**Interdependence between the implied volatility indices of developed and emerging markets: A new Markov-switching approach**

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**Abstract**

This study examines the interrelatedness of volatility dynamics between the most influential developed market (the US market) and a leading emerging market (the Korean market). Importantly, we consider the endogeneity effects of the US market implied volatility index (VIX) on the dynamics of the Korean implied volatility index (VKOSPI) under an advanced Markov-switching framework mitigating the endogeneity problem. We consider two types of endogeneity in this framework. First, the US variables in the regressors can be correlated with the disturbance term. Second, regime-switching probabilities can be correlated with the disturbance terms. The estimation results show that both types of endogeneity are present in the US variables and more significant during the recent Global Financial Crisis. In addition, the results imply that the US factors are the most important conduit through which global shocks are transmitted to the volatility index of Korea.

**Keywords:** Endogenous Markov-switching, VIX, VKOSPI, US, Korea, Implied volatility index

**JEL classifications:** C22, E44, F36, G17, G19

**1. Introduction**

It has been said that volatility creates both the risk of potential losses and the opportunity for potential gains. Fear of the former and hope for the latter have been the driving force behind the creation of many derivative securities and other financial innovations designed to transfer risk from those unwilling to bear it to those willing to bear it at some price. However, volatility is not constant but changes over time and understanding the behavior of volatility over time or *volatility dynamics* is essential in correctly assessing and hedging exposure to market risk as well as forecasting future volatility. It is also critical in developing and pricing any derivative securities based on the volatility dynamics.

There is a substantial literature on forecasting market volatility. Much of it attempts to look forward by looking backward. That is, by advancing often-complex deterministic or stochastic models that use historical data as inputs. These studies include tons of studies such as Bates (1991, 1996, 2000), [Bekaert](http://www.sciencedirect.com/science/article/pii/S0304407614001110) and [Hoerova](http://www.sciencedirect.com/science/article/pii/S0304407614001110) (2014), Bollerslev, Engle, and Wooldridge (1988), Bollerslev and Wooldridge (1992), Conrad and Loch (2014), Engle, Ghysels, and Sohn (2013), Engle and Ng (1993), [Fernandes](https://scholar.google.co.kr/citations?user=cNd6bjIAAAAJ&hl=en&oi=sra), [Medeiros](https://scholar.google.co.kr/citations?user=nPYJL_MAAAAJ&hl=en&oi=sra), and [Scharth](https://scholar.google.co.kr/citations?user=lL8D32MAAAAJ&hl=en&oi=sra) (2014), Glosten, Jagannathan, and Runkle (1993), Heston (1993), Higgins and Bera (1992), Hull and White (1987), Johnson and Shanno (1987), Madan, Carr, and Chang (1998), Maheu and McCurdy (2004), Melino and Turnbull (1990, 1995), Nelson (1991), Pagan and Schwert (1990), Schwert (1989), Wiggins (1987), and Zakoian (1994). Although the approach taken in these studies has advanced our knowledge of volatility dynamics, it ignores changes in both investor sentiment and market expectations. The use of implied volatilities addresses this issue and may result in better forecasts of future market volatility.

It is well-known that implied volatilities can be extracted from option prices by assuming that a particular option pricing model is the “true” model and then using the market prices of the options to solve for volatility. The downside with taking this approach is also well-known. Namely, the resultant implied volatilities are influenced by model biases and may result in puzzling results such as the volatility smile and smirk phenomena.

One way to circumvent the problem of model biases when estimating volatility is to use “model-free” measures of implied volatility. A number of studies in the literature report that “model-free” measures are consistent with, and superior to, existing volatility measures. These studies include Britten-Jones and Neuberger (2000), Carr and Wu (2006), Demeterfi, Derman, Kamal, and Zou (1999), Jiang and Tian (2007), and Taylor, Yadav, and Zhang (2010). VIX or the Chicago Board Options Exchange (CBOE) volatility index is arguably the most famous and influential model-free implied volatility measure in the US market. The VIX uses S&P 500 spot and options prices as inputs and is based on the “fair-variance swap method.” As might be expected, given an informationally efficient market, these studies show that model-free implied volatility measures are better than historical volatility measures (e.g., see Banerjee, Doran, and Peterson, 2007; Becker, Clements, and White, 2007; Carr and Wu, 2006; Corrado and Miller, 2005; Frijns, Tallau, and Tourani-Rad, 2010; Giot, 2005a, 2005b; Jiang and Tian, 2007; Konstantinidi, Skiadopoulos, and Tzagkaraki, 2008).

It is important to understand that the volatility dynamics of various implied volatility indices can be related to common state variables such as macroeconomic and financial factors. However, the existing literature is silent with respect to *which* state variables matter. Moreover, much of the literature fails to use advanced econometric techniques. Not surprisingly, the existing literature largely focuses on volatility indices for developed markets with little attention given to volatility indices in emerging markets.[[1]](#footnote-1) This is unfortunate as emerging markets can offer greater opportunities to test for various behavioral biases given that trading is often dominated by individual speculators in the emerging markets. Consequently, an empirical analysis of an emerging market’s implied volatility index can provide some different and interesting results.

This study fills these gaps. We examine the dynamics of the Korean implied volatility index (VKOSPI) by considering not only domestic macroeconomic and financial factors, but also cross-country factors that possibly affect the VKOSPI. The VKOSPI was chosen because Korea is has a large, rapidly growing and highly liquid emerging options market —the KOSPI 200 index options market— on which the VKOSPI is based. Unlike the case of developed markets, it is interesting that the individual speculators, who are sensitive to market sentiment and behavioral biases, play an important role in the Korean options market.[[2]](#footnote-2)

When considering cross-country factors, we try to illuminate the link between developed and emerging markets by analyzing the interdependence between the market volatility indices of a representative developed market and those of a leading emerging market. We pay attention to the US market, which is the most influential market in the world, and the Korean market, which is the leading emerging market and garners great investor attention. We are also motivated by the economic, as well as, historical, political, and military ties between these two countries (Kim and Ryu, 2015a; Kim, Ryu, Seo, 2015). Specifically, under an advanced Markov-switching model, we investigate two market volatility indices —VIX (the US implied volatility index) and VKOSPI (the Korean implied volatility index). The VIX is derived from S&P 500 option prices and their underlying stock returns, while the VKOSPI is derived from KOSPI 200 option prices and stock returns. These measures are the representative fear gauges and market indicators of developed and emerging markets, respectively.

For the methodology, we note that Markov-switching models have been successfully applied to analyze the dynamics of global market volatilities. However, most existing studies assume that VIX is an *exogenous* explanatory variable for VKOSPI, which might not be true. Considering the significant cross-country effects, historical ties and bonds, as well as active trade and commerce between the US and Korea, we expect VKOSPI and VIX to share common shocks. That is, the volatility dynamics in both countries are necessarily correlated, especially when global shocks affect both the US and Korean stock markets.

Although two recent studies by Han, Kutan, and Ryu (2015) and Song, Ryu, and Webb (2016) examine the effects of US factors on VKOSPI dynamics under the frameworks of the heterogeneous autoregressive (HAR) and regime-switching models, respectively, their approaches are limited because they fail to account for the potential endogeneity of the regressors from the models. Unless the issue of the potential endogeneity of variables is appropriately addressed, a model may suffer from endogeneity bias in the estimated parameters and transition probabilities. Simply using lagged values for the explanatory variables to avoid the endogeneity problem causes the loss of valuable information about the relationship between the dependent and explanatory variables. On the other hand, proper treatment of endogeneity can improve the efficiency of parameter estimates and transition probabilities because it permits more information to be extracted from the data on the latent states and their transitions in the presence of endogeneity. In this paper, we apply the advanced Markov-switching framework that considers the endogeneity of variables in a reexamination of VKOSPI dynamics.

The Korean stock market is closely related to the US stock market and global economic shocks may affect both Korean and US markets. This makes US financial variables potentially highly correlated with the VKOSPI, causing endogeneity problem in the regression model. To mitigate the endogeneity issue, we usually use lagged values of US variables in the regression model. Meanwhile, we note that there is time lag between US and Korean markets and US market open at time *t*-1 right after Korean market at time *t*-1 closes. Thus, global shocks that occur after the Korean market closes may commonly affect both US market at time *t*-1 and Korean market at time *t*, still causing endogeneity problem. Thus, simply using lagged values of US variables is not a good solution. Moreover, if global shocks are persistent, i.e., shocks last for a few periods, US variables at time *t*-*k* may be correlated with VKOSPI at time *t*. Thus, the correlation structures between US and Korean variables at different time periods need to be carefully examined.

We allow for two types of endogeneity in this study. One model assumes that the US variables in the regressors are correlated with the regression disturbance term (Kim, 2004). This model explores how global shocks affect the correlations between the US and the Korean stock market variables. The other model assumes that regime-switching probabilities are correlated with the regression disturbance terms (Kim, Piger, and Startz, 2008). This model explores how the regime-shifting patterns of the US and the Korean stock markets are interrelated.

Our estimation results show that both types of endogeneity problems affect the US variables. The parameters for endogeneity are statistically significant, and the likelihood ratio (LR) tests strongly reject the null hypothesis of no endogeneity. The parameter estimates for the US variables are thus quite different when endogeneity is allowed, indicating serious endogeneity bias in the parameter estimates. Therefore, the previous literature that ignores endogeneity could suffer from serious endogeneity bias. Clearly, endogeneity must be carefully considered in future research. We also examine endogeneity during the sub-periods and show that both types of endogeneity are strongest during the Global Financial Crisis (GFC) period.

The contributions of this paper are summarized as follows. First, we consider cross-country effects (i.e., US market volatility and its stock market performance) in analyzing the dynamics of the VKOSPI. Second, and most importantly, we carefully examine the interdependence of VIX and VKOSPI using new Markov-switching models that allow for endogenous explanatory variables. Third, we compare the performance of the following models: *i*) exogenous explanatory variables with exogenous regime-switching, *ii*) endogenous explanatory variables with exogenous regime-switching, *iii*) exogenous explanatory variables with endogenous regime-switching. Fourth, we examine how the relationship between the VIX and the VKOSPI varies over different sub-periods including the crisis period, by comparing the performance of each model among the sub-periods.

The remainder of this paper is structured as follows. Section 2 introduces motivations for focusing on VKOSPI and the KOSPI 200 options market. Section 3 introduces the econometric models we use in estimating and testing for endogeneity. Section 4 presents the data, and Section 5 presents the estimation results. In section 6, we present our conclusions.

**2. VKOSPI and KOSPI 200 options**

Like its VIX counterpart, which is based on actively traded S&P 500 stock index options in the US market, the VKOSPI is a model-free implied volatility index based on actively traded options in the Korean market (specifically, KOSPI 200 options prices). Given the dependence of the VKOSPI on KOSPI 200 option prices, it is important to consider how KOSPI 200 options trading can impact VKOSPI dynamics. Like the S&P 500 stock index, the KOSPI 200 is a capitalization-weighted stock price index comprised of the 200 largest common stocks listed on the Korea Exchange (KRX) in terms of market capitalization. Not surprisingly, the KOSPI 200 stock index, is a widely used measure of the overall Korean stock market. Options trading in the KOSPI 200 index was introduced by the KRX in 1997. Trading in KOSPI 200 index options took off and the options quickly became one of the most actively traded derivative contracts in the world. A regulatory change designed to discourage speculative trading by small investors resulted in a sharp increase in contract size in 2012 and a significant drop in trading volume. Nevertheless, KOSPI 200 index options remain one of the most actively traded derivative contracts in the world.

As noted earlier, there are a number of reasons for choosing to examine the volatility dynamics of the VKOSPI. First and foremost is the high liquidity of the underlying KOSPI 200 options. Low transactions costs, an absence of taxes on options trading as well as minimal barriers to entry combine to support the liquid options market in Korea as does the existence of an actively traded KOSPI 200 futures market that facilitates hedging KOSPI 200 option positions.[[3]](#footnote-3) Indeed, brokerage and other transactions costs are higher and liquidity is lower in the spot equity market than in the KOSPI 200 options market.

Second, individuals based in Korea (i.e., domestic individuals), account for a large fraction of total trading volume in the KOSPI 200 options market. This differs sharply from most derivative markets in developed countries where total trading volume by institutional investors dominates trading volume of individual investors. This has an important implication for the empirical analysis in our study. Namely, it suggests that if individual investors are more sensitive to changes in market sentiment or risk preferences than institutional investors, then the KOSPI 200 options market could potentially be more prone speculative excesses.[[4]](#footnote-4) Information on the relative trading volumes of domestic individuals, domestic institutions and foreign investors in the Korean options market is reported in Table 1. Interestingly, the relative share of trading volume of both domestic individuals and domestic institutions has decreased as the share of trading volume by foreign investors has increased from almost 12% in 2004 to over 46% in 2013. Nevertheless, domestic individual investors still account for approximately one third of total trading volume.

[Table 1 here]

Third, unlike cash market equity, derivative securities make it as easy to go short as it is to go long. This facilitates the exploitation of information asymmetries across traders and helps market prices to fully reflect available information. Thus, an individual with negative information about a company is able to exploit it as easily as an individual with positive information about a company

Fourth, traders who want to wager on macroeconomic or market-wide information are able to easily do so in the options market because of its high liquidity. This is especially important if profitable trading opportunities based on macroeconomic or market-wide information do not persist as long as trading opportunities based on private information for individual stocks. This has an important implication for the empirical analysis our study. Namely, if traders use the Korean options market to exploit macroeconomic or market-wide information, a strong relationship between VKOSPI dynamics and macroeconomic variables and overseas shocks should be apparent.

Fifth, the ability to trade anonymously provides traders able to do so with a huge comparative advantage over other traders. The Korean market does not have designated market makers or an upstairs market that guarantees the anonymity of options traders when they submit orders. The large trading volume and number of transactions makes it easier to camouflage or hide informed order flows and avoid fragmenting it (i.e., breaking an order up into a series of smaller orders).[[5]](#footnote-5) This market microstructure favors professional and informed traders and should accelerate the impounding new information into options prices including information on macroeconomic shocks.

It is important to point out that most implied volatility indices have a relatively short horizon or forecast period and the VKOSPI, which was introduced by the KRX in April 2009, is no exception. It reports the implied volatility of KOSPI 200 options for one month ahead. The “fair variance swap” approach suggested and explained by Britten-Jones and Neuberger (2000), Jiang and Tian (2007), and Ryu (2012c) is very similar to the method employed to construct the VKOSPI. Essentially, the prices of the nearest- and second-nearest-maturity KOSPI 200 option contract months as well as the prices of their underlying index are used to calculate the VKOSPI. The derivation of the VKOSPI is explained succinctly in Equations (1)–(7):

(1)

(2)

(3)

(4)

(5)

(6)

(7)

The annualized value of VKOSPI is calculated as described in Equation (1) and uses values calculated from Equations (2)–(7). The numbers of days per month and year are denoted by *N*30 and *N*365 respectively. Similarly, the number of days remaining until the nearest- and second-nearest maturity dates, are denoted by and respectively. The continuously compounded risk-free interest rate, *r* is calculated from the 91 day CD rate. The exercise price closest to the underlying index among exercise prices equal to or lower than the spot index is denoted by *K*0. *Ki* is the *i-*th highest (lowest) strike price compared to the level of *K*0 for call (put) options. Similarly, the strike price with the smallest difference between the nearest-maturity (second-nearest-maturity) call and put option prices is denoted by *S*1 (*S*2). The price of the nearest-maturity call (put) option is denoted by *C*1 (*P*1); while the price of the second-nearest-maturity call (put) option is denoted by *C*2 (*P*2). The volatilities of the nearest- and second-nearest-maturity option contracts are described by Equations (2) and (3) respectively. It should be noted that although the KRX has reported VKOSPI values since its introduction in April 2009, it is possible to construct a longer historical time series before that date using the above set of equations.

Panel A of Figure 1 depicts the time series behavior of the VKOSPI and the underlying KOSPI 200 stock index while Panel B depicts the VIX and the underlying S&P 500 stock index. A visual comparison of the time series suggests that they may move together. The similarity in the movements of VIX and VKOSPI suggests that they are affected by common global shocks during the sample period, and/or that the Korean and US business cycles are highly correlated. Either way, the apparently high degree of correlation between the time series raises the question of whether the series are endogenously determined.

[Figure 1 here]

**3. Models**

As noted earlier, this paper considers two types of endogeneity associated with a class of Markov-switching regression models. One type allows the regressors to be correlated with the disturbance term, as in Kim (2004). The other type allows endogenous switching, as in Kim, Piger, and Startz (2008). We briefly summarize the models here.

*Model 1: Benchmark Markov-switching model*

The standard Markov-switching model is as follows:

*yt* = *xt*′+ *et, et* ~ *i.i.d.* N(0,). (8)

Here, the error term *et* follows a Normal distribution. *St* is the latent state variable, and and are state-dependent parameters. The subscript *t* denotes day. *yt* is a 1×1 and *xt* is an 1×1 vector of explanatory variables uncorrelated with *et*. In the Markov-switching model, the evolution of the state variable *St* depends on its past values. Here, we consider the simplest case, in which *St* follows a first-order Markov-switching process. Thus, the probability of a transition from regime *i* in period *t*-1 to regime *j* in period *t* is:

*Pij*=*Pr*(*St*=*j*|*St*–1=*i*). (9)

Here, *St* is exogenously determined, and the maximum likelihood estimation of the Markov-switching model is estimated based on the Hamilton filter (Hamilton, 1989).

*Model 2: Endogeneity in the regressor model*

We consider the following Markov-switching regression model in which the explanatory variables are correlated with the disturbance term:

*yt* = *xt*′+ *y2t*′+ *et*, *et* ~ *i.i.d.* N(0,), (10)

*y2t* = (*Ik zt*′)+ *v*2,*t*, *v*2,*t* ~ *i.i.d.* N(0,), (11)

*Cov*(*v*2,*t*,*et*) = = (1 - *St*) + *St*, (12)

*Cov*(x*t*,*et*) = 0 , , (13)

where *y2t* is a *k*×1 vector of regressors correlated with *et* and *zt* is an L×1 vector of instrumental variables uncorrelated with *et* but correlated with *y2t*.

When we estimate this model, the Hamilton filter is invalid in the presence of endogenous variables. To employ the Hamilton filter, we need to transform the model appropriately to correct for the endogeneity bias by introducing a new disturbance term that is not correlated with any of the regressors. Thus, the transformed model is

*y*1*t* = *xt*′+ *y2t*′ + (*y2t* – (*Ik zt*′))′+ *ε*2,*t*. (14)

Here, the explanatory variables are no longer correlated with the disturbance terms, and we can apply the Hamilton filter. The parameters can be estimated by maximizing the quasi-likelihood function. For more details about the estimation procedure of this model, see Kim (2004).

The term (*y2t* – (*Ik zt*′)) is a bias correction term. If the coefficients are jointly significant, then an endogeneity problem exists. If they are not jointly significant, then we can assume no endogeneity in the model. We can test for the existence of endogeneity using the LR test. Defining ln*LU* and ln*LR* as the log likelihood values from unrestricted and restricted maximum likelihood estimations, respectively, the LR test statistic is

LR = 2(ln*LU* – ln*LR*)~ *χ*2(*J*), (15)

where *J* is the dimension of .

*Model 3: Endogenous switching models*

The previous studies using the Markov-switching model typically assume that the regime shifts are exogenous. Kim, Piger, and Startz (2008) develop a Gaussian model of endogenous Markov regime switching based on a probit specification for realization of the latent state. Exogenous regime switching implies that the future states are completely determined by the current state and do not depend on the realizations of underlying time series. This is highly unlikely in many practical applications. Thus, more specifically, we consider, as in Kim, Piger, and Startz (2008),

*y*1*t* = *xt*′ + *εt*, where *εt* ~ *i.i.d.* N(0,1). (16)

Here, *yt* is a 1x1 and *xt* is a *k*×1 vector of exogenous or predetermined variables. The state variable is assumed to evolve according to a first-order Markov chain with transition probabilities:

*Pij*=*Pr*(*St*=*j*|*St*–1=*i, zt*) = *Pij*(*zt*). (17)

The transition probabilities are influenced by a *q*×1 vector of covariance-stationary exogenous or predetermined variables *zt*. We use a probit specification for *St*:

, where *ηt* ~ *i.i.d.* N(0,1). (18)

To model endogenous switching, we assume that the joint density function of *εt* and *ηt* is bivariate normal:

~ *i.i.d.* N(0,Σ), , (19)

where *E*(*εtηt-h*) = 0for all *h ≠*0. We assume that both *yt* and *xt* are covariance-stationary variables. To test for existence of endogeneity, we use the LR statistic[[6]](#footnote-6):

LR = 2(ln*LU* – ln*LR*)~ *χ*2(1), (20)

where ln*LU* is the maximized value of the likelihood function, and ln*LR* is the maximized value of the likelihood function under the restriction that *ρ*=0. If we reject the null hypothesis of *ρ*=0, we conclude that endogeneity exists in the regime switching, and that parameters must be estimated accounting for the endogeneity.

The vast majority of the studies on finance and macroeconomic policy apply the benchmark model (Model 1) to their analysis. However, Kim (2004) and Kim, Piger, and Startz (2008) and our results below show that the cost of ignoring an endogeneity bias can be substantial. Therefore, the endogeneity issue needs to be handled carefully using more advanced Markov-switching models. In addition, Models 2 and 3 can be applied to various topics in finance and macroeconomic policy issues. For example, Model 2 is applied to the estimation of a forward-looking monetary reaction function of the Fed with an unknown break date (Kim, 2004), and Model 3 is applied to the volatility feedback model of equity returns of Turner, Startz, and Nelson (1989) (Kim, Piger, and Startz, 2008).

**4. Sample Data**

We analyze the daily VKOSPI index data from March 29, 2004 to December 30, 2013. The explanatory variables we consider are the KOSPI200 spot return as a domestic financial variable and the KRW/USD exchange rate, risk-free CD91 interest rate, term spread (the difference between the yield on a five-year government bond and the three-month CD91 rate), and credit spread (the yield difference between BBB and AA corporate bonds) as domestic macroeconomic variables. To investigate the interdependencies of the US volatility index with the VKOSPI, we consider the VIX and the log return of the S&P 500 spot index.

Some of the variables are shown to be nonstationary. To generate stationary series, we transform the original data in the following ways: VKOSPI: level; KOSPI200: log return; Exchange rate: log return; CD91: level; Term spread: level; Credit spread: difference; VIX: level; and S&P500: log return. To facilitate comparisons among coefficients, we use a standardized series with a zero mean and a standard deviation of one for each explanatory variable. The explanatory variables are all lagged by one to avoid the potential endogeneity problem. The following Table 2 shows the descriptive statistics for the variables used in the paper.

[Table 2 here]

The variables used in each model introduced above are as follows. In all models, VKOSPI is used as the dependent variable. Independent variables commonly included in the regressors are one lagged dependent variable, KOSPI200, four macroeconomic variables, and two US variables. Model 1 runs the usual Markov-switching regression and estimates the state-dependent parameters of the model.

Model 2 assumes that endogenous variables exist in the regressors. In particular, we examine the endogeneity of the US variables in Model 2. US variables at time *t*-1 are included in the regression with the assumption that they are exogenous to VKOSPI at time *t*. However, there is a time lag between the US and Korea, and the US market at time *t*-1 opens after the Korean market at time *t*-1 closes. Thus, if global shocks that affect both the US and Korea occur after the Korean market closes at time *t*-1, those shocks could affect both US variables at time *t*-1 and Korean variables at time *t*. Hence, there could be correlations between US variables at time *t*-1 and Korean variables at time *t*, causing an endogeneity problem in the model. Model 2 tests for the endogeneity of US variables at time *t*-1, and we use US variables at times *t*-2 and *t*-3 as instruments to estimate the parameters of the model.

The test for US variables at time *t*-1 assumes that global shock is short-lived at time *t* in Korean market. However, if global shocks are persistent, i.e., shocks last for a few periods, US variables at time *t*-*k* may be correlated with KOSPI at time *t*. Thus, the correlation structures between US and Korean variables at different time periods need to be carefully examined. Also, the other variables in the model, domestic financial variable and macroeconomic variables, may be also affected by the global shocks and may be correlated with the regression disturbance term. Thus, potential endogeneity of all other variables also need to be carefully examined.

Model 3 investigates whether regime shifting is exogenous or correlated with the regression disturbance terms. In particular, we examine whether US variables in the transition probabilities are involved in the regime-switching process. In the model, regressors and the variables in the transition probabilities are all assumed to be exogenous or predetermined. To guarantee the exogeneity of the regressors, we use the results of Model 2. In the analysis of Model 2, we find the time lags of each variable in the regressors that make the variables exogenous to the model. Hence, we use only exogenous variables in the estimation of Model 3.

**5. Empirical Findings**

As a preliminary step, we estimate the benchmark Markov-switching model. For the number of latent states in the Markov process, we focus on the two-regime model because it is a popular specification in applied works, and our main interest in this paper is to determine the endogeneity of the US factors rather than to calculate the optimal number of states.[[7]](#footnote-7)

Table 3 reports the results of the benchmark Markov-switching regression model.[[8]](#footnote-8) State 1 reports the results of the case with small σ, and state 2 reports the results for large σ. All the variables are appropriately transformed to have covariance-stationary processes, as shown in Table 2, and are lagged by one period. The estimated standard deviations show large differences between the two states. The high-volatility state has a standard deviation about four times as large as that of the low-volatility state. All of the variables except credit spread are significant in at least one state. The coefficients of the variables show large differences between the two states. In particular, VIX shows substantial differences between the low-volatility state and the high-volatility state. In the high-volatility state, VIX shows a larger influence on VKOSPI.

[Table 3 here]

Table 4 reports the results of the Markov-switching regression model with endogenous regressors. The VIX and S&P500 variables are assumed to be endogenous to the disturbance terms. Thus, we use lagged values of the two US variables as instruments, i.e., VIX*t*-2, S&P500*t*-2, VIX*t*-3, and S&P500*t*-3 are used as instrumental variables. The coefficient *γ* indicates the importance of the bias correction terms for each potentially endogenous variable for each state. A statistically significant coefficient *γ* means that the variable of interest is endogenous for that state, and an insignificant coefficient *γ* indicates no bias from endogeneity of the variable of interest for that state. The right panel of Table 4 shows the results when the coefficients *γ* are estimated, and the left panel shows the results when the coefficients *γ* are restricted to zero, ignoring the endogeneity.

[Table 4 here]

The LR test statistic compares the unrestricted likelihood values and restricted likelihood values where all the *γ* coefficients are jointly restricted to zero. If this hypothesis is not rejected, we conclude that the *γ* coefficients are jointly zero, and that there is no endogeneity between the US variables and the disturbance term, and vice versa. The results of the estimated *γ* coefficients show that all *γ* except S&P500 in state 2 are statistically significant. The LR test also shows that *γ* are jointly significant; thus, we conclude that strong endogeneity exists between the US variables and the disturbance term.

When we consider the endogeneity in the US variables, the coefficients of the other variables are not much different. When we compare the coefficients of VIX and S&P500 with and without endogeneity, however, they are quite different. The VIX in the low state is not significant, which is in contrast to the results of the benchmark model. In the high state, VIX is significant in both panels, but the magnitude of the parameter when endogeneity is allowed is about 23% smaller. The S&P500 shows large differences in the low state. The coefficient becomes very large in the low state when endogeneity is allowed. The coefficient of S&P500 in the high state is similar in magnitude with and without endogeneity, but it loses significance when endogeneity is considered. Therefore, the bias from the presence of endogenous variables is substantial, and we should pay more attention to endogenous variables in model construction.

Table 4 assumes that US variables at time *t*-2 and higher lags are exogenous and other explanatory variables are exogenous at time *t*-1 and higher lags. This assumption is valid only if global shock is temporary at time t in Korean market. However, global shocks may be persistent and last for several periods. In this case, the model in Table 4 is mis-specified. Hence, we need to check whether the assumption of exogeneity of regressors is valid for the US variables at time *t*-2 and other variables as well.

[Table 5 here]

Table 5 reports the results of endogeneity test for the variables used in the analysis. We vary the time lags of the variables that are being tested from *t*-1 to *t*-6 with the time lags of the other variables fixed at *t*-1. We use two own lagged variables as instruments. For example, in testing the endogeneity of KOSPI200 at time *t*-2, two own lagged values at *t*-3 and *t*-4 are used as instruments.

Table 5 shows that financial variables and macroeconomic variables display different behaviors. KOSPI and two US variables have high correlations with the regression disturbance term in short lags. Macro variables have none or low correlations with the disturbance term in short lags (exchange rate) and have high correlations in long lags (exchange rate and term spread). Interest rate and credit spread shows no correlations in all the lags we consider in the paper. The source of the shocks in long lags is expected to be a global shock because US variables also show high correlations in long lags.[[9]](#footnote-9) If the source of the shock is domestic, US variables would not be correlated with the disturbance term. This result implies that a global shock is persistent and lasts as long as six periods. Thus, the effects of a global shock do not die out gradually as time goes but they recur at later periods of time. The magnitude of the endogeneity is largest in US variables, followed by domestic financial variables and macro variables. Thus, global shocks affect the volatility index of Korea mainly through the US variables.[[10]](#footnote-10)

[Table 6 here]

Table 6 reports the results of model 3 where endogenous switching is allowed. In particular, we examine how the US variables affect the correlations between the transition probabilities and the disturbance terms. This model assumes that the explanatory variables and the variables in the transition probabilities are all exogenous or predetermined. To select the time lags of each variable that make it exogenous, we use the results of an endogeneity test for individual variables in Table 5. Thus, we select lags of *t*-4 for KOSPI, *t*-1 for the interest rate, credit spread and term spread, *t*-3 for exchange rate, and *t*-5 for S&P 500 and VIX.

The parameter *ρ* measures the correlations between the transition probabilities and the disturbance terms. If *ρ* is statistically significant, we conclude that the regime switching is endogenous. If *ρ* is not statistically different from zero, we have a usual time-varying transition probability Markov-switching regression model. The LR statistic in the last row tests the null hypothesis that the coefficient *ρ* is zero. If this hypothesis is rejected, we conclude that the regime switching is endogenous.

The estimated value of *ρ* is 0.287 and is highly significant at the 5% level. Also, the LR statistic shows that the null hypothesis of *ρ* = 0 is strongly rejected at the 1% significance level. Hence, we conclude that the regime switching is endogenous, and that the US variables affect the transition probabilities of the VKOSPI. In other words, this result implies that the movements of the US variables affect the states of the VKOSPI variable, which seems obvious from the existence of large trade volumes and strong financial links between the two countries that could cause common business cycles.

The left panel of Table 6 shows the results when endogenous switching is not allowed, i.e., when *ρ* is restricted to zero, and the right panel shows the results when endogenous switching is allowed. Note that the explanatory variables in this model are all exogenous following the results of Table 5. However, the coefficients in both sides are still different with some variables having different magnitude (VKOSPI, interest rate, credit spread and VIX) or other variables losing significances (KOSPI, term spread and VIX). Thus, endogeneity bias still exists even when we control for the endogeneity in the regressors.[[11]](#footnote-11) Therefore, it is important to consider potential endogeneity in regime-switching when modeling Markov-switching regression model. Moreover, the regression standard errors, , are also slightly biased downward as illustrated in Kim et al. (2008, p.268).

In conclusion, the results of Models 2 and 3 show that estimation bias is serious when endogeneity is ignored; thus, endogeneity needs to be carefully handled when analyzing the VKOSPI dynamics using the Markov-switching regression model.

We assert that the US variables are correlated with the regression disturbance term due to global shocks. Consequently, we expect that the endogeneity between VKOSPI and the US variables may be largest around the worst period of the Global Financial Crisis in 2008. To test this hypothesis, we divide the sample period into three sub-periods. Thus, Period 2 covers the period of the subprime mortgage crisis, from August 2007 (BNP Paribas halts redemptions on three investment funds) to June 2009 (recession in the United States ends). Period 1 covers the sample before the crisis, and Period 3 covers the sample after the crisis. Table 7 reports the results of endogeneity tests for three sub-periods. Unrestricted LL is the log-likelihood (LL) value when the endogeneity parameters are estimated and Restricted LL is the LL value when the endogeneity parameters are restricted to zero. The LR statistic compares the two LL values and tests the hypothesis that the difference of the two LL values is zero.

[Table 7 here]

The upper panel of Table 7 shows the test results for Model 2, which considers endogeneity in the regressors. For Period 1, the null hypothesis is rejected at the 5% significance level; for Periods 2 and 3, the null hypothesis is rejected at the 1% significance level. The LR test statistic is highest for Period 2, when the Global Financial Crisis occurs and becomes slightly lower in Period 3. Thus, we suggest that global shocks commonly affect both the US and Korean stock markets, and related variables become strongly correlated. In this situation, properly modeling the endogeneity in the regressors is important to prevent endogeneity bias.

The results for Model 3 indicate that endogenous switching is strong only in Period 2 when the Global Financial Crisis occurs and the LR statistic is insignificant in Periods 1 and 3. Thus, although we have weaker evidence of endogenous switching, the results show that the US variables strongly affect the states of the Korean stock market especially during the Global Financial Crisis period.

Note that the types of endogeneity assumed in Models 2 and 3 are different. Model 2 postulates that the US variables are correlated with the regression disturbance terms for some states. Thus, during the Global Financial Crisis, US and Korean stock market variables share common effects from the shocks. Model 3 postulates that the US variables affect the regime-switching probabilities of VKOSPI and illustrate how the movements of the US stock market correlate with the movements of the Korean stock market. The results in Table 7 show that the synchronization between the two markets is highest during the Global Financial Crisis and it is weak in normal times.

**6. Conclusion**

This paper examines the effects of endogeneity of the US volatility indices on the VKOSPI dynamics using Markov-switching regression models. Two types of endogeneity are considered: One model assumes that the US variables in the regressors are correlated with the regression disturbance term. This model explores how global shocks affect the correlations between US and Korean stock market variables. The other model assumes that regime-switching probabilities are correlated with the regression disturbance terms. This model explores how the regime-shifting patterns of the US and Korean stock markets are correlated. We also provide test results for endogeneity using the LR statistic.

The estimation results show that the US variables have both types of endogeneity problems. The parameters for endogeneity are statistically significant, and the LR tests strongly reject the null hypothesis of no endogeneity. Because endogeneity is present, the parameter estimates for the US variables when endogeneity is allowed are quite different from those when endogeneity is ignored. This means that endogeneity bias in the parameter estimates is substantial. Therefore, the previous studies that ignore endogeneity issue could suffer from serious endogeneity bias. Therefore, endogeneity must be carefully considered in future research. Our sub-period results show that endogeneity in the regressors is very strong during the Global Financial Crisis, which implies that global shocks commonly affect both the US and Korean stock markets. In addition, endogeneity through regime-shifting probabilities also shows the high correlations between the US and Korean markets due to global shocks, which implies that the co-movements of the US and Korean stock markets are high during the GFC.

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**Figure 1. Time trends of VKOSPI and VIX**

*Note:* This figure shows the time trends of the Korean implied volatility index (VKOSPI) and the US implied volatility index (VIX) from March 29, 2004 to December 30, 2013. Panel A shows the time series of VKOSPI (solid line) and KOSPI 200 (dotted line). Panel B shows the time series of VIX (solid line) and S&P 500 (dotted line). We refer to the websites of the Korea Exchange (www.krx.co.kr) and CBOE.

Panel A. Time-series of KOSPI 200 and VKOSPI

Panel B. Time-series of S&P 500 and VIX

**Table 1. Trading Volume by Investor Types**

*Note:* This table categorizes the trading volume trend for KOSPI 200 options during the sample period (2004–2013) according to the following three investor types: domestic individuals (*Individuals*), domestic institutions (*Institutions*), and foreigners (*Foreigners*). Trading volume is presented as the number of options contracts (*No. of contracts*). The *Percent* columns indicate the proportion of the trading volume attributable to each investor type in percentage values. Source: Korea Exchange (www.krx.co.kr).

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Individuals | | Institutions | | Foreigners | |
| Year | No. of contracts | Percent | No. of contracts | Percent | No. of contracts | Percent |
| 2004 | 2,518,055,127 | 49.9% | 1,923,553,686 | 38.1% | 601,505,735 | 11.9% |
| 2005 | 2,172,436,231 | 42.8% | 2,168,324,054 | 42.8% | 729,643,101 | 14.4% |
| 2006 | 1,806,619,467 | 37.4% | 2,257,968,033 | 46.8% | 764,258,410 | 15.8% |
| 2007 | 1,997,894,273 | 36.9% | 2,326,813,984 | 42.9% | 1,094,979,897 | 20.2% |
| 2008 | 1,986,468,165 | 35.9% | 2,022,267,136 | 36.5% | 1,524,213,507 | 27.5% |
| 2009 | 2,031,590,461 | 34.8% | 1,943,958,904 | 33.3% | 1,866,431,945 | 31.9% |
| 2010 | 2,289,980,791 | 32.5% | 2,472,791,217 | 35.1% | 2,289,025,116 | 32.5% |
| 2011 | 2,344,518,997 | 31.9% | 2,179,651,714 | 29.7% | 2,819,153,811 | 38.4% |
| 2012 | 878,716,432 | 27.9% | 910,873,669 | 28.9% | 1,361,198,397 | 43.2% |
| 2013 | 343,069,921 | 29.6% | 281,274,986 | 24.2% | 536,575,821 | 46.2% |
| Total | 18,369,349,865 | 36.4% | 18,487,477,383 | 36.6% | 13,586,985,740 | 26.9% |

**Table 2. Descriptive Statistics**

*Note:* To generate stationary series, the data used in this study are transformed from the original data in the following way: VKOSPI: level; KOSPI200: log return; Exchange rate: log return; CD: level; Term spread: level; credit spread: difference; VIX: level; S&P500: log return. In the analysis, all of the variables are standardized to have a zero mean and standard deviation of one. ADF stands for Augmented Dickey-Fuller unit root test; the Dickey-Fuller generalized least squares (DF-GLS) unit root test is a more powerful unit root test, suggested in Elliott, Rothenberg, and Stock (1996).

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Variable | Mean | Min | Max | S.D. | Skew | Kurt | ADF | DF-GLS |
| VKOSPI | 23.727 | 12.600 | 89.300 | 9.634 | 2.564 | 12.170 | -3.014b | -3.009a |
| KOSPI200 | 0.035 | -10.903 | 11.540 | 1.483 | -0.434 | 8.896 | -48.658a | -2.517b |
| Exchange rate | -0.004 | -13.243 | 10.229 | 0.796 | -0.749 | 52.035 | -30.456a | -30.090a |
| CD | 3.718 | 2.410 | 6.180 | 1.006 | 0.606 | 2.229 | -1.796 | -1.730c |
| Term spread | 0.619 | -1.480 | 2.590 | 0.767 | 0.719 | 2.675 | -2.123 | -1.916c |
| Credit spread | 0.001 | -0.050 | 0.160 | 0.012 | 4.070 | 41.289 | -6.926a | -6.912a |
| VIX | 20.251 | 9.890 | 80.860 | 10.033 | 2.297 | 9.751 | -3.084b | -2.977a |
| S&P500 | 0.021 | -9.470 | 10.957 | 1.297 | -0.258 | 14.126 | -39.814a | -1.603 |

**Table 3. Estimation Results with No Endogeneity**

*Note:* This table reports the results of the benchmark Markov-switching regression model. State 1 reports the results of the case with small *σ*, and state 2 reports the results for large *σ*. All of the variables are appropriately transformed to have covariance-stationary processes, as shown in Table 2. All of the variables are lagged by one period. Standard errors are in parentheses. \*\*\*: *p* < 0.01, \*\*: *p* < 0.05 and \*: *p* < 0.1.

|  |  |  |
| --- | --- | --- |
|  | State 1 | State 2 |
| VKOSPI | 0.962 (0.006)\*\*\* | 0.768 (0.036)\*\*\* |
| KOSPI | 0.188 (0.027)\*\*\* | 0.316 (0.131)\*\* |
| Interest rate | 0.089 (0.025)\*\*\* | 0.658 (0.211)\*\*\* |
| Credit spread | -0.017 (0.032) | 0.112 (0.168) |
| Exchange Rate | -0.020 (0.029) | 0.226 (0.124)\* |
| Term spread | 0.039 (0.021)\* | -0.024 (0.023) |
| VIX | 0.109 (0.056)\* | 1.736 (0.301)\*\*\* |
| S&P500 | -0.412 (0.025)\*\*\* | -0.689 (0.114)\*\*\* |
| σ | 0.760 (0.015)\*\*\* | 3.375 (0.151)\*\*\* |
| Log-likelihood | -3,501.526 | |

**Table 4. Estimation Results with Endogeneity in Regressors**

*Note:* This table reports the results of the Markov-switching regression model with endogeneity in the regressors. The US variables are assumed to be endogenous to the disturbance terms. Lagged values of the two US variables are used as instruments, i.e., VIX*t*-2, S&P500*t*-2, VIX*t*-3, and S&P500*t*-3 are used as instrumental variables. The likelihood ratio (LR) statistic tests the null hypothesis that all of the *γ* coefficients are jointly zero. If this hypothesis is rejected, we conclude that endogeneity exists between the US variables and the disturbance term. Standard errors are in parentheses. \*\*\*: *p* < 0.01, \*\*: *p* < 0.05 and \*: *p* < 0.1.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Ignoring Endogeneity | | Accounting for Endogeneity | |
|  | State 1 | State 2 | State 1 | State 2 |
| VKOSPI | 0.960 (0.006)\*\*\* | 0.814 (0.031)\*\*\* | 0.961 (0.006)\*\*\* | 0.842 (0.031)\*\*\* |
| KOSPI | 0.176 (0.025)\*\*\* | 0.320 (0.110)\*\*\* | 0.178 (0.035)\*\*\* | 0.394 (0.117)\*\*\* |
| Interest rate | 0.087 (0.026)\*\*\* | 0.544 (0.175)\*\*\* | 0.092 (0.032)\*\*\* | 0.460 (0.118)\*\*\* |
| Credit spread | -0.018 (0.027) | 0.083 (0.149) | -0.027 (0.042) | 0.086 (0.266) |
| Exchange rate | -0.005 (0.006) | 0.195 (0.094)\*\* | -0.003 (0.050) | 0.194 (0.102)\* |
| Term spread | 0.030 (0.025) | -0.041 (0.087) | 0.031 (0.060) | -0.069 (0.045) |
| VIX | 0.072 (0.060) | 1.493 (0.282)\*\*\* | 0.373 (0.251) | 1.157 (0.368)\*\*\* |
| S&P500 | -0.451 (0.032)\*\*\* | -0.546 (0.086)\*\*\* | -2.784 (1.316)\*\* | -0.443 (0.967) |
| *γ*VIX |  |  | 1.210 (0.462)\*\*\* | 2.755 (0.846)\*\*\* |
| γS&P500 |  |  | 2.519 (1.310)\* | 0.290 (1.064) |
| σ | 0.753 (0.015)\*\*\* | 3.087 (0.107)\*\*\* | 0.746 (0.014)\*\*\* | 3.051 (0.105)\*\*\* |
| Log-likelihood | -3,322.986 | | -3,304.158 | |
| LR statistic | 37.655\*\*\* | | | |

**Table 5. Results of Endogeneity Test for Regressors**

*Note:* This table reports the results of endogeneity test for the variables used in the analysis. We vary the time lags of the variables that are being tested from *t*-1 to *t*-6 with the time lags of the other variables fixed at *t*-1. We use two own lagged variables as instruments.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | KOSPI | | | Interest rate | | |
|  | Unrestricted | Restricted | LR statistic | Unrestricted | Restricted | LR statistic |
| t-1 | -8,785.672 | -8,802.178 | 33.011\*\*\* | 2772.727 | 2772.681 | 0.092 |
| t-2 | -8,824.280 | -8,832.366 | 16.171\*\*\* | 2762.490 | 2761.203 | 2.574 |
| t-3 | -8,848.135 | -8,852.685 | 9.101\*\* | 2743.682 | 2743.348 | 0.668 |
| t-4 | -8,852.702 | -8,854.539 | 3.673 | 2738.765 | 2737.927 | 1.676 |
| t-5 | -8,863.560 | -8,865.723 | 4.327 | 2732.230 | 2732.112 | 0.236 |
| t-6 | -8,865.824 | -8,868.902 | 6.156\*\* | 2715.839 | 2715.484 | 0.710 |
|  | | | | | | |
|  | Credit spread | | | Exchange rate | | |
|  | Unrestricted | Restricted | LR statistic | Unrestricted | Restricted | LR statistic |
| t-1 | -8,092.637 | -8,092.645 | 0.018 | -8,369.661 | -8,373.594 | 7.866\*\* |
| t-2 | -8,105.088 | -8,105.791 | 1.405 | -8,378.903 | -8,381.893 | 5.981\* |
| t-3 | -8,104.837 | -8,105.265 | 0.856 | -8,384.953 | -8,386.784 | 3.663 |
| t-4 | -8,117.945 | -8,118.195 | 0.500 | -8,390.129 | -8,390.253 | 0.248 |
| t-5 | -8,123.892 | -8,123.908 | 0.033 | -8,390.317 | -8,393.608 | 6.583\*\* |
| t-6 | -8,135.540 | -8,136.014 | 0.948 | -8,385.742 | -8,392.003 | 12.521\*\*\* |
|  | | | | | | |
|  | Term spread | | | VIX | | |
|  | Unrestricted | Restricted | LR statistic | Unrestricted | Restricted | LR statistic |
| t-1 | -2,582.452 | -2,582.725 | 0.545 | -4,114.556 | -4,134.235 | 39.358\*\*\* |
| t-2 | -2,590.508 | -2,591.430 | 1.844 | -4,148.858 | -4,155.395 | 13.075\*\*\* |
| t-3 | -2,602.929 | -2,603.509 | 1.161 | -4,162.675 | -4,162.771 | 0.192 |
| t-4 | -2,615.022 | -2,618.011 | 5.977\* | -4,168.145 | -4,172.605 | 8.921\*\* |
| t-5 | -2,618.642 | -2,623.072 | 8.861\*\* | -4,194.043 | -4,194.534 | 0.980 |
| t-6 | -2,625.873 | -2,625.882 | 0.019 | -4,204.117 | -4,206.041 | 3.847 |
|  | | | | | | |
|  | S&P 500 | | |  | | |
|  | Unrestricted | Restricted | LR statistic |  |  |  |
| t-1 | -8,575.292 | -8,576.416 | 2.249 |  |  |  |
| t-2 | -8,714.912 | -8,720.846 | 11.869\*\*\* |  |  |  |
| t-3 | -8,717.616 | -8,723.969 | 12.707\*\*\* |  |  |  |
| t-4 | -8,721.638 | -8,725.852 | 8.429\*\* |  |  |  |
| t-5 | -8,729.033 | -8,730.738 | 3.409 |  |  |  |
| t-6 | -8,732.715 | -8,735.369 | 5.309\* |  |  |  |

**Table 6. Estimation Results with Endogenous Switching**

*Note:* This table reports the results when endogenous switching is allowed. In particular, we examine how the US variables affect the correlations between the transition probabilities and disturbance terms. This model assumes that the explanatory variables and the variables in the transition probabilities are all exogenous or predetermined. To select the time lags of each variable that make it exogenous, we use the results of endogeneity test for individual variables in Table 5. Thus, we select lags of *t*-4 for KOSPI, *t*-1 for interest rate, credit spread and term spread, *t*-3 for exchange rate, and *t*-5 for S&P500 and VIX. The parameter *ρ* measures the correlations between the transition probabilities and the disturbance terms. If *ρ* is statistically significant, we conclude that the regime switching is endogenous. The LR statistic tests the null hypothesis that the coefficient *ρ* is zero. If this hypothesis is rejected, we conclude that the regime switching is endogenous. Standard errors are in parentheses. \*\*\*: *p* < 0.01, \*\*: *p* < 0.05 and \*: *p* < 0.1.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Ignoring Endogeneity | | Accounting for Endogeneity | |
|  | State 1 | State 2 | State 1 | State 2 |
| VKOSPI | 0.963 (0.004)\*\*\* | 0.783 (0.034)\*\*\* | 0.964 (0.006)\*\*\* | 0.803 (0.045)\*\*\* |
| KOSPI | 0.068 (0.027)\*\*\* | -0.230 (0.153) | 0.064 (0.027)\*\* | -0.236 (0.168) |
| Interest rate | 0.108 (0.025)\*\*\* | 0.821 (0.213)\*\*\* | 0.109 (0.026)\*\*\* | 0.708 (0.243)\*\*\* |
| Credit spread | -0.016 (0.029) | 0.302 (0.145)\*\* | -0.018 (0.078) | 0.282 (0.214) |
| Exchange rate | -0.040 (0.028) | -0.001 (0.015) | -0.038 (0.030) | 0.012 (0.061) |
| Term spread | 0.059 (0.025)\*\* | 0.018 (0.021) | 0.059 (0.031)\* | -0.026 (0.174) |
| VIX | 0.015 (0.009)\* | 1.365 (0.300)\*\*\* | 0.039 (0.065) | 1.396 (0.310)\*\*\* |
| S&P500 | 0.044 (0.030) | 0.084 (0.136) | 0.040 (0.039) | 0.089 (0.103) |
|  | 0.813 (0.017)\*\*\* | 3.890 (0.171)\*\*\* | 0.820 (0.017)\*\*\* | 3.929 (0.175)\*\*\* |
| *ρ* |  | | 0.287 (0.113)\*\* | |
| Log-likelihood | -3,665.9067 | | -3,662.3895 | |
| LR statistic | 7.0344\*\*\* | | | |

**Table 7. Sub-period Results**

*Note:* This table reports the results of endogeneity tests for sub-periods. We divide the sample period into three sub-periods considering the global financial crisis in 2008. Thus, Period 2 covers the sample period from August 2007 (BNP Paribas halts redemptions on three investment funds) to June 2009 (recession in the United States ends). Period 1 covers the sample before the crisis, and Period 3 covers the sample after the crisis. Unrestricted LL is the log-likelihood (LL) value when the endogeneity parameters are estimated, and Restricted LL is the LL value when the endogeneity parameters are restricted to be zero. The likelihood ratio (LR) test compares the two LL values with the p-values in parentheses.

|  |  |  |  |
| --- | --- | --- | --- |
| Model 2 | Unrestricted LL | Restricted LL | LR statistic |
| Period 1 | -235.100 | -240.019 | 9.8387\*\* |
| Period 2 | -1,405.497 | -1,423.363 | 35.7322\*\*\* |
| Period 3 | -1,179.651 | -1,190.138 | 20.9730\*\*\* |
|  | | | |
| Model 3 | Unrestricted LL | Restricted LL | LR statistic |
| Period 1 | -1,138.517 | -1,139.842 | 2.6494 |
| Period 2 | -967.479 | -970.800 | 6.6435\*\*\* |
| Period 3 | -1,445.001 | -1,445.082 | 0.1630 |

1. Some recent studies, including Corsi (2009), Baba and Sakurai (2011), and Fernandes, Mederios, and Scharth (2014), attempt to analyze these issues in the US financial market. However, very little research has been conducted on emerging markets. Although some studies examine the forecasting performance and applicability of implied volatility indices in emerging markets, such as the Korean market (Ryu, 2012c, Han, Guo, Ryu, and Webb, 2012; Lee B. and Ryu, 2013; Lee C. and Ryu, 2014; Kim and Ryu 2015b), they do not provide any indication of how VKOSPI dynamics are determined in relation to market state variables. [↑](#footnote-ref-1)
2. See Ahn, Kang, and Ryu (2008, 2010), Kim and Ryu (2012), Ryu (2011, 2013a, 2015), and Chung, Park, and Ryu (2016), among others. [↑](#footnote-ref-2)
3. The heavy trading volume of the KOSPI 200 options and futures markets is noted in studies by Guo, Han, and Ryu (2013); Kim and Ryu (2015a); Lee and Ryu (2014); Lee, Kang, and Ryu (2015); and Ryu, Kang, and Suh (2015). [↑](#footnote-ref-3)
4. Previous studies analyzing intraday data from the KOSPI 200 index derivatives market consistently find that domestic individuals are speculative and more easily affected by sentiment and market psychology than are institutional investors, which makes domestic individuals net losers in this market (Ahn, Kang, and Ryu, 2008, 2010; Choe and Eom, 2009; Hwang, Kang, and Ryu, 2010; Ryu, 2012a, 2012b, 2013b, 2015). [↑](#footnote-ref-4)
5. Informed investors tend to split their orders and spread their trades in relatively illiquid markets. The order-splitting strategy is also frequently used in trading environments in which investors are easily identified. This strategy is called stealth trading (Anand and Chakravarty, 2007; Barclay and Warner, 1993; Chae and Lee, 2011; Chakravarty, 2001; Kim and Ryu, 2012; Kyle, 1985; Ryu, 2012b). [↑](#footnote-ref-5)
6. Kim, Piger, and Startz (2008) also suggest the t-statistic to test for the endogeneity but the simulation results show that the likelihood ratio test appears to be a fairly reliable test for endogenous switching. [↑](#footnote-ref-6)
7. Song, Ryu, and Webb (2016) estimate a three-regime Markov-switching model for the same data set. In this paper, however, we estimate two-regime models 1) because we want to focus on the endogeneity issue using more parsimonious models, and 2) because the cost of estimating the three-regime model is huge. Model 2 has 52 estimated parameters with two-regimes, and that number increases to 81 parameters for three-regime models. Thus, it is very difficult to achieve convergence for Model 2 with three regimes. We will investigate the results with three regimes in future research. [↑](#footnote-ref-7)
8. We thank Professor Chang-Jin Kim for sharing his GAUSS codes. [↑](#footnote-ref-8)
9. VIX also has high correlation with the disturbance term at the lag *t*-7 (not shown in the table). [↑](#footnote-ref-9)
10. We do not attempt to identify global shocks in this paper. The identification and analysis of the effects of global shocks requires developing structural economic models, which is beyond the scope of the current paper. [↑](#footnote-ref-10)
11. If the regressors in Model 3 are endogenous, the biases in the estimated coefficients are even more severe. This result is available from the authors upon request. [↑](#footnote-ref-11)