Variance-Based Spillover Analysis between Stock Markets: A Time Varying Parameter Approach

A. Özün[a,*] and H.M. Ertuğrul[b]

[a]Bradford University, School of Management, Emm Ln, Bradford, West Yorkshire BD9 4JL, United Kingdom

[b]Undersecretariat of Treasury, Republic of Turkey, Inonu Bulvari No:36, 06510 Emek, Ankara, Turkey

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This paper proposes a variance-based spillover impact analysis embedded with a dynamic Kalman filtering in order to detect a causality relationship from the US stock markets into the European and emerging stock markets during the financial crisis. It has mainly two new contributions to the literature. Firstly, it uses variance rather than returns to analyze the spillover impact between the markets. Secondly, and more importantly, it is an econophysics research as it examines causality relationship with the Kalman filtering in physics. We calculate time-dependent conditional stock market variances for Dow Jones, DAX, FTSE, RTS (Russia), and BIST (Turkey) by employing SWARCH model. The empirical analysis examines the causal relationship between Dow Jones into the other stock markets employing Granger causality tests in order to detect the direction of volatility spillover relationship. As an embedded analysis, we follow a dynamic approach by using the Kalman filtering as a time varying parameter model to depict the time varying interaction between stock markets volatilities. The empirical results point out unidirectional Granger causality from Dow Jones to the other markets indicating the spillover impact of the volatility starting from the US markets and expanded into the world in the latest global crisis.

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1. Motivation

In this study, differently from the recent literature, we analyze spillover relationship between stock markets by employing variance instead of mean variables. Conditional volatility variables instead of level stock market data is used to investigate volatility spillover relationship between stock markets focusing to the global financial period term. We use daily stock exchange return variables for Dow Jones, DAX, FTSE, RTS (Russia), and BIST (Turkey) covering the period 1/10/2008–4/9/2009. We use stock market data from Bloomberg Data Terminal.

To obtain stock market volatility data, firstly we calculate time-dependent conditional stock market variances for DJI, DAX, FTSE, RTS, and BIST by employing SWARCH methodology proposed by Hamilton and Susmel [1]. One of the most important lack of ARCH and GARCH types of models is that they include high persistency. A number of researchers have suggested that the poor forecasting performance and spuriously high persistence of ARCH models might both be related to structural change in the ARCH process [1]. Following the works of Hamilton [2, 3] on switching regimes, Hamilton and Susmel [1] propose a new ARCH model, the switching ARCH or SWARCH model. This model captures more realistically the time-series properties of dramatic economic events such as a stock market crash. In this model, volatility depends on past news and the state of the economy (Susmel and Kane [4]).

SWARCH models are found to be superior over traditional ARCH type models for exchange rates, stock exchange and interest rates in the literature (Beine et al. [5], Cheung and Erlandsson [6] and Gur and Ertugrul [7] for exchange rates, Cai [8] for interest rates). After we obtained volatility series, firstly we investigate causal relationship between DJI and other stock markets employing Granger causality tests in order to detect the direction of volatility spillover relationship.

Finally, after we determine the direction of volatility spillover relationship between stock markets, we followed a dynamic approach by using the Kalman filter to depict the time varying interaction between stock markets volatilities. In time varying parameter (TVP) models, the parameters are allowed to change with each new observation (Koop and Potter [9]).

The empirical test indicates that SWARCH model estimation results are statistically meaningful for all markets. When we examine the causality direction of spillover relationship between stock markets with Granger causality test, we detect that unidirectional Granger causality from the US markets to other stock markets in the global business period. The dynamic Kalman filtering test results also pointed out a time-varying variance-based spillover impact from the US market to the European and emerging markets.

In the next chapter, we explain the SWARCH model, Granger causality test methodology and dynamic Kalman filtering approach by providing empirical results with the existing data. In the third chapter, we discuss the practical implications of the empirical results for portfolio management. The paper ends with a conclusion and some suggestions for the research in the future.

*corresponding author; e-mail: alper.ozun@hotmail.com

2. Methodology and findings

Hamilton [2] suggested following regime-switching model for conditional mean:

$$y_t = \mu_{s_t} + \tilde{y}_t. \quad (1)$$

Here μ_{s_t} denotes the parameter μ_1 when the process is in the regime represented by $s_t = 1$, while μ_{s_t} shows μ_2 when $s_t = 2$, and so on. The variable $\tilde{y}_t$ was assumed to follow a zero-mean q-th-order autoregression:

$$\tilde{y}_t = \phi_1 \tilde{y}_{t-1} + \phi_2 \tilde{y}_{t-2} + \ldots + \phi_q \tilde{y}_{t-q} + u_t. \quad (2)$$

In the switching-ARCH framework, the error process is described by the following equations:

$$u_t = \sqrt{g_{st}}\,\tilde{u}_t. \quad (3)$$

Here $\tilde{u}_t$ is assumed to follow a standard ARCH process,

$$\tilde{u}_t = h_t v_t, \quad (4)$$

with v_t a zero mean, unit variance, independently and identically distributed sequence and

$$h_t^2 = a_0 + a_1 \tilde{u}_{t-1}^2 + a_2 \tilde{u}_{t-2}^2 + \ldots + a_q \tilde{u}_{t-q}^2. \quad (5)$$

The underlying ARCH (q) variable $\tilde{u}_t$ is then multiplied by the constant $\sqrt{g_1}$ when the process is in the regime represented by $s_t = 1$, multiplied by $\sqrt{g_2}$ when $s_t = 2$, and so on. The factor for the first state g_1 is normalized at unity with $g_j \geq 1$ for $j = 2, 3 \ldots, K$. By doing so, we could model changes in regime as changes in the scale of the process. u_t in (3) follows state K, q-th order Markov-switching ARCH process, denoted as SWARCH (K, q) [1].

In our study, it is assumed that there are only two volatility states: low volatility (state 1) and high volatility (state 2). Hence, the transition probability matrix simplifies to: $\boldsymbol{P} = \left|\begin{smallmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{smallmatrix}\right|$ where $\sum_{j=1}^{2} p_{ij} = 1$.

The results of SWARCH model estimations for every stock market are presented in Table I below.

TABLE I

SWARCH(2,1) model results.

Variable	(DJI)	(DAX)	(FTSE)	(BIST)	(RTS)
Mean equation					
constant	0.002^*	0.002^{**}	0.002^{**}	0.002^*	0.004^{**}
Y_{t-1}	0.217^*	0.241^*	0.262^*	0.292^*	0.352^*
Variance equation					
constant	0.004^*	0.001^*	0.001^*	0.004^*	0.001^*
ε_{t-1}^2	0.470^*	0.562^*	0.361^*	0.434^*	0.414^*

* 1% significance level and ** 5% significance level

Table I indicates that SWARCH model estimation results are statistically meaningful for all markets.

After we obtain conditional volatility series firstly we investigate causality relationship between DJI and other stock markets in order to detect the causality direction of spillover relationship between stock markets by employing Granger causality test. Granger causality test results are presented in Table II.

According to Table II, we found unidirectional Granger causality from DJI to other stock markets including RTS, FTSE, BIST, and DAX.

TABLE II

Granger causality results.

Causality direction		F statistics	Prob. value	Result
DAX	DJI	0.71	0.70	no causality
DJI	DAX	37.40	0.00	causality
RTS	DJI	4.90	0.43	no causality
DJI	RTS	27.91	0.00	causality
FTSE	DJI	6.84	0.23	no causality
DJI	FTSE	56.58	0.00	causality
BIST	DJI	11.83	0.16	no causality
DJI	BIST	20.94	0.00	causality

After investigating causality relationship, we examine dynamic spillover relationship between stock markets employing the Kalman filter model. A dynamic approach by employing the Kalman filter method based on recursive estimation is used to detect the statistically significant spillover relationship between stock markets.

We base our dynamic approach on a classical reference of Harvey [10] that introduces the Kalman filter approach. The Kalman filter approach is based on a form of state space representation. A linear state space of the dynamics of an equation can be represented as

$$y_t = c_t + Z_t \alpha_t + \varepsilon_t, \quad (6)$$

$$\alpha_{t+1} = d_t + T_t \alpha_t + v_t, \quad (7)$$

where in our case α_t is a 2×1 vector of unobserved state variables, c_t, Z_t, d_t, and T_t are adaptable vectors and matrices, and ε_t and v_t are vectors of mean zero, Gaussian disturbances. As stated in Eq. (7), unobserved state vector α_t is assumed to change over time as a first-order vector autoregression. The Kalman filter recursively estimates the parameters by updating the estimation with every additional observation (Mangir and Ertuğrul [11]).

The Kalman filter specification employed in our study in order to investigate volatility spillover between DJI and DAX, FTSE, RTS and BIST is presented in Eqs. (8)–(12), respectively, with Eq. (13). We used these specifications because the causality direction between stock markets is from DJI to other markets as a result of Granger causality model.

$$\mathrm{VOLDAX}_t = a_0 + a_{1,t}\mathrm{VOLDJI}_t + \varepsilon_t, \quad (8)$$

$$\mathrm{VOLFTSE}_t = a_0 + a_{1,t}\mathrm{VOLDJI}_t + \varepsilon_t, \quad (9)$$

$$\mathrm{VOLRTS}_t = a_0 + a_{1,t}\mathrm{VOLDJI}_t + \varepsilon_t, \quad (10)$$

$$\mathrm{VOLBIST}_t = a_0 + a_{1,t}\mathrm{VOLDJI}_t + \varepsilon_t, \quad (12)$$

$$a_{i,t} = a_{i,t-1} + v_{i,t}. \quad (13)$$

$a_{1,t}$ coefficient in Eqs. (8)–(12) indicates the effects of change in DJI volatility on other markets which could be considered as spillover coefficient.

The dynamic Kalman filtering variance-based spillover impact model produces following empirical results with the existing data. The empirical results show that the spillover impact from DJI to the other stock markets is material in the bear market periods. Spillover impact from DJI to BIST disappears after the first shock of the crisis as BIST outperformed in the crisis period. The variance-based spillover impact from DJI into DAX, FTSE, and RTS are material, but the impact is observed on DAX. The empirical findings are in line with the practical observations as the crisis has been mostly observed in the advanced markets rather than emerging economies.

3. Practical implications and conclusion

In this paper, we set up a variance-based spillover impact analysis embedded with a dynamic Kalman filtering. The paper contributes into econophysics by embedding the Kalman filtering into causality analysis to establish a dynamic time-varying causality relationship. In addition, on the methodological side, instead of using return, we use variances of the markets to detect spillover impacts between the markets.

We also provide an empirical analysis by using stock market indices from the US, the UK, Germany, Russia and Turkey during the recent global crisis period. The purpose of the empirical research is to investigate the causality relationship from the US stock market, Dow Jones Industrial Index, from the main European and emerging stock markets during the financial crisis. As the root of the crisis stems from the US economy, we examine the level of the spillover of the risk, as the variance is used from the US equity markets into the other markets.

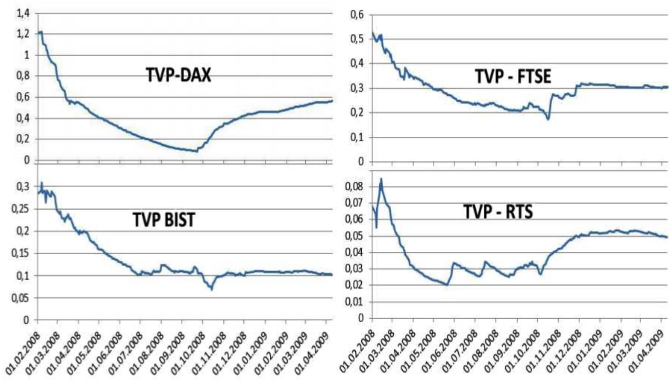

Fig. 1. Dynamic Kalman filtering variance-based spillover impact.

The empirical findings show that the methodology in the paper successfully detects variance-based time-varying spillover impact between the stock market indices. There exists a unidirectional Granger causality from Dow Jones to the UK, German, Russian, and Turkish markets. The results are in line with the expectations as the crisis has stemmed from the volatility in the US markets and expanded into the world in the latest global crisis. The levels of the spillover impact can be followed in Fig. 1. Accordingly, the level of risk spillover impact from the US markets into the Turkish markets is relatively lower. The plenty of liquidity has been helpful to protect the emerging economies from the crisis. The short-term investment opportunity that provides higher returns in the emerging economies provides a comfort for those markets against the crisis. On the other hand, the risk spillover impact from the US markets into the European markets is stronger. The financial connectivity and dependence between the US and the European markets via financial institutions are the main reasons for a such strong spillover impact.

In this paper, we present a dynamic, time-varying Kalman filtering methodology to detect the risk spillover between the financial markets. In the empirical part, we examine the spillover causality during the recent global crisis with certain selected markets. For the future analysis, the researchers can use the model established in this paper to examine the spillover impact between different markets in different time periods. Alternatively, that econophysics methodology can be used by employing different economic parameters to examine the risk spillovers among them. For example, the spillover causality impact of variances in foreign exchange rates, interest rates, current-deficit and oil prices on the inflation can be investigated.

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