Structure of interdependencies among international stock markets and contagion patterns of 2008 global financial crisis

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ABSTRACT

In this study, we apply directed acyclic graphs and search algorithm designed for time series with non-Gaussian distribution to obtain causal structure of innovations from an error correction model. The structure of interdependencies among six international stock markets is investigated. The results provide positive empirical evidence that there exist long-run equilibrium and contemporaneous causal structure among these stock markets.

DAG analysis results show that Hong Kong is influenced by all other open markets in contemporaneous time, whereas Shanghai is not influenced by any of the other markets in contemporaneous time. Historical decompositions indicate that New York and Shanghai stock markets are highly exogenous and Germany and Hong Kong are the least exogenous markets. Further, we find that New York is the most influential stock market with consistent impact on price movements.

One implication is that diversification between US and Germany may not provide desired immunity from financial crisis contagion as much as it does diversification between US and Shanghai.

Keywords: VAR, cointegration, error correction, DAG, causality, financial contagion

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1. Introduction

Financial crisis of 2008 is considered to be the worst crisis since Great Depression by some prominent economists, including the chairman of the U.S. Federal Reserve Ben Bernanke. Among the main causal factors of the crisis are credit market failure and inefficient regulatory framework which lagged behind recent financial innovations. Global contagion of financial market crisis started soon after it manifested itself in the U.S. financial market crash. As a result, several foreign banks failed, stock and commodity market values declined throughout the world.

King and Wadhwani (1990) argue that stock markets move together despite of their differing economic circumstances. Furthermore, financial contagion between markets occurs when a change in one market transmits to another one where agents react to stock price changes in another market in addition to public information about the company's economic conditions. The stock market crash of October 1987 is investigated by several researchers to test whether the U.S. caused the crisis and financial market contagion during the 1987 crash. However, the conclusions are mixed and sometimes controversial (Yang and Bessler 2008).

This study investigates whether the U.S. alone contributed to the 2008 global financial crisis, existence of contagion, and the propagation pattern of financial contagion during the crisis. In particular, this study explores the existence of such phenomena in six major stock markets. This study contributes to the literature in that it employs Linear Non-Gaussian Acyclic Model (LiNGAM) search algorithm, which assumes non-Gaussian distribution of variables (Shimizu et al. 2006) for causal discovery to model contemporaneous innovations between international stock markets.

The rest of this study is organized as follows: Section 2 introduces and explains the empirical methodology; Section 3 describes the data; Section 4 exhibits empirical results of the model on the long-run structure of stock markets interdependencies; Section 5 exhibits empirical results of the model on the short-run and contemporaneous structures of stock markets interdependencies; and Section 6 concludes.

2. Empirical methodology

2.1. Historical decomposition

To accomplish the research objectives, data-determined historical decomposition method is employed to analyze the existence of contagion and propagation patterns of price changes in the market. Cointegrated vector autoregression (VAR) model is used for modeling the fluctuations in above-mentioned stock markets. Directed acyclic graphs (DAGs) are exploited to identify the contemporaneous causality of VAR innovations. LiNGAM algorithm is used to obtain contemporaneous causal structure of innovations of non-normally distributed series, which enables us to impose data determined causal structure in implementing Bernanke factorization.

Formally, the (6x1) vector of stock market indexes is represented as

$$X_t = (X_{1t}, X_{2t}, X_{3t}, X_{4t}, X_{5t}, X_{6t})' = (KAS_t, RUS_t, DAX_t, NY_t, HS_t, SH_t)'$$

then, vector X_t is modeled in an error correction model (ECM) as

$$\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-I} + \mu + \epsilon_t \qquad (t = 1, 2, \ldots, T), \qquad (1)$$

where X_t is a vector of stock market index prices, $\Delta X_t = X_t - X_{t-1}$, $\Pi = \alpha \beta'$ is a (6x6) matrix and the rank of Π is equal to the number of independent cointegrating vectors (r), Γ_i (6x6) gives the coefficients of short-run dynamics, and ϵ_t is (6x1) vector of innovations. The parameters of Eq. (1) provide information to identify the long-run, short-run, and contemporaneous structure of stock markets interdependence by testing hypotheses on β, α, and Γ_i (Johansen and Juselius, 1994; Johansen, 1995).

The dynamic interrelationships among the ECM series are better described through its vector moving-average (VMA) representation. Assume that Eq. 1 has a moving-average representation at levels X_t

$$X_t = \sum_{i=0}^{\infty} \phi_i \epsilon_i , \tag{2}$$

In general, due to contemporaneous correlations between the stock markets, the elements of the innovations vector ϵ are not orthogonal (Yang and Bessler, 2008). Let there exists lower triangular matrix P such that $\upsilon_i \equiv P^{-1} \epsilon_i$ and $E\{\epsilon_i \epsilon'_i\}$ is a diagonal matrix. We can then write vector X_t as VMA in terms of orthogonal residuals from the estimated error correction model

$$X_t = \sum_{i=0}^{\infty} \Theta_i \upsilon_i , \tag{3}$$

To obtain causal structure between six stock markets in contemporaneous time, the structural factorization of Bernanke (1986) performed. The causal ordering in Bernanke factorization is dictated by the data-driven outcome of DAG via the use of LiNGAM search algorithm. LiNGAM search algorithm assumes (i) the data generating process is linear, (ii) there are no unobserved confounders, and (iii) disturbance variables have non-Gaussian distributions of non-zero variances. The solution is obtained by using the statistical method known as independent component analysis, which does not require any pre-specified time-ordering of the variables Shimizu et al. (2006),

3. Data

Daily stock index closing prices, in U.S. dollars, of five stock markets are used in this study. Specifically, data on the following stock indices are considered: United States S&P 500 Composite Index (NY), Germany's DAX 30 Composite Stock Index (DAX), Russia's RTS Composite Index (RUS), Kazakhstan's KASE Composite Index (KAS), Hong Kong's Hang Seng Composite Index (HS) and Shanghai's SSE Composite Index (SH). The series covers the period of two years starting from October 2007 to October 2009 with a total of

543 observations. All stock indexes are well diversified and fairly reflect the general state of the economy in their respective countries. Each series is obtained from its respective stock exchange's website.

Closing prices of each series are matched in terms of Monday to Friday trading days. However, there are some missing observations among the series due to country specific official holidays where trading does not occur. The problem of missing observation is handled by assigning the last observed closing price prior to the missing observation trading day. It is important to test stochastic order of each series before doing VAR or error correction (ECM) modeling. Augmented Dickey Fuller, Phillips Perron, Sims Bayes, and KPSS tests are conducted for testing the stochastic order of each series. All tests uniformly indicate that each stock market indexes are non-stationary both at levels and in logarithms.

The summary statistics of each stock market indexes is presented in Table 1. Each series exhibits patterns of non-normal distribution, a positive skewness and lower than normal kurtosis. Heng Seng, KASE, and S&P500 composite indexes exhibit more symmetry then others; however, they too exhibit low pickedness.

Table 1. Summary statistics of six stock market indexes

Series	Obs	Mean	Std.Dev.	Min	Max	Skewness	Kurtosis
Hongkong (HS)	543	20364.52	4995.53	11015.84	31638.22	.0554	2.0497
Shanghai (SH)	543	3174.24	1138.23	1706.70	6092.06	.9282	2.7906
KAS	543	1737.84	775.66	576.89	2858.11	.0202	1.3164
RUS	543	1447.23	659.94	498.20	2487.92	.0684	1.3866
DAX	543	5874.79	1211.90	3666.41	8076.12	.1946	1.8710
NY	543	1132.68	244.99	676.53	1565.15	.0653	1.5592

Normality tests confirm that each individual series have non-normal distribution. This necessitates the use of search algorithms such as LiNGAM algorithm which explicitly assumes that variables have non-Gaussian distribution.

4. Identification of the long-run structure

The estimation of the model is based on maximum likelihood procedure developed by Johansen and Juselius (1990). The optimal number of lags in levels VAR is selected by using Schwarz loss and Hannan and Quinn loss metrics. Both metrics indicate that the optimal number of lags is two. For the estimation of the model, RATS and CATS in RATS (program for cointegration analysis) software are used. The number of cointegrated vectors is found by using trace test results. Table 2 shows the trace test results for both with linear trend and without linear trend in the cointegration space. The test results, at 5% significance level, indicate that the number of independent cointegrating vectors found to be one.

Table 2. Trace tests on number of cointegrating vectors on price indexes of six stock markets

Null	**Without linear trend**			**With linear trend**		
	Trace*	C (5%)	Decision*	Trace*	C (5%)	Decision*
r = 0	107.46	101.84	R	105.32	93.92	R
r ≤ 1	67.13	75.74	F	65.15	68.68	F
r ≤ 2	43.93	53.42	F	42.03	47.21	F
r ≤ 3	26.35	34.80	F	24.96	29.38	F
r ≤ 4	14.85	19.99	F	13.94	15.34	F
r ≤ 5	6.26	9.13	F	5.43	3.84	F

Table 3. Exclusion tests for each series in cointegration space (restrictions on β vector)

Series	χ^2	**p-value**	**Decision**
Kazakhstan (KAS)	0.02	0.89	F
Russia (RUS)	4.67	0.03	R
Germany (DAX)	16.36	0.00	R
United States (NY)	15.01	0.00	R
China, Hong Kong (HS)	4.53	0.03	R
China, Shanghai (SH)	0.00	0.97	F
Constant	0.69	0.41	F

Decision rule: the null hypothesis is rejected if the p-value of corresponding test statistic is smaller than 0.05.

Parameter estimates of ECM are tested in order to identify the long-run structure of interdependencies among the markets. We first test the exclusion hypothesis that one of the series is not in the cointegrating space. Here, the null hypothesis is that the series *i* does not belong to cointegrating space. The likelihood ratio test statistic is distributed chi-squared with one degree of freedom and the decision is made at 5 percent significance level. Table 3 presents the results of exclusion tests on each series. The test results indicate that Russia, Germany, New York, and Hong Kong are in the long-run equilibrium, whereas Kazakhstan and Shanghai do not enter the long-run equilibrium. Also, the test results indicate that constant does not enter the cointegration vector.

We now test the hypothesis that some of the markets do not respond to shocks in the long-run equilibrium. The weak exogeneity test is performed on each series with a null hypothesis that series *i* does not respond to shocks in the cointegration vector. The likelihood ratio test statistic is distributed chi-squared with one degree of freedom. Table 4 shows the results of weak exogeneity tests on each series. The test results indicate, at 10 percent significance level, that only Kazakhstan and Germany respond to perturbations in the long-run equilibrium and the other markets do not respond. In addition, joint hypothesis test is performed with a null hypothesis that Russia, New York, Hong Kong, and Shanghai are jointly exogenous. With four degrees of freedom, the marginal significance level of $\chi^2 = 3.95$ is 0.41. This indicates that these markets are jointly weakly exogenous.

Table 4. Weak exogeneity tests for each series in cointegration space (restrictions on α vector)

Series	χ^2	**p-value**	**Decision**
Kazakhstan (KAS)	3.55	0.06	R
Russia (RUS)	0.18	0.67	F
Germany (DAX)	3.07	0.08	R
United States (NY)	1.79	0.18	F
China, Hong Kong (HS)	0.17	0.68	F
China, Shanghai (SH)	0.31	0.58	F

$$\alpha\,\beta' = \begin{bmatrix} -0.098 \\ 0.000 \\ 0.101 \\ 0.000 \\ 0.000 \\ 0.000 \end{bmatrix} [0.000 \quad -0.160 \quad -0.961 \quad 1.000 \quad 0.248 \quad 0.000 \quad 0.000] \tag{4}$$

In order to complete the identification of long-run equilibrium structure, joint test with a null hypothesis that exclusion and weak exogeneity restrictions obtained above hold simultaneously. Under this null hypothesis, the likelihood ratio test statistic is distributed chi-squared with seven degree of freedom. The joint likelihood ratio test yields test statistics of $\chi^2 = 3.95$ and a p-value = 0.41. This indicates that we fail to reject the null hypothesis and the imposed zero restrictions are acceptable. Thus, the identified $\Pi = \alpha\,\beta'$ matrix, after normalizing the β vector on the New York series, is given in Eq. (4)

5. Identification of the contemporaneous and the short-run structure

After obtaining long-run equilibrium structure shown in Eq. (4), contemporaneous innovation correlation matrix $\Sigma\,(\hat{e}_t)$ from the ECM is saved to perform innovation accounting purposes. This correlation matrix is shown in Eq. (5). Eq. (5) shows that strongest correlation exists between New York and Germany. Other set of significant correlations exist between pairs Russia-Germany and Hong Kong-Shanghai.

$$\Sigma\,(\hat{e}_t) = \begin{bmatrix} 1.0000 & & & & & \\ 0.3808 & 1.0000 & & & & \\ 0.2493 & 0.4822 & 1.0000 & & & \\ 0.1968 & 0.3574 & 0.7320 & 1.0000 & & \\ 0.2631 & 0.4027 & 0.4059 & 0.3545 & 1.0000 & \\ 0.0983 & 0.1709 & 0.1447 & 0.0684 & 0.4787 & 1.0000 \end{bmatrix} \qquad (5)$$

5.1. Identification of the contemporaneous structure

TETRAD IV software and LiNGAM search algorithm is used to conduct directed acyclic graph analysis. The raw data at levels is uploaded into TETRAD IV and contemporaneous causal structure between six stock markets is obtained using LiNGAM search algorithm. Causal sufficiency assumption is maintained in DAG analysis. However, this assumption may not be too realistic given the number and selection of stock market series in this study. In addition set of temporal restrictions are imposed among the different groups of stock markets where certain markets cannot cause other markets in contemporaneous time. The need for this restriction naturally arises due to the fact that some markets are closed before other markets start their trading day. For instance, New York cannot cause Hong Kong, Shanghai, Kazakhstan, and Russia (with 30 minute overlap) in contemporaneous time. Figure 1 shows the DAG of contemporaneous causal structure between six stock markets.

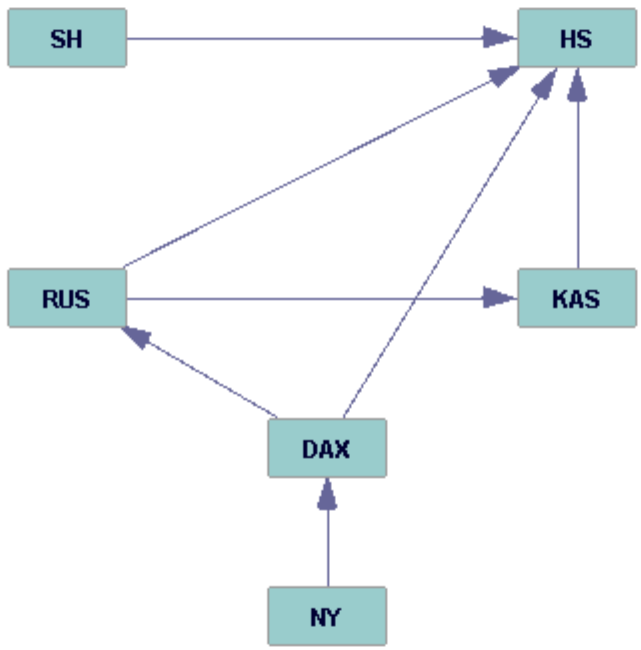


Fig. 1. Directed acyclic graph (DAG) on innovation from six stock market indexes.

The Fig. 1 exhibits very interesting contemporaneous causal structure between the markets. Hong Kong Stock Exchange is led by all other markets, except New York, in contemporaneous time. New York leads Germany, Germany, in turn, leads Russia and Hong Kong despite the short time overlap (30 minutes) between Germany and Hong Kong. In addition, Russia causes both Kazakhstan and Hong Kong and Shanghai causes Hong Kong only and is not caused by any other market. The graph suggests that New York and Shanghai markets lead others, where New York seems to be the most influential of all.

The DAG given in Fig. 1 aids us to impose correct causal ordering in performing Bernanke factorization. Table 5 shows the forecast error variance decomposition, which is based on Fig. 1 and Eq. 5.

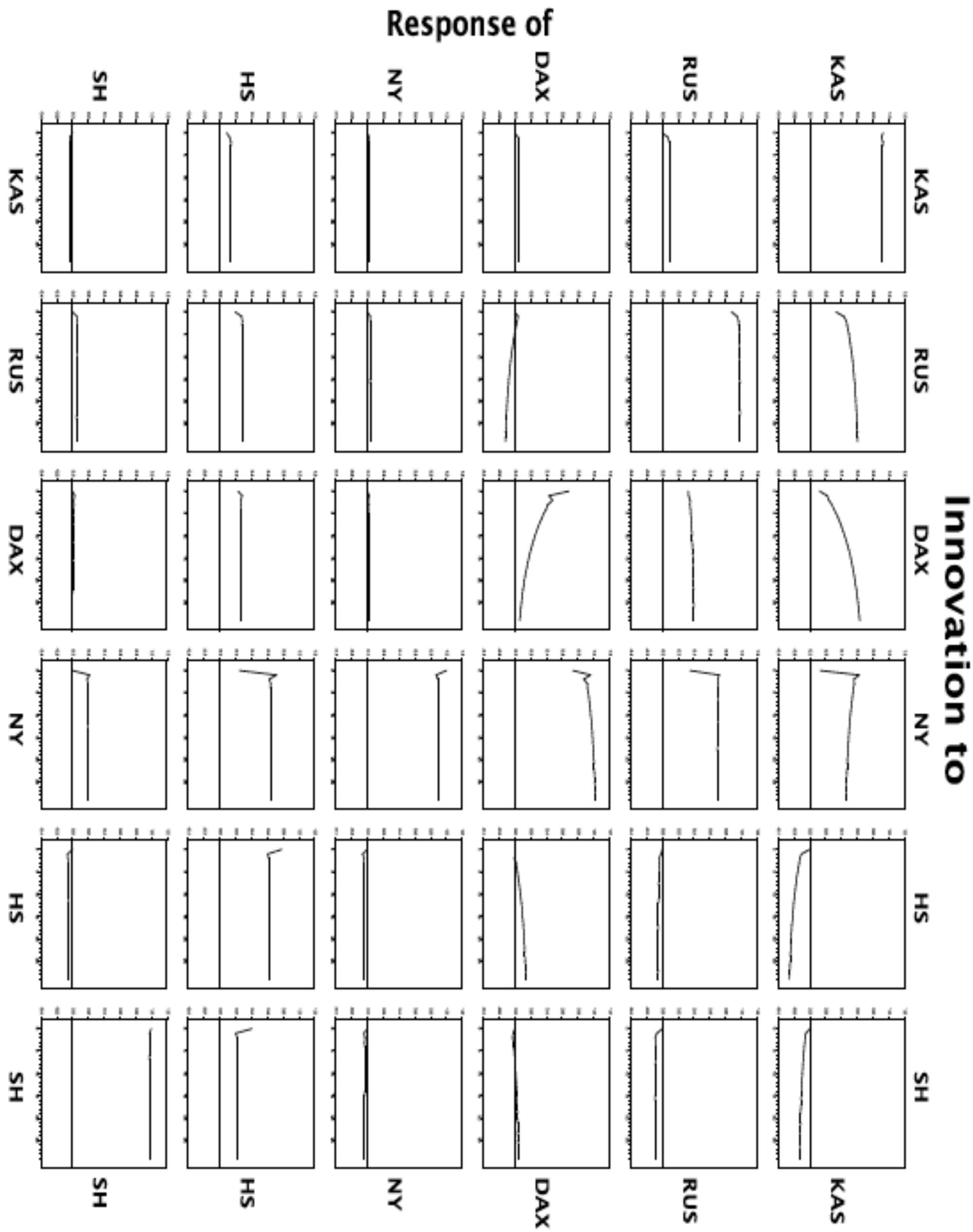
Table 5. Forecast error variance decompositions from a levels VAR with the contemporaneous structure imposed as in Fig. 2

Step	**KAS**	**RUS**	**DAX**	**NY**	**HS**	**SH**
KAS						
1	85.50027	11.12832	1.56489	1.80652	0.00000	0.00000
2	68.16863	12.05846	2.60617	16.57519	0.48753	0.10401
3	64.60306	13.01881	3.14285	18.34986	0.71923	0.16619
10	57.34126	15.36956	6.88712	18.60384	1.44914	0.34908
20	53.01784	16.86327	11.26858	16.22062	2.11171	0.51798
30	50.30059	17.65450	14.32278	14.55044	2.54307	0.62862
RUS						
1	0.00000	76.74841	10.79258	12.45901	0.00000	0.00000
2	0.21530	65.69066	8.60882	25.27288	0.01379	0.19855
3	0.30746	63.38011	8.35136	27.59322	0.05229	0.31557
10	0.41639	60.47847	8.30065	30.26348	0.10035	0.44066
20	0.43354	59.96688	8.71986	30.26793	0.12981	0.48199
30	0.43758	59.81152	9.03540	30.06474	0.14839	0.50237
DAX						
1	0.00000	0.00000	46.41652	53.58348	0.00000	0.00000
2	0.09422	0.07023	30.95582	68.84934	0.00157	0.02882
3	0.12405	0.07729	28.35264	71.39388	0.00250	0.04965
10	0.17227	0.05887	17.05547	82.55535	0.13662	0.02142
20	0.18255	0.29450	10.31091	88.65606	0.51778	0.03820
30	0.18374	0.57898	7.03538	91.25092	0.87407	0.07691

NY						
1	0.00000	0.00000	0.00000	100.00000	0.00000	0.00000
2	0.02826	0.08549	0.03092	99.52986	0.20033	0.12513
3	0.03686	0.10272	0.02609	99.51335	0.20005	0.12093
10	0.05000	0.13913	0.03139	99.40240	0.23806	0.13902
20	0.05305	0.14895	0.03422	99.37263	0.24778	0.14336
30	0.05409	0.15297	0.03608	99.35982	0.25189	0.14516
HS						
1	0.81723	3.97954	5.77118	6.66228	65.35180	17.41797
2	1.13695	5.54934	6.58533	28.33866	48.29495	10.09477
3	1.41497	6.39163	6.72420	31.94089	45.16021	8.36811
10	1.73416	7.43314	7.02617	38.13071	39.89101	5.78481
20	1.80364	7.66144	7.09390	39.43590	38.77081	5.23431
30	1.82677	7.73858	7.11932	39.86857	38.39602	5.05073
SH						
1	0.00000	0.00000	0.00000	0.00000	0.00000	100.00000
2	0.06204	0.14594	0.03814	2.40639	0.18838	97.15910
3	0.06327	0.21799	0.03701	2.74561	0.23563	96.70049
10	0.06758	0.29940	0.02844	3.47557	0.28719	95.84181
20	0.06828	0.30000	0.01724	3.67082	0.28342	95.66025
30	0.06846	0.29334	0.01173	3.75243	0.27613	95.59791

The table shows the percentage of each series' (in rows) forecast error variance at horizon *k* due to shock from all markets (in columns).

Fig. 2. Plots of historical decompositions (impulse responses) of six stock market indexes



For the economy of space, only decomposition of forecast error variance at horizon 1, 2, 3, 10, 20, and 30 days presented. Shanghai and New York are highly exogenous throughout the entire 30-day horizon. Over 95 percent of volatility in these markets is explained by innovation in their own markets. On the other hand, two thirds of the volatility in Hong Kong in 1-day horizon accounted by itself and Shanghai is being the most influential market in a short horizon. In longer horizon, the US accounts for more than 35 percent volatility in Hong Kong market. In 1-day horizon, more than half of the volatility in German market is explained by the US, which increases to more than 90 percent at the end of 30-day horizon. Russia and Kazakhstan are significantly influenced by Germany and New York, especially, in longer horizon. Fig. 2 plots the historical decompositions given in Table 5 and provides more detailed visual inspection.

6. Conclusions

In this study, we apply directed acyclic graphs and search algorithm designed for time series with non-Gaussian distribution to obtain causal structure of innovations from an error correction model. The structure of interdependencies among six international stock markets is investigated by applying set of cointegration analysis, directed acyclic graphs, and innovation accounting tools. The results provide positive empirical evidence that there exist long-run equilibrium and contemporaneous causal structure among these stock markets. We find that stock index prices from all these stock markets are cointegrated with one cointegrating vector. The exclusion hypotheses indicate that Kazakhstan and Shanghai do not enter the long-run equilibrium. Further, the results show that only Kazakhstan and Germany respond to perturbations in the long-run equilibrium and the other markets do not respond.

In addition, contemporaneous causal structure on innovations from all markets is explored and used in innovation accounting procedure to obtain forecast error variance decompositions. DAG analysis results show that Hong Kong is influenced by all other open markets in contemporaneous time. Surprisingly, Shanghai is not influenced by any other market in contemporaneous time. Historical decompositions indicate that New York and Shanghai stock markets are highly exogenous, where each market is highly influenced by its own historical innovations. On the other hand, Germany and Hong Kong are the least exogenous markets.

Further, we find that New York is the most influential stock market with consistent impact on price movements (except for Shanghai) in other stock markets, especially in 30-day horizon. This result is consistent with findings of Eun and Shim (1989) and Bessler (2003) on 1987 financial crisis studies.

The finding of this study on propagation patterns present important implications for risk management, in particular for international diversification purposes. One implication is that diversification between US and Germany may not provide desired immunity from financial crisis contagion as much as it does diversification between US and Shanghai.

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