock market indices.

3.2 VAR model and Impulse Response Functions (IRFs)

The VAR model is the statistical foundation to generate corresponding impulse response functions (IRFs) for each market index in the sample. In order to have a good model fitting and strong forecasting power, 2 lags are specified, which yields a 10-variable VAR(2) model for the analysis.

Table 5: The VAR Model

This table shows the VAR model for the 10 stock market indices. 2 lags are specified in the model. Since table 3 shows that all indices in the sample are I(1), the first-differenced indices are required for the VAR model. "D" refers to first-differencing. "L1" refers to one-period lagged. "L2" refers to two-period lagged. "*" denotes significance at 10% level, "**" denotes significance at 5% level. "***" denotes significance at 1% level. AIC: -65.69. HQIC: -65.60. SBIC: -65.44. Log Likelihood: 185,511.1

	D_LNSP500		**D_LNASX**		**D_LNFTSE100**		**D_LNDAX**		**D_LNTSX**	
	Coefficient	**Z**	**Coefficient**	**Z**	**Coefficient**	**Z**	**Coefficient**	**Z**	**Coefficient**	**Z**
D_LNSP500L1.	-0.020	-0.93	0.228***	14.01	0.413***	20.58	0.405***	15.31	0.093***	4.76
D_LNSP500L2.	-0.057**	-2.50	0.010	0.57	0.137***	6.58	0.136***	4.96	0.023	1.16
D_LNASXL1.	0.098***	4.95	-0.177***	-11.96	0.108***	5.95	0.133***	5.53	0.102***	5.77
D_LNASXL2.	0.053***	2.72	-0.024*	-1.64	0.050***	2.78	0.070***	2.94	0.073***	4.15
D_LNFTSE100L1.	0.026	0.94	0.095***	4.62	-0.159***	-6.27	-0.130***	-3.88	0.008	0.31
D_LNFTSE100L2.	-0.034	-1.25	0.015	0.75	-0.071***	-2.80	-0.046	-1.38	-0.073***	-2.96
D_LNDAXL1.	0.081***	2.78	0.032	1.46	0.032	1.18	-0.018	-0.52	0.036	1.39
D_LNDAXL2.	0.040	1.39	-0.028	-1.28	-0.036	-1.36	-0.054	-1.54	0.012	0.45
D_LNTSXL1.	-0.083***	-3.60	0.053***	3.10	-0.008	-0.38	-0.068**	-2.45	-0.052**	-2.52
D_LNTSXL2.	-0.028	-1.22	0.080***	4.61	0.002	0.11	0.016	0.57	-0.075***	-3.60
D_LNHangSengL1.	0.014	0.98	-0.002	-0.14	0.025*	1.89	0.016	0.90	0.011	0.86
D_LNHangSengL2.	-0.013	-0.89	-0.017*	-1.64	-0.009	-0.73	0.004	0.21	-0.008	-0.61
D_LNMervalL1.	-0.013	-1.53	0.024***	3.62	0.013	1.60	0.024**	2.21	0.001	0.11
D_LNMervalL2.	0.000	0.04	-0.010	-1.50	-0.012	-1.54	-0.014	-1.35	-0.001	-0.16
D_LNNikkeiL1.	-0.001	-0.10	-0.059***	-5.60	-0.040***	-3.10	-0.031*	-1.78	-0.011	-0.87
D_LNNikkeiL2.	0.003	0.24	-0.020**	-1.99	-0.005	-0.37	-0.006	-0.35	0.003	0.23
D_LNEurostoxx50L1.	-0.064*	-1.88	-0.011	-0.44	-0.137***	-4.37	-0.094**	-2.28	-0.042	-1.37
D_LNEurostoxx50L2.	-0.026	-0.78	0.039	1.54	-0.016	-0.53	-0.019	-0.46	0.029	0.96
D_LNShanghaiL1.	0.004	0.34	-0.001	-0.16	-0.022**	-2.15	-0.013	-0.98	-0.008	-0.81
D_LNShanghaiL2.	-0.002	-0.14	-0.015*	-1.81	-0.001	-0.11	-0.020	-1.50	-0.010	-1.05

Table 5 (continued): The VAR Model

(Table 5 continued) This table shows the VAR model for the 10 stock market indices. 2 lags are specified in the model. Since table 3 shows that all indices in the sample are I(1), the first-differenced indices are required for the VAR model. "D" refers to first-differencing. "L1" refers to one-period lagged. "L2" refers to two-period lagged. "*" denotes significance at 10% level, "**" denotes significance at 5% level. "***" denotes significance at 1% level. AIC: -65.69. HQIC: -65.60. SBIC: -65.44. Log Likelihood: 185,511.1

	D_LNHangSeng		**D_LNMerval**		**D_LNNikkei**		**D_LNEurostoxx50**		**D_LNShanghai**	
	Coefficient	**Z**	**Coefficient**	**Z**	**Coefficient**	**Z**	**Coefficient**	**Z**	**Coefficient**	**Z**
D_LNSP500L1.	0.343***	14.51	0.080**	2.10	0.365***	16.06	0.459***	18.10	0.069**	2.46
D_LNSP500L2.	0.065***	2.65	0.011	0.28	0.034	1.46	0.147***	5.59	-0.004	-0.14
D_LNASXL1.	0.259***	12.08	0.108***	3.13	0.281***	13.64	0.115***	4.99	0.131***	5.19
D_LNASXL2.	0.040*	1.89	0.038	1.12	0.032	1.56	0.061***	2.68	-0.002	-0.08
D_LNFTSE100L1.	0.120***	4.00	-0.058	-1.20	0.044	1.52	-0.145***	-4.50	0.070**	1.99
D_LNFTSE100L2.	-0.008	-0.28	-0.050	-1.05	-0.052*	-1.83	-0.034	-1.07	-0.064*	-1.83
D_LNDAXL1.	0.016	0.50	0.069	1.36	0.067**	2.21	0.095***	2.83	-0.032	-0.88
D_LNDAXL2.	-0.003	-0.09	0.085*	1.68	0.003	0.09	-0.053	-1.56	0.006	0.17
D_LNTSXL1.	0.115***	4.63	-0.082**	-2.03	0.043*	1.81	-0.049*	-1.82	0.020	0.69
D_LNTSXL2.	0.025	1.02	-0.047	-1.16	-0.003	-0.11	0.012	0.45	0.007	0.24
D_LNHangSengL1.	-0.082***	-5.23	0.037	1.47	-0.035**	-2.34	0.031*	1.83	-0.011	-0.59
D_LNHangSengL2.	0.007	0.47	0.002	0.06	0.025*	1.74	0.007	0.41	0.014	0.75
D_LNMervalL1.	0.034***	3.52	0.101***	6.56	0.014	1.54	0.019*	1.82	0.023**	2.04
D_LNMervalL2.	-0.004	-0.43	-0.004	-0.28	-0.012	-1.32	-0.012	-1.21	0.005	0.48
D_LNNikkeiL1.	-0.133***	-8.67	0.022	0.88	-0.148***	-10.00	-0.042*	-2.54	-0.058***	-3.20
D_LNNikkeiL2.	-0.016	-1.06	0.015	0.63	0.003	0.20	-0.012	-0.78	0.009	0.52
D_LNEurostoxx50L1.	-0.029	-0.79	-0.071	-1.19	0.063*	1.78	-0.211***	-5.33	0.029	0.67
D_LNEurostoxx50L2.	0.046	1.24	-0.049	-0.83	0.041	1.16	-0.040	-1.01	0.030	0.69
D_LNShanghaiL1.	-0.040***	-3.39	-0.009	-0.46	-0.022*	-1.95	-0.024*	-1.86	0.048***	3.44
D_LNShanghaiL2.	-0.007	-0.60	-0.014	-0.72	-0.018	-1.56	-0.018	-1.38	-0.015	-1.09

Table 6-0: Impulse Response Functions (IRFs) Identifications

This table serves as an explanatory table for the following table 6-1 to table 6-10. Symbol (1) to (100) identifies each individual IRF with one "impulse" and one "response". The "impulse" is the index that is assumed to generate a hypothetical one-standard-deviation shock to the equation system of the VAR model (as presented in table 5). The "response" is the corresponding index that takes responsive time-series fluctuations with respect to the shock generated by the "impulse" index. (note: an index's response to its own hypothetical shock is also included). For each IRF, 5 steps are incorporated to ensure sufficient measurements, since most shock effects dissipate within 5 steps. (1) to (10) has a common impulse of "S&P500"; (11) to (20) has a common impulse of "ASX"; (21) to (30) has a common impulse of "FTSE100"; (31) to (40) has a common impulse of "DAX"; (41) to (50) has a common impulse of "TSX"; (51) to (60) has a common impulse of "HangSeng"; (61) to (70) has a common impulse of "Merval"; (71) to (80) has a common impulse of "Nikkei"; (81) to (90) has a common impulse of "Eurostoxx50"; (91) to (100) has a common impulse of "Shanghai";

(1)	impulse = D_LNSP500	response = D_LNSP500	(51)	impulse = D_LNHangSeng	response = D_LNSP500
(2)	impulse = D_LNSP500	response = D_LNASX	(52)	impulse = D_LNHangSeng	response = D_LNASX
(3)	impulse = D_LNSP500	response = D_LNFTSE100	(53)	impulse = D_LNHangSeng	response = D_LNFTSE100
(4)	impulse = D_LNSP500	response = D_LNDAX	(54)	impulse = D_LNHangSeng	response = D_LNDAX
(5)	impulse = D_LNSP500	response = D_LNTSX	(55)	impulse = D_LNHangSeng	response = D_LNTSX
(6)	impulse = D_LNSP500	response = D_LNHangSeng	(56)	impulse = D_LNHangSeng	response = D_LNHangSeng
(7)	impulse = D_LNSP500	response = D_LNMerval	(57)	impulse = D_LNHangSeng	response = D_LNMerval
(8)	impulse = D_LNSP500	response = D_LNNikkei	(58)	impulse = D_LNHangSeng	response = D_LNNikkei

(9)	impulse = D_LNSP500	response = D_LNEurostoxx50
(10)	impulse = D_LNSP500	response = D_LNShanghai
(11)	impulse = D_LNASX	response = D_LNSP500
(12)	impulse = D_LNASX	response = D_LNASX
(13)	impulse = D_LNASX	response = D_LNFTSE100
(14)	impulse = D_LNASX	response = D_LNDAX
(15)	impulse = D_LNASX	response = D_LNTSX
(16)	impulse = D_LNASX	response = D_LNHangSeng
(17)	impulse = D_LNASX	response = D_LNMerval
(18)	impulse = D_LNASX	response = D_LNNikkei
(19)	impulse = D_LNASX	response = D_LNEurostoxx50
(20)	impulse = D_LNASX	response = D_LNShanghai
(21)	impulse = D_LNFTSE100	response = D_LNSP500
(22)	impulse = D_LNFTSE100	response = D_LNASX
(23)	impulse = D_LNFTSE100	response = D_LNFTSE100
(24)	impulse = D_LNFTSE100	response = D_LNDAX
(25)	impulse = D_LNFTSE100	response = D_LNTSX
(26)	impulse = D_LNFTSE100	response = D_LNHangSeng
(27)	impulse = D_LNFTSE100	response = D_LNMerval
(28)	impulse = D_LNFTSE100	response = D_LNNikkei
(29)	impulse = D_LNFTSE100	response = D_LNEurostoxx50
(30)	impulse = D_LNFTSE100	response = D_LNShanghai
(31)	impulse = D_LNDAX	response = D_LNSP500
(32)	impulse = D_LNDAX	response = D_LNASX
(33)	impulse = D_LNDAX	response = D_LNFTSE100
(34)	impulse = D_LNDAX	response = D_LNDAX
(35)	impulse = D_LNDAX	response = D_LNTSX
(36)	impulse = D_LNDAX	response = D_LNHangSeng
(37)	impulse = D_LNDAX	response = D_LNMerval
(38)	impulse = D_LNDAX	response = D_LNNikkei
(39)	impulse = D_LNDAX	response = D_LNEurostoxx50
(40)	impulse = D_LNDAX	response = D_LNShanghai
(41)	impulse = D_LNTSX	response = D_LNSP500
(42)	impulse = D_LNTSX	response = D_LNASX
(43)	impulse = D_LNTSX	response = D_LNFTSE100
(44)	impulse = D_LNTSX	response = D_LNDAX
(45)	impulse = D_LNTSX	response = D_LNTSX
(46)	impulse = D_LNTSX	response = D_LNHangSeng
(47)	impulse = D_LNTSX	response = D_LNMerval
(48)	impulse = D_LNTSX	response = D_LNNikkei
(49)	impulse = D_LNTSX	response = D_LNEurostoxx50
(50)	impulse = D_LNTSX	response = D_LNShanghai
(59)	impulse = D_LNHangSeng	response = D_LNEurostoxx50
(60)	impulse = D_LNHangSeng	response = D_LNShanghai
(61)	impulse = D_LNMerval	response = D_LNSP500
(62)	impulse = D_LNMerval	response = D_LNASX
(63)	impulse = D_LNMerval	response = D_LNFTSE100
(64)	impulse = D_LNMerval	response = D_LNDAX
(65)	impulse = D_LNMerval	response = D_LNTSX
(66)	impulse = D_LNMerval	response = D_LNHangSeng
(67)	impulse = D_LNMerval	response = D_LNMerval
(68)	impulse = D_LNMerval	response = D_LNNikkei
(69)	impulse = D_LNMerval	response = D_LNEurostoxx50
(70)	impulse = D_LNMerval	response = D_LNShanghai
(71)	impulse = D_LNNikkei	response = D_LNSP500
(72)	impulse = D_LNNikkei	response = D_LNASX
(73)	impulse = D_LNNikkei	response = D_LNFTSE100
(74)	impulse = D_LNNikkei	response = D_LNDAX
(75)	impulse = D_LNNikkei	response = D_LNTSX
(76)	impulse = D_LNNikkei	response = D_LNHangSeng
(77)	impulse = D_LNNikkei	response = D_LNMerval
(78)	impulse = D_LNNikkei	response = D_LNNikkei
(79)	impulse = D_LNNikkei	response = D_LNEurostoxx50
(80)	impulse = D_LNNikkei	response = D_LNShanghai
(81)	impulse = D_LNEurostoxx50	response = D_LNSP500
(82)	impulse = D_LNEurostoxx50	response = D_LNASX
(83)	impulse = D_LNEurostoxx50	response = D_LNFTSE100
(84)	impulse = D_LNEurostoxx50	response = D_LNDAX
(85)	impulse = D_LNEurostoxx50	response = D_LNTSX
(86)	impulse = D_LNEurostoxx50	response = D_LNHangSeng
(87)	impulse = D_LNEurostoxx50	response = D_LNMerval
(88)	impulse = D_LNEurostoxx50	response = D_LNNikkei
(89)	impulse = D_LNEurostoxx50	response = D_LNEurostoxx50
(90)	impulse = D_LNEurostoxx50	response = D_LNShanghai
(91)	impulse = D_LNShanghai	response = D_LNSP500
(92)	impulse = D_LNShanghai	response = D_LNASX
(93)	impulse = D_LNShanghai	response = D_LNFTSE100
(94)	impulse = D_LNShanghai	response = D_LNDAX
(95)	impulse = D_LNShanghai	response = D_LNTSX
(96)	impulse = D_LNShanghai	response = D_LNHangSeng
(97)	impulse = D_LNShanghai	response = D_LNMerval
(98)	impulse = D_LNShanghai	response = D_LNNikkei
(99)	impulse = D_LNShanghai	response = D_LNEurostoxx50
(100)	impulse = D_LNShanghai	response = D_LNShanghai

Table 6-1: Impulse Response Functions (IRFs) with Impulse of "S&P500"

step	(1) irf	(1) Lower	(1) Upper	(2) irf	(2) Lower	(2) Upper
0	1	1	1	0	0	0
1	-.020377	-.063145	.022391	.228044	.196151	.259936
2	-.024016	-.065752	.01772	-.003663	-.03765	.030323
3	-.002577	-.019314	.014159	-.004941	-.022733	.012852
4	-.003001	-.008268	.002265	-.008394	-.014905	-.001884
5	.001664	-.001404	.004732	-.000214	-.003106	.002678

step	(3) irf	(3) Lower	(3) Upper	(4) irf	(4) Lower	(4) Upper
0	0	0	0	0	0	0
1	.412979	.373657	.452301	.405334	.353428	.45724
2	.0301	-.01108	.07128	.043019	-.009338	.095376
3	-.069906	-.090714	-.049097	-.060668	-.083745	-.037592
4	.008269	.00029	.016247	.007384	-.000674	.015443
5	.003723	-.000539	.007985	.003465	-.000998	.007928

step	(5) irf	(5) Lower	(5) Upper	(6) irf	(6) Lower	(6) Upper
0	0	0	0	0	0	0
1	.093013	.054722	.131304	.34262	.296342	.388898
2	.037958	.00053	.075387	.093517	.041941	.145093
3	-.009745	-.02409	.0046	-.000996	-.030487	.028495
4	-.005039	-.010435	.000357	-.009821	-.019374	-.000269
5	.001864	-.001016	.004745	-.003066	-.007028	.000896

step	(7) irf	(7) Lower	(7) Upper	(8) irf	(8) Lower	(8) Upper
0	0	0	0	0	0	0
1	.080025	.005431	.15462	.364809	.320284	.409335
2	.026148	-.046613	.098908	.103044	.052089	.153999
3	.001125	-.02416	.02641	-.008315	-.039229	.022599
4	.004024	-.004304	.012352	-.012086	-.022465	-.001706
5	.000479	-.003616	.004574	.000486	-.003451	.004423

step	(9) irf	(9) Lower	(9) Upper	(10) irf	(10) Lower	(10) Upper
0	0	0	0	0	0	0
1	.458744	.409069	.508419	.068666	.014003	.123329
2	.036646	-.014377	.087669	.035857	-.017875	.089588
3	-.069142	-.09327	-.045013	-.00696	-.027731	.013811
4	.008506	-.000438	.017451	-.004216	-.011005	.002573
5	.003739	-.00099	.008468	.001902	-.001371	.005175

Table 6-2: Impulse Response Functions (IRFs) with Impulse of "ASX"

step	(11) irf	(11) Lower	(11) Upper	(12) irf	(12) Lower	(12) Upper
0	0	0	0	1	1	1
1	.098099	.059261	.136938	-.176771	-.205733	-.147808
2	.034135	-.002778	.071047	.033567	.003382	.063751
3	-.023051	-.036798	-.009303	.013505	-.001587	.028598
4	.001305	-.001566	.004177	-.006429	-.011703	-.001155
5	.001562	-.000249	.003373	-.002223	-.003982	-.000463

step	(13) irf	(13) Lower	(13) Upper	(14) irf	(14) Lower	(14) Upper
0	0	0	0	0	0	0
1	.108411	.072702	.144121	.132888	.085751	.180025
2	.035597	-.000945	.07214	.048292	.001923	.094662
3	-.007289	-.024692	.010114	-.011003	-.029631	.007624
4	-.005662	-.011283	-.000042	-.002354	-.007437	.002728
5	-.000236	-.002776	.002305	-.000378	-.003095	.002339

step	(15) irf	(15) Lower	(15) Upper	(16) irf	(16) Lower	(16) Upper
0	0	0	0	0	0	0
1	.102383	.06761	.137156	.258975	.216949	.301001
2	.058325	.025237	.091413	-.0089	-.05479	.036991
3	-.020155	-.030913	-.009398	.036712	.011586	.061837
4	-.001386	-.004271	.001499	-.009066	-.015695	-.002437
5	.001446	-.000307	.003199	-.001582	-.004236	.001071

step	(17) irf	(17) Lower	(17) Upper	(18) irf	(18) Lower	(18) Upper
0	0	0	0	0	0	0
1	.108198	.040457	.175939	.281412	.240977	.321847
2	.038913	-.02538	.103206	-.008913	-.05431	.036483
3	-.004968	-.022065	.012129	.035576	.008823	.062329
4	.00188	-.002663	.006423	-.012008	-.019719	-.004296
5	.001138	-.001325	.003602	.000605	-.002069	.003279

step	(19) irf	(19) Lower	(19) Upper	(20) irf	(20) Lower	(20) Upper
0	0	0	0	0	0	0
1	.114792	.069681	.159903	.131327	.081686	.180968
2	.048772	.003543	.094002	-.020209	-.067725	.027307
3	-.008683	-.02845	.011083	.01346	-.002393	.029314
4	-.004972	-.010899	.000955	-.002567	-.006587	.001452
5	-.000109	-.002926	.002708	.000115	-.001788	.002018

Table 6-3: Impulse Response Functions (IRFs) with Impulse of "FTSE100"

step	(21) irf	(21) Lower	(21) Upper	(22) irf	(22) Lower	(22) Upper
0	0	0	0	0	0	0
1	.026113	-.028121	.080346	.095383	.05494	.135825
2	-.028742	-.082333	.024849	-.017149	-.060715	.026417
3	.008812	-.002613	.020237	-.014387	-.033149	.004375
4	.000633	-.004352	.005619	.005224	.000067	.010381
5	-.001633	-.003483	.000217	.000109	-.002503	.00272

step	(23) irf	(23) Lower	(23) Upper	(24) irf	(24) Lower	(24) Upper
0	1	1	1	0	0	0
1	-.15943	-.209294	-.109566	-.130203	-.196024	-.064382
2	-.009476	-.062286	.043334	.011854	-.055362	.079069
3	.013623	-.007528	.034774	.017157	-.00358	.037894
4	-.006377	-.012932	.000179	-.007578	-.014185	-.000972
5	.001179	-.002728	.005086	.000673	-.002936	.004282

step	(25) irf	(25) Lower	(25) Upper	(26) irf	(26) Lower	(26) Upper
0	0	0	0	0	0	0
1	.00759	-.040966	.056146	.119798	.061114	.178483
2	-.060365	-.108467	-.012264	-.011119	-.077185	.054946
3	.010175	.000247	.020102	-.012803	-.045896	.02029
4	.003628	-.001435	.008691	.001457	-.005395	.00831
5	-.001503	-.003241	.000236	.001256	-.001768	.00428

step	(27) irf	(27) Lower	(27) Upper	(28) irf	(28) Lower	(28) Upper
0	0	0	0	0	0	0
1	-.057831	-.152423	.036762	.043728	-.012734	.100191
2	-.029101	-.122664	.064462	-.053379	-.118592	.011834
3	.003933	-.011173	.019038	.002091	-.033088	.037269
4	-.000282	-.006862	.006299	.003856	-.003452	.011165
5	-.000086	-.001987	.001815	-.000646	-.003709	.002417

step	(29) irf	(29) Lower	(29) Upper	(30) irf	(30) Lower	(30) Upper
0	0	0	0	0	0	0
1	-.144749	-.207741	-.081757	.070459	.001141	.139776
2	.028786	-.036687	.094259	-.062623	-.131662	.006415
3	.014627	-.00871	.037965	-.000644	-.015696	.014408
4	-.007335	-.014601	-.000069	.001252	-.004325	.006829
5	.000749	-.003243	.004741	-.000189	-.0018	.001423

Table 6-4: Impulse Response Functions (IRFs) with Impulse of "DAX"

step	(31) irf	(31) Lower	(31) Upper	(32) irf	(32) Lower	(32) Upper
0	0	0	0	0	0	0
1	.080513	.023664	.137361	.031547	-.010846	.073939
2	.030934	-.025668	.087535	-.013806	-.059785	.032172
3	-.012697	-.023792	-.001602	.013463	-.006088	.033014
4	-.000245	-.004292	.003802	-.003615	-.008589	.001359
5	.000266	-.001729	.002262	-.000148	-.002595	.002299

step	(33) irf	(33) Lower	(33) Upper	(34) irf	(34) Lower	(34) Upper
0	0	0	0	1	1	1
1	.031534	-.020734	.083802	-.018151	-.087145	.050844
2	-.019348	-.0751	.036404	-.032175	-.103193	.038843
3	.027025	.005248	.048801	.028576	.007716	.049435
4	-.005924	-.01166	-.000189	-.005076	-.0106	.000448
5	-.003847	-.007584	-.000111	-.003408	-.006976	.00016

step	(35) irf	(35) Lower	(35) Upper	(36) irf	(36) Lower	(36) Upper
0	0	0	0	0	0	0
1	.036071	-.014826	.086968	.01559	-.045923	.077104
2	.015857	-.03501	.066724	.031162	-.038541	.100865
3	.002972	-.00585	.011795	.012281	-.022418	.04698
4	-.001921	-.006388	.002547	.00043	-.005546	.006406
5	-.000753	-.00258	.001075	-.0016	-.004786	.001586

step	(37) irf	(37) Lower	(37) Upper	(38) irf	(38) Lower	(38) Upper
0	0	0	0	0	0	0
1	.068553	-.0306	.167706	.066809	.007624	.125993
2	.091351	-.007669	.190371	.040027	-.028719	.108774
3	.006294	-.004996	.017583	.002636	-.034359	.039631
4	-.001071	-.007198	.005057	.002823	-.003721	.009367
5	-.0001	-.002313	.002113	-.002567	-.005747	.000614

step	(39) irf	(39) Lower	(39) Upper	(40) irf	(40) Lower	(40) Upper
0	0	0	0	0	0	0
1	.095492	.029462	.161521	-.032463	-.105123	.040196
2	-.04049	-.109647	.028668	.01808	-.054915	.091075
3	.029942	.006203	.05368	.00169	-.01233	.01571
4	-.005451	-.011653	.000752	.003598	-.00131	.008507
5	-.003808	-.007668	.000052	-.001383	-.003231	.000465

Table 6-5: Impulse Response Functions (IRFs) with Impulse of "TSX"

step	(41) irf	(41) Lower	(41) Upper	(42) irf	(42) Lower	(42) Upper
0	0	0	0	0	0	0
1	-.082826	-.127943	-.03771	.053162	.019518	.086806
2	-.016904	-.06219	.028383	.041443	.004705	.078181
3	.017644	.009062	.026225	-.024383	-.039966	-.008801
4	.002588	-.002743	.007918	.002255	-.002016	.006526
5	-.002731	-.004626	-.000837	.002744	.000017	.00547

step	(43) irf	(43) Lower	(43) Upper	(44) irf	(44) Lower	(44) Upper
0	0	0	0	0	0	0
1	-.007988	-.04947	.033493	-.068475	-.123231	-.013719
2	-.020139	-.064696	.024418	-.001657	-.058441	.055128
3	-.001662	-.019327	.016003	.004927	-.012399	.022254
4	.006255	-.000032	.012541	.004247	-.002436	.01093
5	.00071	-.003207	.004628	-.000105	-.003719	.003508

step	(45) irf	(45) Lower	(45) Upper	(46) irf	(46) Lower	(46) Upper
0	1	1	1	0	0	0
1	-.052034	-.092427	-.011641	.115429	.066611	.164248
2	-.073988	-.114677	-.033299	-.01459	-.070251	.041071
3	.010348	.0018	.018897	-.00703	-.034818	.020758
4	.007697	.002403	.012991	-.000583	-.006905	.005738
5	-.001776	-.003477	-.000074	.003537	.000399	.006675

step	(47) irf	(47) Lower	(47) Upper	(48) irf	(48) Lower	(48) Upper
0	0	0	0	0	0	0
1	-.081505	-.160195	-.002815	.043291	-.00368	.090261
2	-.047219	-.126418	.031981	-.04028	-.095164	.014605
3	.006333	-.007914	.02058	.007127	-.022242	.036496
4	.004516	-.002255	.011288	.001228	-.005195	.007651
5	-.001021	-.003117	.001076	.00256	-.000561	.005681

step	(49) irf	(49) Lower	(49) Upper	(50) irf	(50) Lower	(50) Upper
0	0	0	0	0	0	0
1	-.048768	-.10117	.003634	.020171	-.037493	.077835
2	-.012688	-.067971	.042595	.00301	-.055374	.061395
3	.00349	-.016095	.023076	.002313	-.010393	.015018
4	.005685	-.001522	.012891	-.002548	-.008359	.003264
5	.000078	-.003936	.004092	.001277	-.000549	.003103

Table 6-6: Impulse Response Functions (IRFs) with Impulse of "HangSeng"

step	(51) irf	(51) Lower	(51) Upper	(52) irf	(52) Lower	(52) Upper
0	0	0	0	0	0	0
1	.014184	-.014262	.04263	-.001563	-.022776	.01965
2	-.015605	-.043295	.012084	-.007489	-.030052	.015073
3	-.000938	-.005386	.00351	-.002257	-.011638	.007124
4	.000462	-.001488	.002411	-.002162	-.00442	.000096
5	.000103	-.000656	.000862	.000691	-.000446	.001829

step	(53) irf	(53) Lower	(53) Upper	(54) irf	(54) Lower	(54) Upper
0	0	0	0	0	0	0
1	.025229	-.000926	.051383	.015921	-.018604	.050445
2	-.011496	-.038833	.015841	.002684	-.032072	.037441
3	-.00777	-.018132	.002592	-.007847	-.017632	.001939
4	-.000284	-.002862	.002294	-.001117	-.003747	.001512
5	.001067	-.000636	.00277	.000825	-.000713	.002363

step	(55) irf	(55) Lower	(55) Upper	(56) irf	(56) Lower	(56) Upper
0	0	0	0	1	1	1
1	.011143	-.014326	.036611	-.082151	-.112932	-.051371
2	-.0081	-.032949	.016748	.028345	-.005905	.062594
3	-.003019	-.006923	.000885	-.016441	-.033221	.000339
4	.000309	-.001834	.002452	.000059	-.003117	.003235
5	.000184	-.000511	.000878	-.000943	-.002498	.000613

step	(57) irf	(57) Lower	(57) Upper	(58) irf	(58) Lower	(58) Upper
0	0	0	0	0	0	0
1	.037268	-.012347	.086883	-.035352	-.064967	-.005736
2	-.000927	-.04925	.047396	.043693	.009862	.077524
3	-.001598	-.007064	.003868	-.018194	-.03603	-.000358
4	.000341	-.002748	.003429	.001348	-.001802	.004497
5	-.000117	-.00092	.000685	-.001241	-.002796	.000314

step	(59) irf	(59) Lower	(59) Upper	(60) irf	(60) Lower	(60) Upper
0	0	0	0	0	0	0
1	.03092	-.00212	.06396	-.010957	-.047315	.025401
2	.003693	-.03018	.037565	.019964	-.015707	.055635
3	-.009118	-.020376	.002141	-.00655	-.012898	-.000201
4	-.001297	-.004121	.001526	.001258	-.001085	.003601
5	.001058	-.000645	.00276	-.000409	-.001188	.00037

Table 6-7: Impulse Response Functions (IRFs) with Impulse of "Merval"

step	(61) irf	(61) Lower	(61) Upper	(62) irf	(62) Lower	(62) Upper
0	0	0	0	0	0	0
1	-.013498	-.030765	.003768	.023811	.010935	.036687
2	.003091	-.014151	.020333	-.013876	-.027875	.000123
3	-.000726	-.003445	.001993	-.000777	-.006753	.005199
4	-.000652	-.00189	.000587	.000202	-.001196	.001599
5	.000145	-.0002	.00049	.000083	-.000567	.000733

step	(63) irf	(63) Lower	(63) Upper	(64) irf	(64) Lower	(64) Upper
0	0	0	0	0	0	0
1	.012943	-.002932	.028819	.023644	.002688	.0446
2	-.018263	-.035238	-.001287	-.01848	-.040107	.003147
3	.000299	-.006389	.006988	-.000184	-.00692	.006551
4	.001649	-.000103	.003401	.001068	-.000913	.00305
5	-.000804	-.001789	.000182	-.000737	-.001551	.000078

step	(65) irf	(65) Lower	(65) Upper	(66) irf	(66) Lower	(66) Upper
0	0	0	0	0	0	0
1	.0009	-.01456	.016359	.033576	.014892	.05226
2	.000175	-.015318	.015667	-.003247	-.024464	.01797
3	-.000571	-.004079	.002938	-.002892	-.013645	.007862
4	-.000575	-.002021	.000872	-.00048	-.003558	.002599
5	-.000061	-.000384	.000262	-.000078	-.000873	.000716

step	(67) irf	(67) Lower	(67) Upper	(68) irf	(68) Lower	(68) Upper
0	1	1	1	0	0	0
1	.100722	.070606	.130838	.014119	-.003858	.032095
2	.008236	-.02192	.038392	-.00936	-.030285	.011565
3	.000864	-.006237	.007965	-.004838	-.015993	.006317
4	-.000858	-.003066	.00135	-.000209	-.002929	.002512
5	-.000331	-.000865	.000203	-.000092	-.000926	.000741

step	(69) irf	(69) Lower	(69) Upper	(70) irf	(70) Lower	(70) Upper
0	0	0	0	0	0	0
1	.018586	-.001469	.038642	.023017	.000948	.045086
2	-.017648	-.038707	.003411	.010519	-.011712	.03275
3	.000073	-.007447	.007593	-.000881	-.006142	.00438
4	.001395	-.000613	.003402	.00046	-.001047	.001967
5	-.000832	-.001769	.000106	.00003	-.000309	.000369

Table 6-8: Impulse Response Functions (IRFs) with Impulse of “Nikkei”

step	(71) irf	(71) Lower	(71) Upper	(72) irf	(72) Lower	(72) Upper
0	0	0	0	0	0	0
1	-.001352	-.029135	.02643	-.059145	-.079862	-.038427
2	-.004588	-.031005	.021829	-.005342	-.026964	.01628
3	-.000309	-.005309	.004691	.005002	-.004187	.014191
4	.000536	-.000834	.001905	-.000975	-.003109	.001158
5	.000236	-.000415	.000887	.0002	-.000788	.001189

step	(73) irf	(73) Lower	(73) Upper	(74) irf	(74) Lower	(74) Upper
0	0	0	0	0	0	0
1	-.040436	-.06598	-.014892	-.030703	-.064422	.003015
2	.003873	-.02231	.030056	.000113	-.033137	.033364
3	.000239	-.009958	.010437	-.00178	-.011709	.00815
4	-.000602	-.002985	.001781	-.000551	-.002767	.001665
5	.00063	-.00091	.002171	.000681	-.000694	.002057

step	(75) irf	(75) Lower	(75) Upper	(76) irf	(76) Lower	(76) Upper
0	0	0	0	0	0	0
1	-.011036	-.03591	.013838	-.132944	-.163006	-.102881
2	-.001829	-.025581	.021923	-.00308	-.035969	.029809
3	-.00183	-.006305	.002644	-.005808	-.022169	.010553
4	-.00019	-.001969	.001589	.001697	-.001562	.004956
5	.000444	-.000205	.001092	-.000317	-.001699	.001064

step	(77) irf	(77) Lower	(77) Upper	(78) irf	(78) Lower	(78) Upper
0	0	0	0	1	1	1
1	.021837	-.02662	.070294	-.147575	-.1765	-.118651
2	.007032	-.039204	.053268	.006859	-.025634	.039353
3	-.00204	-.009284	.005203	-.008866	-.026158	.008425
4	-.00023	-.002541	.002081	.00169	-.001569	.004949
5	.000092	-.000606	.000791	-.000523	-.001836	.00079

step	(79) irf	(79) Lower	(79) Upper	(80) irf	(80) Lower	(80) Upper
0	0	0	0	0	0	0
1	-.041876	-.074145	-.009607	-.058031	-.093541	-.022522
2	-.003568	-.035997	.02886	.005633	-.028468	.039733
3	-.000414	-.01162	.010793	-.001746	-.008762	.005269
4	-.00071	-.003228	.001807	.000744	-.001034	.002522
5	.000754	-.00077	.002278	-.000431	-.001104	.000242

Table 6-9: Impulse Response Functions (IRFs) with Impulse of "Eurostoxx50"

step	(81) irf	(81) Lower	(81) Upper	(82) irf	(82) Lower	(82) Upper
0	0	0	0	0	0	0
1	-.064157	-.131036	.002723	-.011302	-.061174	.03857
2	-.019777	-.08633	.046777	.005121	-.048944	.059186
3	.010917	-.001672	.023506	-.015684	-.038527	.007158
4	-.001503	-.0061	.003094	.008314	.002895	.013734
5	-.000302	-.002239	.001635	-.00086	-.003705	.001985

step	(83) irf	(83) Lower	(83) Upper	(84) irf	(84) Lower	(84) Upper
0	0	0	0	0	0	0
1	-.137157	-.198647	-.075666	-.094288	-.175456	-.013119
2	-.000834	-.06639	.064722	-.008449	-.09195	.075052
3	.00268	-.022815	.028175	-.002528	-.026893	.021836
4	.001189	-.005496	.007874	.001529	-.004688	.007745
5	.000667	-.003742	.005077	.000675	-.00337	.00472

step	(85) irf	(85) Lower	(85) Upper	(86) irf	(86) Lower	(86) Upper
0	0	0	0	0	0	0
1	-.041805	-.101683	.018073	-.029207	-.101574	.043161
2	.027296	-.032508	.087101	-.005226	-.087189	.076737
3	.001507	-.008863	.011877	-.015266	-.055905	.025373
4	-.003587	-.008794	.001621	.001733	-.00472	.008185
5	-.000242	-.002117	.001634	.001213	-.002226	.004651

step	(87) irf	(87) Lower	(87) Upper	(88) irf	(88) Lower	(88) Upper
0	0	0	0	0	0	0
1	-.07082	-.187468	.045827	.0634	-.006227	.133027
2	-.042952	-.15936	.073456	-.023029	-.103873	.057815
3	.003393	-.010202	.016987	-.008005	-.051312	.035303
4	-.003008	-.008956	.00294	.000189	-.006926	.007304
5	-.000343	-.002193	.001508	.001062	-.00221	.004334

step	(89) irf	(89) Lower	(89) Upper	(90) irf	(90) Lower	(90) Upper
0	1	1	1	0	0	0
1	-.211253	-.288932	-.133573	.029249	-.05623	.114729
2	-.01879	-.100105	.062525	.006707	-.079114	.092527
3	.000155	-.027651	.027961	.001519	-.014819	.017857
4	.001979	-.005196	.009155	-.001124	-.006323	.004076
5	.00064	-.003813	.005093	.000387	-.001212	.001986

Table 6-10: Impulse Response Functions (IRFs) with Impulse of "Shanghai"

step	(91) irf	(91) Lower	(91) Upper	(92) irf	(92) Lower	(92) Upper
0	0	0	0	0	0	0
1	.00376	-.017724	.025245	-.001295	-.017316	.014726
2	-.001417	-.022938	.020105	-.015232	-.032698	.002234
3	.000299	-.002685	.003282	.001784	-.00551	.009078
4	-.000697	-.00243	.001035	.000593	-.001007	.002193
5	.000165	-.000306	.000636	-.000175	-.00111	.000761

step	(93) irf	(93) Lower	(93) Upper	(94) irf	(94) Lower	(94) Upper
0	0	0	0	0	0	0
1	-.021622	-.041375	-.001869	-.013022	-.039097	.013053
2	.005345	-.015837	.026527	-.013528	-.040521	.013465
3	.001995	-.006151	.01014	.000463	-.007514	.008439
4	-.000322	-.002536	.001891	-.000107	-.002525	.002311
5	-.000182	-.001576	.001212	-.000023	-.001207	.001161

step	(95) irf	(95) Lower	(95) Upper	(96) irf	(96) Lower	(96) Upper
0	0	0	0	0	0	0
1	-.007971	-.027206	.011265	-.040226	-.063473	-.016979
2	-.009923	-.029264	.009418	-.005115	-.031582	.021351
3	.000109	-.003744	.003962	-.003237	-.016427	.009952
4	-.000861	-.002765	.001043	.000741	-.002541	.004024
5	.000078	-.000378	.000533	-.000222	-.001275	.000831

step	(97) irf	(97) Lower	(97) Upper	(98) irf	(98) Lower	(98) Upper
0	0	0	0	0	0	0
1	-.008702	-.046174	.02877	-.022289	-.044657	.000078
2	-.014138	-.051789	.023512	-.016922	-.04302	.009175
3	-.002833	-.010291	.004625	-.005392	-.019176	.008393
4	-.001499	-.003988	.000991	.000699	-.002232	.00363
5	-.000109	-.000759	.00054	-.000287	-.001338	.000763

step	(99) irf	(99) Lower	(99) Upper	(100) irf	(100) Lower	(100) Upper
0	0	0	0	1	1	1
1	-.023641	-.048595	.001313	.048231	.020771	.07569
2	-.010317	-.036598	.015963	-.013245	-.040997	.014508
3	.000814	-.008236	.009864	-.002707	-.008552	.003138
4	.000321	-.002202	.002843	-.000304	-.002204	.001597
5	-.000111	-.001463	.001241	-.000267	-.000734	.0002

Table 5 shows the estimates of the VAR model. For the fact that VAR model demands that all time-series variables should be stationary while all original indices being I(1), the first-differenced index data is used (denotes D_*index name*). On the other hand, since 2 lags are specified in the model, both the one-period-lagged-differenced indices (denotes D_*index name*L1.) and two-period-lagged-differenced indices (denotes D_*index name*L2.) are serving as regressors.

Table 7 shows the explaining power for each index, which yields interesting findings. As the definition, 1 power is recognized if a time-lagged index (in the first-differenced format) is significant (either L1 or L2 or Both L1 and L2) in describing another index's movements (including its own). Because the analysis is based the 10-variable VAR(2) model, the maximum power # an index can have is 10 and the minimum power # an index can have is 0. Interestingly but not surprisingly, as two developed markets, S&P500 (U.S.) and ASX (Australia) both have a full power of 10. However, emerging markets such as Shanghai Composite (China) and Merval (Argentina) both have a lower-than-average power of 6. Nevertheless, two developed markets DAX(Germany) and Eurostoxx50 (Europe) also have lower-than-average power, with 4 and 5 respectively. As an implication, table 7 suggests that the condition of being a developed market may not be sufficient to make the index itself have more power in describing other market indices' performance, because index's explaining power could also depend on the country's economic integration degree, market openness & regulations, and political ideologies. However, a power of 10 (such as S&P500) could still provide a potent argument that the underlying stock market has a strong influence power over other markets. The good news is that the "Influence Index" based on IRFs will make it possible to quantify and order the influence power for each market (detailed in section 3.3).

Table 7: Index Explaining Power

This table shows the explaining power for each index. If a time-lagged index (in the first-differenced format) is significant (either L1 or L2 or Both L1 and L2) in describing another index's movements (including its own), this will count as 1 power. Since the analysis is based the 10-variable VAR(2) model, the maximum power # an index can have is 10 and the minimum power # an index can have is 0.

Index	**Power #**
S&P500	10
ASX	10
FTSE100	8
DAX	4
TSX	8
Hangseng	5
Merval	6
Nikkei	7
Eurostoxx50	5
Shanghai	6
Average	**6.9**

The impulse response functions (IRFs) are the key to analyze the time series behaviors of stock market indices. Table 6-1 to table 6-10 present the IRFs for each stock market index. Within each table, one impulse index is identified (denote "impulse"), which is assumed to generate a hypothetical one-standard-deviation shock to other stock market indices (including its own). The corresponding IRFs (denote "response") of other indices in the same table will show the reacting behaviors with respect to the hypothetical shock initiated by the impulse index. If a country's stock market has a strong influential power over others (assume this market is the "impulse"), then the IRFs of those "response" indices should have relatively large magnitudes in movements, and vice versa. For each IRFs, 5 steps are included, which can track the "response" index's movements 5 periods into the future. The reason that 5-step is chosen is that the majority of shock effects dissipate within 5 periods, left with only noises after then. Therefore, 5-step IRFs will guarantee to capture sufficient shock effects for the analysis.

For example, table 6-1shows the IRFs for all indices with impulse of "S&P500". In table 6-1, the sum of IRFs in absolute value of step (1) of all other indices[2] is 2.45. However, in table 6-6 which has the impulse of "HangSeng", the sum of IRFs in absolute value of step (1) of all other indices[3] is 0.18. This is so interesting, because the huge difference in summed step (1) IRFs in absolute value between the impulse of "S&P500" and impulse of "HangSeng" (2.45 versus 0.18) sends out a compelling signal that the U.S. stock market (proxied by S&P500 index) is considered to have a much stronger market influence than the Hong Kong stock market (proxied by HangSeng index). Fueled by this exciting discovery, the following "Influence Index" is invented to quantify and order the influential power for major stock markets across the globe (detailed in section 3.3).

3.3 The Influence Index

The "Influence Index" is the major contribution and innovation of this research paper, which is based on the IRFs of each individual stock market index. The influence index can be expressed in equation (5). The essence of the influence index is to estimate the cross-market impact generated by the underlying stock index on all other stock indices into a foreseeable future.

$$\text{Influence Index for stock market "I"} = \sum_{i=1,s=1}^{i=G,s=S} \mathrm{IRF}(i,s) \tag{5}$$

$$\text{where } i \neq \text{"I" and "I" is acting as the impluse index}$$

Notations:

- "i" is the index identifier. For G-number market indices, "i" can take 1, 2, …, G
- "s" is the step identifier, which is specified by IRFs. "s" can take 1, 2, …, S
- "I" indicates the underlying stock market proxied by stock index "I"
- Condition of i ≠ I excludes the market's influence on its own.
- Variable formats are based on the underlying VAR model

[2] The sum of irf(2) to irf(10) [in absolute values of step (1)] is 2.45. The identification of (1) to (10) are specified in table 6-0. Note: irf(1) is not included in the calculation, because irf(1) [SP500] is the impulse index itself and the goal to find its influence over other indices.

[3] The sum of irf(51) to irf(60) [in absolute values of step (1)] is 0.18. The identification of (51) to (60) are specified in table 6-0. Note: irf(56) is not included in the calculation, because irf(51) [HangSeng] is the impulse index itself and the goal to find its influence over other indices.

Table 8: Market Influential Power Across Major Global Stock Markets

This table presents influence index, shock absorption, and net effect for major stock markets across the globe. The variable formats are based on the underlying 10-variable VAR(2) model (table 5) and the related IRFs (table 6-0 to table 6-10). The influence index is calculated based on equation (5). Five steps are assumed in the computation, which will capture sufficient statistical effects initiated by the "impulse index" with a hypothetical one-standard-deviation shock to other market indices (response indices). The shock absorption is the total shock that one market would take from all other markets within the system, when the underlying market index is acting as the "response index".

Market Index	**Country/Region**	**Influence Index**	**Shock Absorption**	**Net Effect**
S&P500	United States	**3.18**	0.63	2.55
ASX 200	Australia	**1.85**	0.75	1.10
FTSE100	Britain	**1.12**	1.10	0.017
DAX	Germany	**0.91**	1.20	-0.29
TSX	Canada	**0.84**	0.61	0.23
EUROSTOXX50	Europe	**0.77**	1.36	-0.59
Nikkei 225	Japan	**0.46**	1.41	-0.95
HangSeng	Hong Kong	**0.37**	1.40	-1.03
Merval	Argentina	**0.28**	0.89	-0.61
Shanghai Composite	China	**0.26**	0.69	-0.43

Table 8 presents the influence index for major stock markets across the globe. As one well-established capital market, the U.S. stock market (proxied by S&P500) achieved the highest influence index of 3.18. The result provides strong statistical evidences that the U.S. stock market dominates other major global markets by possessing the highest market influential power. Furthermore, the "Shock Absorption" measures the total shock that one market would take from all other markets within the system, when the underlying market index is acting as the "response index". It is very astonishing that the U.S. market received the second lowest shock absorption value of 0.63 within the system (slightly higher than Canada's 0.61). Given the evidences presented above, it yields a firm argument that the U.S. stock market is able to generate the strongest impacts to other countries' markets. While, itself is relatively immune to impacts initiated by others.

Table 8 is also consistent with the claim that stock markets located in developed economies are generally having higher influence indices than markets residing in developing economies. Australia (proxied by ASX200) and Britain (proxied by FTSE100) achieved the second and the third highest influence index of 1.85 and 1.12 respectively, indicating that, following the U.S. stock market, the Australian and the British stock markets are also playing big roles and having their own powers to influence global equity markets. But it is noteworthy that the British market has a higher-than-average shock absorption value, which implies that the British market is relatively vulnerable to the impacts generated by other markets. On the other hand, China (proxied by Shanghai Composite) and Argentina (proxied by Merval) are attached with the lowest and the second lowest influence index of only 0.26 and 0.28 respectively. The results confirmed a widely accepted observation that financial markets in developing economies are generally immature and lacking of international recognitions. Moreover, developing markets are also obtained high shock absorption values, consequently, leading to the negative net effects. The result leads to an interpterion that developing markets are prone to be affected by changes of market conditions of more developed markets, but not vice versa.

4 Conclusion

Stock markets across different countries and regions are integrated with each other, as all markets proxied by corresponding stock indices within the sample are significantly correlated. Moreover, market indices are showing time-series stationarity of I(1), indicating that, within each market, index level movements don’t show a mean-reverting behavior and could continue drifting away from its long-run mean. Nevertheless, statistical evidences strongly support the existence of cointegration relationships among stock markets across various countries and regions. Therefore, long-run market equilibrium has been established globally.

More importantly, by utilizing the VAR model and the corresponding impulse response functions (IRFs), the main innovation of this research paper is to construct the “Influence Index” to quantify and order the influential power for major stock markets across the globe. Empirically-valued influence indices show that the U.S. stock market dominates the global stock markets by achieving the highest influence index of 3.18, followed by Australia (1.85) and Britain (1.12). However, stock markets housed in developing economies show very weak influential power, which could be due to the lack of international recognitions and market establishment. Stock markets in China and Argentina possess the lowest and the second lowest market power with influence index of only 0.26 and 0.28 respectively. Corresponding evidences also offer an important indication that established markets are much less sensitive to impacts generated from other markets, while developing markets are more prone to outside influences.

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