Author Answers [R&R; Revise and Resubmit] for

"Heejoon Han, Ali M. Kutan, and Doojin Ryu (2015). Modeling and Predicting the Market Volatility Index: The Case of VKOSPI. Economics Discussion Papers, No 2015-7, Kiel Institute for the World Economy. http://www.economics-ejournal.org/economics/discussionpapers/2015-7"

We change the title of paper as "Effects of the US stock market return and volatility on the VKOSPI" for the clarity.

Thank you very much for the great comments of two anonymous referees and for your favorable decision (R&R; Revise and Resubmit). We have revised our paper based on the valuable comments.

Comment 1 of the 1st Referee

This paper employs seven versions of HAR models to exam the predictive ability of a set of exogenous variables for implied volatility index that appears very redundant exercise. I can't see the point why the authors need a variety of models which are only different from each other by having different combinations of the same set of variables. There should be a very simple alternative available to deal with the same issue instead. That is, one can firstly include all the considered variables in the model, use the stepwise procedure to remove all the insignificant variables at the second step, and at the end to analyse predictive ability just relying on the final version of the model

Answer 1-1

We have already tested all nested models as you suggested. After deleting insignificant or economically inconsistent coefficients, we confirm that the model "M6" is the most explanatory model. This is the exactly sample logic and process that you suggest. The M6 model performs better than other models in terms of in-sample fitting and it also outperforms the other models in terms of out-of-sample forecasting, which is confirmed by the DMW and SPA tests. We clarify this point in the revised version.

Our models include many macroeconomic variables and domestic and oversea financial variables. Especially, considering that stock market returns between the US and Korean markets are correlated, we tabulate various models which include Korean market variables or US market variables or both. We find that Korea's stock market returns are not able to predict the future VKOSPI after controlling the US market variables and/or Korea's macroeconomic variables. This is an interesting and notable finding that previous studies have overlooked. We emphasize this in the revised version.

One may argue that, to improve the model fitness, we should include an additional domestic variable such as realized volatility. However, adding the realized volatility incurs serious multicollinearity issue because our models already include the lag of VKOSPI, which are strongly related to the realized volatility. The correlation coefficient between the VKOSPI (model-free implied volatility) and realized volatility is higher than 0.9. Both of these two types of volatilities are also highly persistent. We explain this in the revised version.

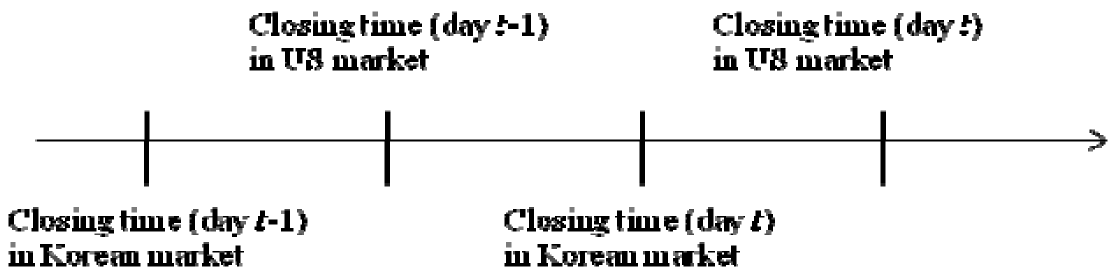
In the revised version, we also emphasize the contribution and motivation of this paper as follows. Though these studies have extended our knowledge on the implied volatility index of the leading emerging market, they do not analyze the statistical properties of the VKOSPI under rigorous and advanced econometric frameworks. Further, they only carry out single market studies, not considering the effects of market linkages and inter-country.

Comment 2 of the 1st Referee

In contrast with the studies in US and other important markets, the authors conclude that the return of stock market does not predict the VKOSPI. This seems a bit counter-intuitive. It is worthwhile to further try stock market realized volatility instead of return to see whether the information from stock market has predictive power on implied volatility index. A simple HAR model may not be appropriate if the two volatilities are highly related. It is interesting to develop a bivariate HAR model with exogenous variables to re-exam the relationship.

Answer 1-2

Based on our model estimation results, the KOSPI 200 spot returns have little predictive power for the VKOSPI after controlling macroeconomic variables and US market performance and shocks. One conjecture is that, considering the market opening hours in the US and Korea, the information from Korean stock market in day *t* is dominated by the information from US stock market in day *t*-1 (US market is open overnight in Korean time.) Related to this, please note that we focus on the leading emerging market where the US market plays a dominant role in its price discovery and information spillover process during the overnight period. This is the first study which analyzes this issue using the dataset of inter-continental markets where the operating hours do not overlap, under the HAR model framework.



Further, we can consistently interpret our results based on the “risk-appetite” explanation

(Our results are not counter-intuitive). The VKOPSI is a fear gauge measure for the leading emerging market. For example, there are many studies on CDS markets, which analyze which factor affects the attitude of investors toward the risk and their fear, among domestic macro-finance variables vs. global market variables most of which are represented by the US market variables. We explain these based on some recent articles of finance literature (Pan and Singleton, 2008; Longstaff et al. 2011) in the revised version. These studies also explain that the risk appetite of investors estimated from CDS markets are not explained by domestic market variables but by global market variables such as VIX. Considering that S&P 500 spot returns and VIX are global market indicators (they are not confined as US domestic indicators), these explanations are quite plausible. We also add this interpretation in the revised version.

Of course, as you suggested, one may consider a bivariate model using the realized volatility measure. However, we are very skeptical for the additional implication that the bivariate model can provide. Further, more importantly, as we explain in our Answer 1-1, adding the realized volatility incurs serious multicollinearity issue. Please note that the correlation coefficient between the VKOSPI (model-free implied volatility) and realized volatility is quite high and both of these two types of volatilities are also highly persistent. Since our models already include the lag of VKOSPI to consider the persistence of the implied volatility process, it is not appropriate to add the lagged realized volatility in our framework. For this reason, it is difficult to develop a bivariate model due to this multicollinearity issue. We fully explain this difficulty in the revised version.

Comment 3 of the 1st Referee

From empirical study perspective, it is not clear to me why the author particularly focused on Korean market. Does this market significantly different from US market which needs either new model development or new empirical analysis? Therefore, it would be better to state the purpose of this study more clearly in Section 2.

Answer 1-3

As we explained in Answers 1-1 and 1-2, we focus on the leading emerging market where the US market plays a dominant role in its price discovery and information spillover process during the overnight period. This is the first study that analyzes this issue using the dataset of inter-continental markets where the operating hours do not overlap, under the HAR model framework. As you suggested, we add more explanation why we focus on the KOSPI 200 options market and the VKOSPI in the Section 2 of our revised version. The ample liquidity, unique investor participation rates, fast growth, and little market frictions are the reasons.

Further, through the analysis, we derive a novel finding that the VKOSPI process is more affected by global market indicators than by domestic market variables. Our findings on the KOSPI

200 options market reflect the characteristics of the Korean market that it is an open and growing economy and the fast growing number of foreign investors actively participate in the Korean market, especially in the KOSPI 200 options market, both of which increase the vulnerability to financial and macroeconomic shocks from overseas markets and fluctuations in global market indicators. This is a meaningful finding. We emphasize our findings and interpret our results in line with the recent finance literature as we explained in Answer 1-2.

Comment 4 of the 1st Referee

The sample period of the data spans from 2004-2013 which undergoes the financial crisis period. It would be interesting to conduct the same analysis using subsample periods, such as pre-crisis and post-crisis periods, and see whether there is a structure break in predictive ability of these variables.

Answer 1-4

As you suggests, we carry out the additional sub-sample analysis considering the recent global financial crisis. Our sample period can be divided into three subsamples, which are pre-crisis period (2004-2006), during-the-crisis period (2007-2009), and post-crisis period (2010-2013). We re-estimate Table 3 (In-sample model fitness) for each sub-period. The results of this additional sub-sample analysis are provided in the new Table 4 (Table 4: Sub-sample analysis results for the in-sample model fitness) of the revised version as follows. As you can see, our overall conclusion remains the same through the sub-sample analysis.

Table 4: Sub-sample analysis results for the in-sample model fitness

Notes: Considering the effects of the global financial crisis, we divided our sample period into three sub-samples, which are the pre-crisis period (2004-2006), during-the-crisis period (2007-2009), and post-crisis period (20010-2013). This table shows the in-sample fitness of the pure HAR model (HAR) and its extended HAR model (HAR-X) with exogenous variables (models M1-M7) for each subsample period. Panels A, B, and C presents the results for the three sub-periods, respectively. y_t^h denotes the average value of the logarithm of VKOSPI over the last h days. Ex_{t-1} is the log return of USD/KRW (US Dollar/Korean Won) exchange rate at time t-1 (positive Ex value means that Korean Won (KRW) appreciates). Rf denotes the 3-month CD rate, which is a proxy for the risk-free rate. *Credit* is the yield difference between BBB and AA corporate bonds. *Term* is calculated as the difference between the yields on the 5-year government bonds and the 3-month CD rates. $ln(VIX)$ is the logarithm of VIX. $Return^{US}$ is the log return of S&P 500 index and $Return^{KOR}$ is the log return of KOSPI 200 index. The table reports the least squares estimates of the coefficients and their t-statistics provided in parentheses are based on heteroskedasticity-consistent standard errors. The last row shows the adjusted R^2 ($Adj.\ R^2$) for each model.

Panel A: Pre-crisis period (2003-2006)

	HAR	M1	M2	M3	M4	M5	M6	M7
y^1_{t-1}	0.911	0.904	0.889	0.850	0.880	0.904	0.845	0.881
	(21.18)	(28.72)	(28.91	(21.11)	(29.08	(27.15	(27.40	(19.85

			)		)	)	)	)
y^5_{t-1}	-0.043			0.082				0.052
	(-0.49)			(2.00)				(1.17)
y^{10}_{t-1}	0.162	0.079	0.076		0.086	0.062	0.102	
	(1.71)	(2.49)	(2.28)		(2.68)	(1.74)	(3.34)	
y^{22}_{t-1}	-0.051							
	(-1.15)							
Ex_{t-1}			0.006	0.003		0.007		0.004
			(1.31)	(0.82)		(1.55)		(1.08)
Rf_{t-1}			0.019		0.017	0.020	-0.001	
			(1.65)		(1.59)	(1.68)	(-0.41)	
$Credit_{t-1}$			0.018		0.017	0.018		
			(1.88)		(1.87)	(1.90)		
$Term_{t-1}$			0.006			0.006		
			(1.52)			(1.43)		
$ln(VIX)_{t-1}$				0.083			0.065	0.084
				(4.59)			(3.60)	(4.62)
$Return^{US}_{t-1}$					-1.782		-1.522	
					(-5.86)		(-4.92)	
$Return^{KOR}_{t-1}$						0.169		0.219
						(0.97)		(1.26)
Adj. R^2	0.948	0.948	0.948	0.949	0.951	0.948	0.952	0.949

Panel B. During-the-crisis period (2007-2009)

	HAR	M1	M2	M3	M4	M5	M6	M7
y^1_{t-1}	0.813	0.876	0.851	0.747	0.863	0.862	0.788	0.763
	(14.38)	(22.73)	(23.26)	(14.11)	(24.21)	(21.87)	(21.66)	(12.71)
y^5_{t-1}	0.106			0.166				0.148
	(0.98)			(3.09)				(2.42)
y^{10}_{t-1}	0.144	0.113	0.133		0.122	0.122	0.106	
	(1.52)	(3.04)	(3.63)		(3.50)	(3.12)	(3.04)	
y^{22}_{t-1}	-0.076							
	(-1.57)							
Ex_{t-1}			0.003	0.004		0.005		0.005
			(1.59)	(1.78)		(1.67)		(1.82)
Rf_{t-1}			0.012		0.012	0.012	0.009	
			(1.74)		(1.67)	(1.75)	(3.98)	
$Credit_{t-1}$			0.009		0.008	0.009		
			(1.29)		(1.39)	(1.28)		
$Term_{t-1}$			-0.003			-0.003		
			(-0.41)			(-0.36)		

ln(*VIX*)$_{t-1}$				0.066			0.082	0.067
				(4.98)			(4.58)	(5.01)
Return$^{US}_{t-1}$					-1.093		-0.906	
					(-5.03)		(-4.34)	
Return$^{KOR}_{t-1}$						0.149		0.134
						(0.77)		(0.66)
Adj. R^2	0.974	0.974	0.974	0.975	0.978	0.974	0.979	0.975

Panel C. Post-crisis period (2010-2013)

	HAR	M1	M2	M3	M4	M5	M6	M7
y^1_{t-1}	0.979	0.913	0.895	0.875	0.893	0.897	0.853	0.887
	(17.47)	(21.71)	(21.81)	(16.94)	(25.28)	(21.64)	(25.24)	(15.41)
y^5_{t-1}	-0.187			0.028				0.015
	(-2.06)			(0.52)				(0.25)
y^{10}_{t-1}	0.222	0.072	0.073		0.079	0.071	0.064	
	(2.28)	(1.74)	(1.73)		(2.23)	(1.65)	(1.79)	
y^{22}_{t-1}	-0.029							
	(-0.57)							
Ex$_{t-1}$			0.005	0.003		0.006		0.004
			(1.73)	(0.83)		(1.41)		(1.00)
Rf$_{t-1}$			0.012		0.010	0.013	0.019	
			(1.57)		(1.94)	(1.56)	(3.26)	
Credit$_{t-1}$			0.016		0.013	0.016		
			(1.11)		(2.15)	(1.07)		
Term$_{t-1}$			0.000			0.000		
			(0.08)			(0.09)		
ln(*VIX*)$_{t-1}$				0.080			0.051	0.080
				(6.47)			(4.55)	(6.46)
Return$^{US}_{t-1}$					-2.385		-2.162	
					(-10.49)		(-9.96)	
Return$^{KOR}_{t-1}$						0.037		0.152
						(0.16)		(0.60)
Adj. R^2	0.956	0.956	0.956	0.958	0.967	0.956	0.967	0.958

Comment 5 of the 1st Referee

With respect to forecasting comparison, the author uses DM test that is useful to make pairwise *comparison. It would be better to use SPA test of Hansen which is more suitable to rank a set of candidate models.*

Answer 1-5

As you suggest, we carry out the SPA tests and report the results in our revised version. The SPA test result confirms that none of other models outperforms our best model (M6). The results are reported in the new Table 8 (Table 8: Tests for superior predictive ability (SPA)).

Comment 1 of the 2nd Referee

By the way, is the dataset cleaner than others? Are those European/American options? What about the dividend yield to estimate?

Answer 2-1

The KOSPI 200 options are European options and one of the most actively traded derivatives. The KOSPI 200 options market has maintained the top-tier position based on its liquidity and trading volume. Until recently, its trading volume is much larger than the trading volume of the US options and that of the Eurozone options. This abundant liquidity makes the KOSPI 200 options market as prominent and "credible". Further, for the research purpose, the Korea Exchange (KRX) provides the "high-quality and clean" dataset on the KOSPI 200 options and its model-free implied volatility index, the VKOSPI. The KRX also provides the adjusted dividend yield for option pricing and valuation. Using this dividend yield, one can exactly calculate the option price and/or the implied volatility. We also obtain the "high-quality dataset" directly from the KRX for the research purpose and carry out the tests. The KRX guarantees that the data are credible and explains how it develops the VKOSPI and constructs the dataset in detail. We explain these in the revised version.

Comment 2 of the 2nd Referee

VKOSPI index is published since April 13, 2009. The index has been recomputed by the authors, in order to extend the sample period from 26 March 2004. As normally the published index undergo many filtering constraints and usually it is computed from intra-daily data, did the author test that their methodology is consistent with the one applied by the Korean Exchange? I suggest to assess the differences between the exchange traded index and their recomputed index from 19 April 2009 on. Moreover the data-set is erroneously recalled in Table 1 (January 2003- Dec 2013), please correct it.

Answer 2-2

As we mentioned in Answer 2-1, the KRX provides us the VKOSPI dataset and its related components. Using the risk-free rate, dividend yield, KOSPI 200 spot and futures indexes, and nearest and second-nearest maturity KOSPI 200 options, one can construct the historical series of the VKOSPI. Actually, our dataset is exactly same to the dataset provided by the KRX. The KRX now announces the historical VKOSPI dataset before its official publication date, and the dataset undergoes the filtering process and rigorous consistent checks. In other words, there is no qualitative difference between the data before April 2009 and the data after April 2009. The KRX guarantees the consistency. About the sample period, it is a typo as you point out. We correct it in the revised version.

Comment 3 of the 2nd Referee

It is not clear if the paper uses non-overlapping time periods (Christensen and Prabhala, 2001), if not a method to correct the errors should be used.

Answer 2-3

It seems that you mention the study of Christensen, Hansen, and Prabhala (2001). They regress the realized volatility on the implied volatility and a measure of past realized volatility (see the equations (7)-(9) in their paper) and develop an alternative asymptotic theory that accounts for both the high degree of overlap and its telescoping nature. However, the model they consider is not relevant to our framework. We do not use realized volatility in any model and therefore such an overlap problem in the model of Christensen et al (2001) is not an issue.

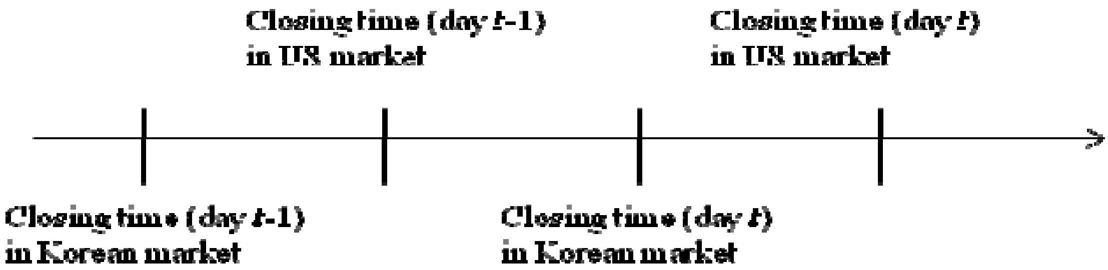
Comment 4 of the 2nd Referee

Another issue is the timing difference between the Korean and the US market (opening and closing times in day t and day t+1), have those differences been taken into account, in order to have a fair treatment of US and Korean factors?

Answer 2-4

Considering the market opening hours in the US and Korea, the information from Korean stock market in day t is dominated by the information from US stock market in day t-1 (US market is open overnight in Korean time.) For this purpose, we match the day t sample of the Korean market and the day t-1 sample of the US market. We exclude the holidays and use the interpolation method to process the dataset.

We focus on the leading emerging market where the US market plays a dominant role in its price discovery and information spillover process during the overnight period. Our analysis is based on the dataset of inter-continental markets where the operating hours do not overlap, as follows. We consider the timing differences as you point out. We add this explanation in the revised version.



Comment 5 of the 2nd Referee

Even if in principle different loss functions can be used and added to the picture, I would stress that the most important results are those based on the MSE function which is considered as robust to the presence of noise in the volatility proxy (Patton 2010).

There is no clear distinction between the "key model" and the "benchmark model", in Table 4 M6 is called the key model, but in the text (eq. 11) when explaining the DMW test, both "key" and "benchmark" models are recalled. I would not call "benchmark model" the other model(s).

Answer 2-5

As you suggest, we will stress the results based on the MSE values. We add the following sentences in the revised paper; "Patton (2011) show that the MSE function is robust to the presence of noise in the volatility proxy while the MAE function is not. Therefore, the results based on MSE function can be more important." We will also use other terms rather than the benchmark model in the revised version.

Comment 6 of the 2nd Referee

The "key" model, model 6, is chosen according to the adjusted R2 (adjusted R2 are pretty high and very similar across models). Based on slight difference the authors conclude that one model is better than the other. No test is conducted in order to see if the difference is significant from a statistical point of view in sample.

Answer 2-6

To reflect your comments, we add new tables of MSE and MAE errors and corresponding DMW test results. Using in-sample fitted values of each model, we calculate MSEs and MAEs and conduct DMW tests. As shown in the new Table 5 (In-sample-fitting evaluation of the HAR-X model (M1-M7)) of the revised paper, the M6 exhibits the smallest losses and the DMW test results show that M6 in general significantly outperforms the rest models. The new Table 5 is as follows.

Table 5: In-sample fitting evaluation of the HAR-X model (M1-M7)

Notes: This table shows in-sample fitting performance of the HAR model (HAR-X) with exogenous variables (models M1-M7). The loss functions used are the mean squared errors (*MSE*) and mean absolute errors (*MAE*). Panel A reports the MSE and MAE of each model. Panel B reports the pair-wise comparison of Diebold-Mariano and West (DMW) tests. *, **, and *** signify rejecting the null hypothesis of equal predictability for 10%, 5%, and 1%, respectively. DMW test statistic is calculated from the distance between M6 (the key model) and the rest models.

Panel A. MSEs and MAEs of HAR-X models

	MSE	*MAE*
M1	0.00271	0.0365
M2	0.00268	0.0365
M3	0.00267	0.0368
M4	0.00231	0.0342
M5	0.00268	0.0365
M6	**0.00229**	**0.0341**
M7	0.00267	0.0367

Panel B. Pair-wise comparison of Diebold-Mariano and West (DMW) tests

		M2	M3	M4	M5	M6	M7
MSE							
	M1	1.53	1.21	3.95***	1.61	4.05***	1.33
	M2		0.42	4.09***	0.68	4.23***	0.60
	M3			4.31***	-0.29	4.52***	0.77
	M4				-4.07	2.22**	-4.29***
	M5					4.20***	0.48
	M6						-4.49***
MAE							
	M1	0.14	-1.28	5.82***	0.65	5.86***	-0.96
	M2		-1.34	6.16***	2.02**	6.25***	-1.03
	M3			6.42***	1.67*	6.83***	1.44
	M4				-5.95***	0.72	-6.27***
	M5					6.04***	-1.41
	M6						-6.65***

Comment 7 of the 2nd Referee

In order to assess which is the best model, I suggest also the methods proposed in Hansen (2005).

Answer 2-7

As you suggest, we carry out the SPA (superiority predictive ability) tests and report the results in our revised version. The SPA test result confirms that none of other models outperforms our best model (M6). The results are reported in the new Table 8 (Table 8: Tests for superior predicative ability (SPA)) of the revised paper. The new Table 8 reports the SPA *p* values for forecasts that are compared to a forecast of M6. The null hypothesis is that none of other models (M1 to M5, and M7) are better than the key model (M6). The *p* value of the SPA test (consistent), SPA_c, is shown in Table 8. The *p* values of lower bound (SPA_l) and upper bound (SPA_u) are also reported. The number of bootstrap replications to calculate the *p*-values is 10,000 and q=0.25 as in Hansen (2005). The new Table 8 is as follows.

Table 8: Tests for superior predictive ability (SPA)

Notes: The table reports the SPA *p* values for forecasts that are compared to a forecast of M6. The null hypothesis is that none of other models (M1 to M5, and M7) are better than the key model (M6). The *p* value of the SPA test (consistent), SPA_c, is in bold type. The *p* values of lower bound (SPA_l) and upper bound (SPA_u) are also reported. We run the 10,000 bootstrap replications to calculate the *p*-values. The dependence parameter q is set to be 0.25.

		Results evaluated by MSE			*Results evaluated by MAE*		
		SPA_l	SPA_c	SPA_u	SPA_l	SPA_c	SPA_u
1-step	SPA *p values*	0.540	**0.955**	0.998	0.218	**0.218**	0.448
5-step	SPA *p values*	0.572	**0.960**	0.996	0.548	**0.943**	0.996
10-step	SPA *p values*	0.545	**0.868**	0.987	0.553	**0.949**	0.998
22-step	SPA *p values*	0.494	**0.576**	0.948	0.520	**0.520**	1.000

Comment 8 of the 2^{nd} Referee

In Table 4, the Diebold and Mariano test is pursued only between the favourite model (M6) and the others, maybe it could have been pursued also between the other couples of models in order to have a more complete picture of the importance of the different variables used (see e.g. Muzzioli, 2013).

Answer 2-8

Considering the study of Muzzioli (2013), we carry out Diebold-Mariano and West (DMW) tests for the pairwise comparison among all models. By following Muzzioli (2013), we report the results in the new Tables 7 (Table 7: Diebold-Mariano and West (DMW) tests: Pair-wise comparison). To carry out the pair-wise comparison among the models (M1-M7), this table reports the DMW test statistics for each couple of forecasts. DMW test statistic is calculated from the distance between M6 (the key model) and the rest models (M1 to M5, and M7). Panels A and B of the new Table 7 show the mean squared errors (MSEs) mean absolute errors (MAEs), respectively. The new Table 7 is as follows.

Table 7: Diebold-Mariano and West (DMW) tests: Pair-wise comparison

Notes: To carry out the pair-wise comparison among the HAR-X models (M1-M7), this table reports DMW test statistics for each couple of forecasts. DMW test statistic is calculated from the distance between M6 (the key model) and the rest models (M1 to M5, and M7). The loss functions used is the mean squared errors (MSEs) and mean absolute errors (MAEs). Panels A and B show the pair-wise comparison results based on MSEs and MAEs, respectively. *, **, and *** signify rejecting the null hypothesis of equal predictability for 10%, 5%, and 1%, respectively.

Panel A. Pair-wise comparison: MSEs

		M2	M3	M4	M5	M6	M7
1 step							
	M1	0.26	0.53	2.69***	0.18	2.90***	0.51
	M2		0.52	2.87***	-0.41	3.08***	0.48
	M3			2.95***	-0.56	3.51***	-0.29
	M4				-2.92***	1.49	-3.03***
	M5					3.12***	0.53
	M6						-3.59***
5 step							
	M1	1.45	0.01	1.52	1.36	2.40**	-0.08
	M2		-1.41	0.90	-1.04	1.55	-1.52
	M3			1.88*	1.30	4.05***	-1.14
	M4				-1.03	1.26	-1.99**
	M5					1.62	-1.43
	M6						-4.25***
10 step							
	M1	1.39	-0.05	1.05	1.41	2.21**	-0.07
	M2		-1.87*	-0.54	0.40	0.74	-1.87*
	M3			1.46	1.92*	3.63***	-0.43
	M4				0.58	1.01	-1.47
	M5					0.71	-1.93*
	M6						-3.62***
22 step							
	M1	1.27	-0.08	0.94	1.24	2.71***	-0.11
	M2		-1.96**	-1.53	-0.04	0.07	-2.06**
	M3			1.44	1.90*	4.83***	-0.32
	M4				1.52	0.53	-1.52
	M5					0.07	-2.01**
	M6						-4.83***

Panel B. Pair-wise comparison: MAEs

		M2	M3	M4	M5	M6	M7
1 step							
	M1	-0.89	-2.89***	4.47***	-0.84	3.34***	-2.95***

	M2		-2.67***	4.99***	0.23	3.62***	-2.71***
	M3			6.35***	2.67***	7.21***	-0.46
	M4				-4.96***	-0.74	-6.37***
	M5					3.59***	-2.73***
	M6						-7.16***
5 step							
	M1	1.69*	-0.88	1.12	1.55	2.72***	-1.11
	M2		-2.23**	-0.64	-1.38	1.16	-2.46**
	M3			1.71*	2.10**	4.63***	-2.72***
	M4				0.39	1.38	-1.91*
	M5					1.28	-2.34**
	M6						-4.92***
10 step							
	M1	0.37	-1.80*	-0.38	0.42	2.17**	-1.76*
	M2		-1.97**	-1.52	0.74	1.40	-1.93*
	M3			1.10	2.03**	4.24***	0.26
	M4				1.59	2.09**	-1.07
	M5					1.34	-1.99**
	M6						-4.17***
22 step							
	M1	0.21	-2.60***	-0.74	0.22	3.17***	-2.66***
	M2		-1.93*	-2.34**	0.24	1.66*	-2.02**
	M3			0.78	1.93*	5.03***	-1.10
	M4				2.38**	2.76***	-0.85
	M5					1.64	-2.02**
	M6						-5.10***

Comment 9 of the 2nd Referee

Recent financial crisis: do the results change before and after the crisis? (the estimation period ends just before the crisis (May 22, 2008))

Answer 2-9

As you suggest, we carry out the subsample analysis considering the recent financial crisis. See the new Table 4 (Table 4: Sub-sample analysis results for the in-sample model fitness). Considering the effects of the global financial crisis, we divide our sample period into three sub-samples, which are the pre-crisis period (2004-2006), during-the-crisis period (2007-2009), and post-crisis period (20010-2013). However, the subsample analysis does not provide the significantly meaningful economic intuition and our overall conclusion remains the same.

Further, we would like to clarify one thing. To obtain the first 1-step ahead out-of-sample forecast, we use the estimation period from the initial date to May 22, 2008. To obtain the second (next) 1-step ahead out-of-sample forecast, we "roll-over" estimation period. So, your comment that "the estimation period ends just before the crisis (May 22, 2008)" is not the case.

Comment 10 of the 2nd Referee

The writing needs improvement. Edit the paper, spell check. Correct the misprints throughout the paper etc...

I would add a Table with the descriptive statistics of all the series under consideration.

Answer 2-10

We revise our paper based on a native speaker's proof-reading. We also add the descriptive statistics table for the series as follows:

Table 2: Descriptive statistics for the logarithm of the VKOSPI index

Notes: This table reports the descriptive statistics of all time-series variables used in this study. The sample period spans from March 26, 2004 to December 30, 2013, which includes 2,430 daily observations. We present the sample mean, median, minimum, maximum, standard deviation, skewness, and kurtosis values of the variables, as well as the *p*-values of Jarque-Bera test for normality and of Augmented Dickey-Fuller (*ADF*) and Phillips-Perron (*PP*) tests for unit roots. We also report the log-periodogram estimates for the memory parameter *d*. *Ex* is the log return of USD/KRW (US Dollar/Korean Won) exchange rate (positive *Ex* value means that Korean Won (KRW) appreciates). *Rf* denotes the 3-month CD rate, which is a proxy for the risk-free rate. *Credit* is the yield difference between BBB and AA corporate bonds. *Term* is calculated as the difference between the yields on the 5-year government bonds and the 3-month CD rates. *ln*(*VIX*) is the logarithm of VIX. $Return^{US}$ is the log return of S&P 500 index and $Return^{KOR}$ is the log return of KOSPI 200 index.

	ln(*VKOSPI*)	*Ex*	*Interest*	*Credit*	*Term*	*ln*(*VIX*)	$Return^{US}$	$Return^{KOR}$
Mean	3.107	-0.004	3.718	4.630	0.619	2.919	0.000	0.000
Median	3.039	-0.027	3.540	5.320	0.400	2.842	0.001	0.001
Maximum	2.534	10.229	6.180	6.300	2.590	4.393	0.110	0.115
Minimum	4.492	-13.243	2.410	2.240	-1.480	2.292	-0.095	-0.109
Std. Dev.	0.323	0.796	1.006	1.353	0.769	0.396	0.013	0.015
Skewness	1.140	-0.749	0.606	-0.352	0.719	0.951	-0.258	-0.434
Kurtosis	4.579	52.035	2.229	1.504	2.675	3.712	14.126	8.896
Jarque-Bera	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ADF	0.044	0.000	0.383	0.809	0.236	0.012	0.000	0.000
PP	0.013	0.000	0.690	0.880	0.218	0.013	0.000	0.000
Estimate of d	0.824	0.015	1.012	0.960	1.003	0.744	-0.074	0.009

Effects of the US stock market return and volatility on the VKOSPI

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Abstract

The KOSPI 200 options are one of the most actively traded derivatives in the world. This paper empirically examines (a) the statistical properties of the Korea's representative implied volatility index (VKOSPI) derived from the KOSPI 200 options and (b) the macroeconomic and financial variables that can predict the implied volatility process of the index, using augmented heterogeneous autoregressive (HAR) models with exogenous covariates. The results suggest that the elaborate HAR framework is proficient at describing the dynamics of the VKOSPI and that some domestic macroeconomic variables explain the VKOSPI. More importantly, we find that the stock market return and implied volatility index of the US market (i.e., the S&P 500 spot return and the VIX from the S&P 500 options) play a key role in predicting the level of the VKOSPI and explaining its dynamics, and their explanatory power dominates that of domestic macro-finance variables. Further, while the domestic stock market return does not predict the VKOSPI, the US stock market return does so rather well. When two global factors, both the US stock market return and the US implied volatility index, are incorporated into the HAR framework, the model exhibits the best performance in terms of both in-sample fitting and out-of-sample forecasting ability.

JEL C22, C50, G14, G15

Keywords Heterogeneous autoregressive (HAR) model, Implied volatility index, KOSPI 200 options, S&P 500, VIX, VKOSPI

1 Introduction

Uncovering the dynamics and processes of market volatilities has been one of the major academic interests in the field of financial economics because of their usefulness for designing trading strategies, quantifying and managing risks, and describing and forecasting economic conditions. Numerous econometric models including the generalized autoregressive conditional heteroskedasticity (GARCH) family models and stochastic volatility models have been developed to measure and predict market volatilities. However, even complicated and advanced econometric models using only historical data when estimating the volatility dynamics convey restricted information and have limited prediction power. Hence, a volatility process based on historical information may not adequately reflect market sentiment and investor expectations regarding future economic fundamentals, which naturally restricts its forecasting ability and trading implications.

An alternative model of volatility dynamics is based on current market prices of tradable financial assets as they contain all available information (assuming market efficiency) and reflect market sentiment and expectations of market participants. The volatilities constructed in this way are named "implied" volatilities; they are not only forward-looking but also have clear advantages over historical volatilities in capturing market conditions and forecasting future states (Blair, Poon, and Taylor, 2001; Giot and Laurent, 2007; Poteshman, 2000; Ryu, 2012).

The implied volatilities are typically derived from option prices. Using popular option pricing models, such as the Black–Scholes–Merton option pricing model, allows us to extract the volatilities of underlying spot returns. However, methods based on a specific option pricing model yield biases, which negatively affect its empirical performance in forecasting future volatilities, quantifying market risk, and managing the risk. Thus, scholars have attempted to develop model-free methods to derive the implied volatilities in order to eliminate the biases and also to increase the efficiency and accuracy of the extracted implied volatilities (Britten-Jones and Neuberger, 2000; Carr and Wu, 2006; Demeterfi, Derman, Kamal, and Zou, 1999; Jiang and Tian, 2007; Taylor, Yadav, and Zhang, 2010). Nowadays, the implied volatility indices of major world exchanges are constructed using model-free methods. The VIX, the most well-known volatility index of the US market, plays a successful role as a market indicator and fear gauge measure. Numerous articles that examine the fitting and forecasting ability of the US' implied volatility index demonstrate its superiority over historical volatilities (Banerjee, Doran, and Peterson, 2007; Becker, Clements, and White, 2007; Carr and Wu, 2006; Corrado and Miller, 2005; Frijns, Tallau, and Tourani-Rad, 2010; Jiang and Tian, 2007; Konstantinidi, Skiadopoulos, and Tzagkaraki, 2008; Simon, 2003). Some studies also investigate implied volatility indices for quantifying market risk and for risk management purposes (Giot, 2005; Kim and Ryu, 2015b). However, a thorough investigation of time-series and statistical properties of implied volatility indices based on advanced econometric approaches is relatively scant. This is a notable weakness in the literature because such an investigation is necessary for examining the statistical mechanics of the implied volatility indices, understanding the properties needed for designing new derivatives underlying these indices (e.g., futures and options on implied volatility indices), developing new risk management models incorporating the implied volatility indices, implementing investment strategies using fear gauge measures, and supporting the use of volatility indices as trading indicators and barometers for market states.

Given the above considerations, our study is inspired by two recent influential studies: Corsi (2009) and Fernandes, Mederios, and Scharth (2014). Corsi (2009) suggests a new way to analyze volatilities based on their persistence and long memory properties, while Fernandes et al. (2014) examine the time-series properties of the VIX using new advances in econometrics and report that the pure heterogeneous autoregressive (HAR) model outperforms the extended HAR models, which incorporate exogenous macro-finance variables in forecasting, particularly short-term ahead forecasting. Extending their studies, we analyze the statistical properties of the VKOSPI, which is the model-free implied volatility index of the South Korean market, under the elaborate HAR model framework. Though some previous studies extend our knowledge about the VKOSPI, the implied volatility index of the South Korean market, which is a leading emerging market, they do not analyze the statistical properties of the VKOSPI, a representative model-free implied volatility index derived from Korea's options market (i.e., the KOSPI 200 options market), under rigorous and advanced econometric frameworks.

In contrast to the relatively extensive research on the implied volatility indices of developed markets, we find that there is scant research on emerging markets, especially the Korean market. This is surprising considering the importance of the Korean financial market as a leading emerging market and the KOSPI 200 options market as a worldwide options market.[1] It is also well known that the

[1] Some recent preliminary studies analyze the VKOSPI. Ryu (2012) introduces a method to construct the VKOSPI and measures its forecasting performance using a basic regression framework. Han, Guo, Ryu, and Webb (2012) and Lee and Ryu (2013) investigate the asymmetric volatility phenomenon using the VKOSPI dataset. Lee and Ryu (2014a) and Kim and Ryu (2015b) examine the applicability of the VKOSPI toward constructing investment strategies and in the value-at-risk framework, respectively. Lee and Ryu (2014b) examine the lead–lag relationship between the VKOSPI and its domestic stock market index (KOSPI 200) using a two-regime threshold vector error correction model. Though these studies make a common important contribution in that they analyze the implied volatility index of the Korean market, they do not consider the statistical properties of the VKOSPI under rigorous and advanced econometric frameworks. Further, they only conduct single market studies and ignore the interaction between domestic and global market indicators.

latter is one of the most liquid and influential derivatives markets in the world (Ahn, Kang, and Ryu, 2008, 2010; Guo, Han, and Ryu, 2013; Ryu, Kang, and Suh, 2015).

Another motivation of this study is some weakness of Corsi (2009) and Fernandes et al. (2014). To mitigate endogeneity problems and measure the forecasting performance of the models, we modify the HAR model framework used in their studies. Further, considering that the previous studies only refer to single markets and do not analyze the effects of market linkages and intercountry spillovers, we examine which factors–domestic versus international–might be more important in describing the time-series properties and dynamics of the VKOSPI. In particular, we examine whether the US stock market return and implied volatility (i.e., the S&P 500 spot return and the VIX from S&P 500 options), which can be regarded as significant global market indicators, explain the dynamics of the VKOSPI, and whether they can help predict future VKOSPI levels after controlling for movements in domestic macro-finance variables.

Our empirical results show that the dynamics of the VKOSPI are well described by our modified HAR framework. However, unlike the findings of Fernandes et al. (2014) for the US market, we find that incorporating domestic macroeconomic variables into the HAR model framework improves both in-sample fitting and out-of-sample forecasting performance. More importantly, we find that the S&P 500 spot returns and VIX of the US market play a dominant role in explaining the VKOSPI dynamics and predicting its future volatility. In addition, while US stock market returns significantly improve predictions about the VKOSPI, Korea's stock market returns are unable to do so. These findings imply that there are significant information flows from the US market to the Korean market and/or the risk appetites of domestic investors are significantly affected by global market indicators, represented by the S&P 500 returns and VIX. Surprisingly, the shocks from US spot returns and implied volatility eliminate most of the explanatory power of Korea's macro-finance variables, except the risk-free rate. The adjusted R^2 values, forecast error values such as the mean squared errors (MSEs) and mean absolute errors (MAEs), and results of the Diebold-Mariano and West (DMW) test and Hansen's (2005) superior predictive ability (SPA) test indicate that the extended HAR model incorporating both the US stock market return and the US VIX as exogenous variables yields the best in-sample fitting and out-of-sample forecasting performance among the models suggested in this study. Overall, our findings reflect the characteristics of the Korean market, especially the KOSPI 200 options market; it is an open and growing economy with a fast-growing number of active foreign investors, both of which increase its vulnerability to financial and macroeconomic shocks from overseas markets and fluctuations in global market indicators. Hence, our results have significant implications for policymakers and investors regarding the influence of global shocks on domestic financial markets and real sector stability.

The rest of this study is organized as follows. Section 2 introduces the KOSPI 200 options market and evaluates the importance of Korea's options market and its implied volatility index, the VKOSPI. The sample data are briefly explained in Section 3. Section 4 introduces the econometric models and estimation procedures used in the study. Section 5 provides the empirical findings and discusses them. Section 6 concludes the paper.

2 The KOSPI 200 Options Market and the VKOSPI

Launched in 1997, the KOSPI 200 options become the representative index derivatives product of the Korea Exchange (KRX). The KOSPI 200 options market, which determines the activity and trading behavior of the VKOSPI level, is classified as a purely order-driven market that operates without the intermediation of designated market makers. All orders submitted by option traders are transacted through the centralized electronic limit order book (CLOB) based on the price and time priority rules. The CLOB is transparent in that it shows the current market liquidity (i.e., bid/ask spread and market depth), but it guarantees the anonymity of investors submitting orders.[2]

In spite of its relatively short history compared to other major derivatives markets in the world, the KOSPI 200 options market has grown very fast and has maintained the top tier position among the worldwide derivatives markets based on its trading volume and influence. Until recently, the KOSPI 200 options trading volume was ranked number one among global derivatives markets, reflecting its extremely high liquidity and global importance. This active transaction of the options market results in little market friction, fewer trading costs, and little temporal illiquidity, all of which yield reliable estimation results from the options sample.

Another interesting feature of the KOSPI 200 options market is the active participation of individual investors, which contrasts with developed derivatives markets where the dominant market players are institutional investors. Though the relative proportion of individual investors has decreased over time on account of the increased proportion of foreign investors, individual trades still explain a substantial portion of total trading in the options market. Table 1 shows trading volumes in the KOSPI 200 options market by three investor types: domestic individuals, domestic institutions, and foreigners. Though the relative proportion of trading volume by domestic individual investors has declined over time, it still explains more than one-third of the total trading volume during our sample period. The

[2] The microstructure of the KOSPI 200 options market is well documented in Ahn, Kang, and Ryu (2008, 2010), Chae and Lee (2011), Eom and Hahn (2005), Kim and Ryu (2012), and Ryu (2011, 2015).

significant proportion of individual investors in the KOSPI 200 options market indicates that the market is quite speculative and oriented towards more short-term profit-seeking, which may be attributed to its fast information flow because of the fierce competition among market participants. Meanwhile, the continuous increase in the proportion of foreign participants in the KOSPI 200 options market reflects the openness and gradual matureness of the Korean market, which makes the options market more vulnerable to global market shocks.

[Table 1 here]

The unique features of the KOSPI 200 options market motivate us to examine the statistical properties of the VKOSPI derived from the option prices. The active participation of individual investors implies that the dynamics of option prices and the derived implied volatility are more likely to be affected by market sentiment and behavioral factors, underscoring the importance of the VKOSPI as a fear gauge measure. The market openness of the KOSPI 200 options market and the heightened interest of foreign investors in this options market increase the possibility that the dynamics of the VKOSPI is heavily dependent on global financial shocks and global market indicators. Considering that US financial institutions comprise the majority of foreign investors in the Korean financial market, it is important to consider the potential influence of US market shocks and/or volatilities to better understand the dynamics of the VKOSPI.

Given the huge success of the KOSPI 200 options market, the KRX decided to constitute Korea's model-free implied volatility index, the VKOSPI, in April 2009. The VKOSPI presents the volatility of the one-month-ahead KOSPI 200 underlying spot index. The VKOSPI level is determined by the expectations and sentiments of investors in the stock and options markets, and thus, it reflects the fears and expectations of the market participants. Based on the "fair variance swap" approach (Britten-Jones and Neuberger, 2000; Jiang and Tian, 2007), the VKOSPI value is calculated using the market prices of the nearest maturity and second nearest maturity KOSPI 200 options.[3]

The VKOSPI value is directly affected by the KOSPI 200 options prices, which reflect market sentiments, investor fear, and prevalent speculative trading motives. As we explained, the KOSPI 200 options product is the representative index derivatives asset, and its price dynamics critically depend

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[3] This approach is similarly used to calculate the model-free VIX of the US market. For the mathematical equations used to construct the VKOSPI and the detailed derivation of the model-free implied volatility index, refer to Ryu (2012) among others. The KRX now announces the historical VKOSPI dataset before its official publication date, and it undergoes the filtering process and rigorous consistency checks.

on macroeconomic shocks, market-wide information, and overseas market news. Therefore, the VKOSPI can be sensitive to changes in the expectations and sentiment of market participants and may immediately reflect public news and overseas shocks, which, once again, necessitates the consideration of US market shocks when examining its dynamics.

3 Data and Sample Period

Although the VKOSPI has been published since April 13, 2009, a historical implied volatility index series can be constructed in the same manner as the VKOSPI. A volatility index series constructed using option prices before the publication of the VKOSPI would also be model-free and would reflect the fears and sentiments of KOSPI 200 options traders. Since a sufficient number of traded options are needed to calculate volatility index values, we consider only post-2004 data. This is because the number of options classified by strike prices is not sufficient for deriving the VKOSPI, and the second nearest maturity options were infrequently traded until the mid-2000s. Our final sample data covers all daily observations of the VKOSPI, KOSPI 200 spot index, VIX, S&P 500 spot index, and Korea's macroeconomic variables (i.e., USD/KRW exchange rate returns, interest rates, credit spreads, and term spreads) from March 26, 2004 to December 30, 2013. Incidentally, this time frame includes the recent global financial crisis period.[4] Figure 1 plots the spot and implied volatility indices used in this study. Panel A presents the movements of the KOSPI 200 spot index and the VKOSPI, while Panel B presents the movements of the S&P 500 spot index and the VIX. Both implied volatility indices capture the major financial and macroeconomic events resulting in a significant stock market decline. It is notable that at the beginning of the recent global financial crisis, the VIX and VKOSPI are at their highest levels during the sample period.

[Figure 1 here]

Table 2 presents the descriptive statistics of all time-series variables used in our analysis. The table also reports unit root test results and the log–periodogram estimates of the memory parameter. Among the variables, $ln(VKOSPI_t)$ denotes the log transformation of the VKOSPI, wherein the sample distribution exhibits a skewed and fat-tailed distribution compared to the normal distribution (see Figure 2). Both the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests reject the null hypothesis of the unit root at the 5% significance level, which indicates that the $ln(VKOSPI_t)$ series is not a unit root process. Meanwhile, the log–periodogram estimate of memory parameter d is 0.824,

[4] Besides using the US and Korean spot markets data, we also test our models using the dataset on index futures (i.e., the KOSPI 200 and the S&P 500 futures), which are tradable and liquid assets. We obtain qualitatively similar results, which are available upon request.

and its standard error is 0.019 for the $ln(VKOSPI_t)$ series, suggesting that the historical time-series of $ln(VKOSPI_t)$ is characterized by a long memory process. The long memory parameter estimates in Table 2 also indicate that the return series of exchange rate, Korean stock market index, and US stock market index are not persistent while the VIX, interest rate, credit spread, and term spread variables are highly persistent.

[Table 2 here]

[Figure 2 here]

4 Methodological Considerations

4.1 Estimated Models

As the results in Table 2 indicate that the time-series logarithm value $ln(VKOSPI_t)$ is a long memory process and not a unit root process, we adopt the modified versions of the HAR frameworks used in both Corsi (2009) and Fernandes et al. (2014). For RV_t, the realized volatility measure at time t, the pure HAR model is defined as

$$RV_t = \beta_0 + \beta_1 RV_{t-1} + \beta_2 RV^{(w)}_{t-1} + \beta_3 RV^{(m)}_{t-1} + \varepsilon_t,$$
$$\text{where } RV^{(w)}_{t-1} = (1/5)\sum^{5}_{i=1} RV_{t-i} \text{ and } RV^{(m)}_{t-1} = (1/22)\sum^{22}_{i=1} RV_{t-i}. \quad (1)$$

In Equation (1), $RV^{(w)}_t$ and $RV^{(m)}_t$ represent the medium-term weekly (w) realized volatility and long-term monthly (m) realized volatility at time t, respectively. The key motivation for including these heterogeneous components is that agents with different time horizons perceive, react to, and cause different types of volatility components. Corsi (2009) shows that the heterogeneous components have important effects in reproducing the long memory property and that the empirical performance of the HAR model is comparable to the autoregressive fractionally integrated moving average (ARFIMA) model, which is typically adopted to model and forecast long memory time series.

For $y_t = ln(VKOSPI_t)$, the pure HAR model can be written as

$$y_t = X_{t-1}\beta + u_t, \text{ where } X_t = [1\ y_{1,t}\ y_{5,t}\ y_{10,t}\ y_{22,t}] \text{ for } y_{h,t} = \frac{1}{h}\sum_{s=1}^{h} y_{t-s+1}. \quad (2)$$

While Fernandes et al. (2014) also include the quarterly component $y_{66,t}$ for modeling the dynamics of the VIX, we exclude it here because the component is found to be statistically insignificant for modeling the dynamics of the VKOSPI index. This result reflects the dominance of short-term traders and speculative individual investors in the KOSPI 200 options market. By incorporating financial and macroeconomic variables into the HAR framework, the extended HAR-X model may be written as follows:

$$y_t = X_{t-1}\beta + Z_{t-1}\gamma + u_t, \quad (3)$$

where $Z_t = [z_{1t}\ z_{2t}\ \dots\ z_{kt}]$ is a k-dimensional vector of explanatory variables. By including relevant macro-finance variables, Z_t, the HAR-X model is expected to improve both in-sample and out-of-sample performance of the model, assuming that the additional exogenous variables in Equation (3) further contribute to the VKOSPI dynamics.

We consider the following macro-finance variables of the Korean market as exogenous variables: a) the log return of the USD/KRW exchange rate, b) the 3-month/91-day certificate of deposit (CD91) rate, which is a proxy for Korea's risk-free interest rate, c) the yield difference between BBB and AA corporate bonds in Korea, which measures the credit spread, d) the difference between the yields on the 5-year government bond and 3-month CD rates in Korea, which measures the term spread, and e) the log return of the KOSPI 200 index, which captures shocks in the underlying spot market. We also consider some US financial market variables, which are the most influential global market indicators, to investigate the effect of US market shocks and news on the dynamics of the VKOSPI. US market shocks are measured by market returns (i.e., the S&P 500 index) and risk (i.e., the VIX). Unlike the framework in Fernandes et al. (2014), we include lagged regressors, Z_{t-1}, instead of the contemporaneous regressors, Z_t, in the HAR-X model in order to avoid possible endogeneity problems. Besides, including a lag structure is more suitable because one of the main purposes of this paper is to measure the out-of-sample forecasting performance of our models.[5]

4.2 Evaluation Criteria and Forecasting Procedure

To evaluate the predictive power, we use the MSE and MAE loss functions.[6] We calculate the difference in MSE or MAE losses between two models as follows:

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[5] To further improve model fitness, one may suggest an inclusion of additional domestic variables such as realized volatility. However, adding the realized volatility incurs serious multicollinearity issues because our models already include the lag of the VKOSPI, which is strongly related to the realized volatility. The correlation between the VKOSPI (model-free implied volatility) and realized volatility is quite high, and both types of volatilities are also persistent.

[6] Patton (2011) shows that the MSE function is robust to the presence of noise in the volatility proxy while the MAE function is not. Though the results based on the MSE function may be more important, we examine both measures to ascertain the robustness of our results.

$$d_t = L(y_{t,i}, y_t) - L(y_{t,0}, y_t), \tag{4}$$

where $y_{t,i}$ denotes the in-sample or out-of-sample forecast of the competing model, $y_{t,0}$ denotes the in-sample or out-of-sample forecast of the key model, and $L(y_{t,i}, y_t)$ and $L(y_{t,0}, y_t)$ are forecast losses measured based on the MSE and MAE, respectively. If the distance, d_t, is found to be positive, we can conclude that the key model outperforms the competing model in that it has a smaller loss.

The significance of any difference in the loss is tested using the Diebold-Mariano and West (henceforth DMW) test (Diebold-Mariano (1995); West (1996)). The DMW statistics are calculated using the difference in the losses of the two models as follows:

$$DMW_{T_F} = \frac{\sqrt{T_F}\bar{d}_T}{\sqrt{\widehat{avar}(\sqrt{T_F}\bar{d}_T)}}, \tag{5}$$

where d_T denotes the sample mean of d_t, and T_F is the number of forecasts. The operator *avar*(.) calculates the asymptotic variance. The asymptotic variance of the average is computed using a Newey–West variance estimator with the number of lags set to $T_F^{1/3}$. The asymptotic distribution of the test statistic is standard normal.

To obtain out-of-sample forecasts for future $ln(VKOSPI_t)$, we adopt the rolling window forecast procedure with moving windows of four years (1,008 trading days). We obtain one-step ahead out-of-sample forecasts (h = 1) and multi-step ahead out-of-sample forecasts (h = 5, 10, and 22) for all models. The number of forecasts are 1400, 1396, 1391, and 1379, respectively, for h = 1, 5, 10, and 22. The forecast period for the one-step ahead out-of-sample forecast is May 23, 2008 to December 30, 2013. For multi-step ahead forecasting, we adopt a direct forecasting procedure: To compute h-day ahead forecasts, we replace y_t with y_{t+h-1} in the models. This allows us to produce multi-step ahead forecasts without imposing any assumption about future realizations of the explanatory variables.

To evaluate out-of-sample forecasting performance, we also adopt the Superior Predictive Ability (SPA) test suggested by Hansen (2005). The SPA test can be used for comparing the performance of two or more forecasting models. The null hypothesis of the SPA test is that none of the other models significantly outperform the key model. The MSE and MAE loss functions are also used for the SPA test. Following Hansen (2005), we set the number of bootstrap replications to calculate the p-values as 10,000.

5 Empirical Findings

We estimate the pure HAR model and the various versions of the HAR-X model with different exogenous variables. To avoid possible multicollinearity problems, we design the following procedure and choose seven alternative models (models M1-M7) based on the significance of the estimated coefficients. In the first step, we estimate the pure HAR model given by Equation (1) and discard the variables with insignificant coefficients, which yields us Model 1 (M1). The estimation result of the pure HAR model yields that only the biweekly component, $y_{10,t}$, is statistically significant. Therefore, we only add this component to M1. In the second step, we estimate the HAR-X model using four domestic macroeconomic variables, the USD/KRW exchange rate return (*Ex*), interest rate (*Rf*), credit spread yield (*Credit*), and term spread yield (*Term*), and we create Model 2 (M2) by discarding the variables with insignificant coefficients. In the third step, we incorporate each financial variable related to the US or Korean market, namely, the logarithm of the US implied volatility index measured by the VIX ($ln(VIX)$), the US stock market return measured by the S&P 500 spot return ($Return^{US}$), or the Korean stock market return measured by the KOSPI 200 spot return ($Return^{KOR}$), and these variables are added to the model in the second step. By discarding the variables with insignificant coefficients, we obtain Model 3 (M3), Model 4 (M4), and Model 5 (M5). At this stage, only statistically significant terms, namely, $y_{1,t}$, $y_{5,t}$, $y_{10,t}$, $y_{22,t}$, and Korea's macroeconomic variables, are included. In the fourth step, we add both $ln(VIX)$ and $Return^{US}$ to the model from the second step, which gives us Model 6 (M6). In the fifth step, we add both $ln(VIX)$ and $Return^{KOR}$ to the model from the second step, which gives us Model 7 (M7). The joint presence of residual autocorrelation and lagged dependent variable among the regressors induces inconsistent coefficient estimates. Therefore, in each case, we ensure that the residual is not serially correlated by adding lagged dependent variables up to lag k (k = 1, 5, and 10) to the model. Consequently, the following alternative seven models (M1-M7) are estimated to check the robustness of our result.

$$
\begin{aligned}
&\text{M1: } y_t = \beta_0 + \beta_1 y_{1,t\text{-}1} + \beta_2 y_{10,t\text{-}1} + \varepsilon_t \\
&\text{M2: } y_t = \beta_0 + \beta_1 y_{1,t\text{-}1} + \beta_2 y_{10,t\text{-}1} + \gamma_1 Ex_{t\text{-}1} + \gamma_2 Rf_{t\text{-}1} + \gamma_3 Credit_{t\text{-}1} + \gamma_4 Term_{t\text{-}1} + \varepsilon_t \\
&\text{M3: } y_t = \beta_0 + \beta_1 y_{1,t\text{-}1} + \beta_2 y_{5,t\text{-}1} + \gamma_1 Ex_{t\text{-}1} + \gamma_2 ln(VIX_{t\text{-}1}) + \varepsilon_t \\
&\text{M4: } y_t = \beta_0 + \beta_1 y_{1,t\text{-}1} + \beta_2 y_{10,t\text{-}1} + \gamma_1 Rf_{t\text{-}1} + \gamma_2 Credit_{t\text{-}1} + \gamma_3 Return^{US}_{t\text{-}1} + \varepsilon_t \\
&\text{M5: } y_t = \beta_0 + \beta_1 y_{1,t\text{-}1} + \beta_2 y_{10,t\text{-}1} + \gamma_1 Ex_{t\text{-}1} + \gamma_2 Rf_{t\text{-}1} + \gamma_3 Credit_{t\text{-}1} + \gamma_4 Term_{t\text{-}1} + \gamma_5 Return^{KOR}_{t\text{-}1} + \varepsilon_t \\
&\text{M6: } y_t = \beta_0 + \beta_1 y_{1,t\text{-}1} + \beta_2 y_{10,t\text{-}1} + \gamma_1 Rf_{t\text{-}1} + \gamma_2 ln(VIX_{t\text{-}1}) + \gamma_3 Return^{US}_{t\text{-}1} + \varepsilon_t \\
&\text{M7: } y_t = \beta_0 + \beta_1 y_{1,t\text{-}1} + \beta_2 y_{5,t\text{-}1} + \gamma_1 Ex_{t\text{-}1} + \gamma_2 ln(VIX_{t\text{-}1}) + \gamma_3 Return^{KOR}_{t\text{-}1} + \varepsilon_t
\end{aligned} \tag{6}
$$

Table 3 reports the least squares estimates of the model coefficients and their t-statistics based on heteroskedasticity-consistent standard errors. For each model, the adjusted R^2 value is also reported to measure the in-sample fitting performance. For the pure HAR model, the coefficients of the daily and biweekly components, $y_{1,t-1}$ and $y_{10,t-1}$, are significantly estimated at the 1% significance level, while those of the weekly and monthly components, $y_{5,t-1}$ and $y_{22,t-1}$, are insignificant. When we conduct the Wald test, $y_{5,t-1}$ and $y_{22,t-1}$ are also jointly insignificant. If the quarterly component, $y_{66,t-1}$, is included as an explanatory variable, as in Fernandes et al. (2014), $y_{5,t-1}$, $y_{22,t-1}$, and $y_{66,t-1}$ are insignificant at the 5% significance level and also jointly insignificant according to the Wald test. Therefore, we discard the insignificant terms and leave only $y_{1,t-1}$ and $y_{10,t-1}$ in the model denoted by M1. These results are different from those in Fernandes et al. (2014); our results indicate that the estimated coefficient for $y_{66,t-1}$ is significant for the VIX index. This reflects the relatively higher participation of domestic individual investors, who are short-term oriented with speculative motives compared to their institutional counterparts in the KOSPI 200 options market, which reduces the medium- or long-term predictability of the VKOSPI.

[Table 3 here]

When the four domestic macroeconomic variables are added to the model, $y_{5,t-1}$ and $y_{22,t-1}$ are still insignificant while the macroeconomic variables are significant. The estimation result of M2 shows that the appreciation of Korea's currency (KRW) and the increase in the interest rate, credit spread, and term spread are associated with a higher VKOSPI level. In M3, when the US implied volatility index, the VIX, is included among the macroeconomic variables, only the exchange rate return remains significant. The lagged VIX value is positively related to the current VKOSPI value, which is quite plausible considering that the VIX captures market-wide volatility. We find that the US stock market return (the S&P 500 spot return) is significantly and negatively related to the future VKOSPI (see the result for M4), whereas the Korean stock market return is not significantly related to the one-step ahead VKOSPI after controlling the macroeconomic variables (see M5). These results indicate that the KOSPI 200 stock market return is not useful for describing the dynamics of the VKOSPI once the domestic macroeconomic factors and/or overseas market returns are considered.

The finding that the VKOSPI dynamics are not explained by its own underlying stock market return but by the US market return is interesting in that it provides a skeptical view of the previous literature, which carries out a single market analysis to examine the return–volatility relationship. Our finding on the relationship between the VKOSPI and the lagged S&P 500 return is consistent with an asymmetric volatility response, which indicates that the stock market return negatively affects the volatility level (Bekaert and Wu, 2000; Wu, 2001; Han, Guo, Ryu and Webb, 2012; Lee and Ryu, 2013). Based on the adjusted R^2 values and the significance of the estimated coefficients, we can conclude that the HAR-X model incorporating both the US stock market return and the implied volatility exhibits the best in-sample fitting performance and has the most explanatory power of all other macroeconomic variables in describing the VKOSPI dynamics (see M6). On the other hand, the stock market returns lose explanatory power when replaced by the Korean stock market return, and the adjusted R^2 values of the model including the Korean stock market return decreases (see M7). One potential reason for this finding can be linked to the market opening hours for the US and Korea; the information from the Korean stock market on day t is dominated by that from the US stock market on day $t – 1$.[7] Another possible reason is based on the "risk appetite" explanation. Considering that the VKOSPI is a fear gauge measure and that Korea is an open economy, which is sensitive to overseas market shocks, the risk appetite of investors may not be fully explained by domestic market variables but by global market indicators such as the S&P 500 spot return and the VIX (Pan and Singleton, 2008; Longstaff, Pan, Pedersen; and Singleton, 2011).

Considering that the recent global financial crisis is a major global financial event, which is likely to have influenced the VKOSPI dynamics and its relationship with other macro-finance variables, we carry out an additional subsample analysis.[8] We divide our sample period into three subsample periods, which are the precrisis (2004-2006), crisis (2007-2009), and postcrisis (2010-2013) periods. Table 4 shows the in-sample model fitness for each subsample. In M6, the coefficient for the US stock market return is estimated to be significant for all three subsample periods, and its estimates are -1.522, -0.906, and -2.162 for the precrisis, crisis, and postcrisis periods, respectively. Its absolute value is the highest for the postcrisis period, while it is the lowest for the crisis period. Importantly, M6 exhibits the best explanatory power for all subsamples, and our finding that the VKOSPI dynamics are significantly explained by global market shocks remains intact.

[Table 4 here]

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[7] The US market is open overnight in Korean time. We focus on the leading emerging market where the US market plays a dominant role in its price discovery and information spillover process during the overnight period. Our analysis is based on the dataset of intercontinental markets where the operating hours do not overlap. We match the day t sample of the Korean market and the day $t – 1$ sample of the US market. We exclude the holidays and use the interpolation method to process the dataset. For more information on the opening and closing times of the US and Korean markets and a discussion on the effects of these differences in trading hours, refer to Kim and Ryu (2015a), Kim, Ryu, and Seo (2015), and Han, Hwang, and Ryu (2015).

[8] Several recent studies show the negative influence of the recent global financial crisis on Asian and other emerging markets. See, among others, Dungey and Gajurel (2014), Gorea and Radev (2014), and Wan and Jin (2014).

To carry out the robustness check for the in-sample model fitness result, we estimate the MSEs and MAEs for all seven versions of the HAR-X model (M1-M7) and DMW test statistics. Panel A of Table 5 shows the MSE and MAE for each model, and Panel B of Table 5 presents the DMW test results for all possible pairs of the models. Table 5 shows that model M6 exhibits the smallest losses, and the DMW test results show that M6, in general, significantly outperforms the rest of the models. Namely, when we measure the in-sample performance of the models using the MSEs, MAEs, and DMW test statistics, the results remain the same, suggesting that our findings are robust. Therefore, we use M6 as our key/preferred model.

[Table 5 here]

Table 6 reports the out-of-sample forecast results. We report the MSEs and MAEs of the seven versions of the HAR-X model (M1-M7) for one-step and multi-step ahead out-of-sample forecasts (h = 1, 5, 10, and 22). We observe that M6 (the preferred key model) outperforms the rest of the models by exhibiting the lowest MSE and MAE losses in almost all cases. This suggests that M6 is indeed the best fitting model for out-of-sample forecasting as well as in-sample fitting. For one-step ahead forecasting, the DMW test between M6 and each model, except M4, rejects the null hypothesis of equal predictability. This finding implies that M6 produces significantly better one-step ahead out-of-sample forecasts. Notably, M4 has the lowest MAE while the DMW tests between M6 and M4 are insignificant for both MSE and MAE. If we exclude M6, M4 has the lowest MSE value. This implies that the stock return of the US market plays an important role in one-day-ahead out-of-sample forecasting of the VKOSPI. Regarding the multi-step-ahead forecasting, the M6 model has the lowest MSE and MAE losses in all cases, and the DMW test rejects the null hypothesis of equal predictability in some cases. For results regarding the 10-step and 22-step ahead forecasting, the DMW test statistics between M6 and M4, in terms of MAEs, are significant at either the 5% or the 1% level, which implies that M6 produces significantly better forecasts than M4. This indicates that the inclusion of the VIX contributes particularly to improving long-term forecasting of the VKOSPI.

[Table 6 here]

When we compare M6 with M1, M6 provides better out-of-sample forecasts in terms of both MSE and MAE losses and for all forecast horizons. The DMW test between these two models rejects the null hypothesis of equal predictability for all cases at the 5% or 1% significance level. This result is interesting and different from the findings reported in Fernandes et al. (2014). Their findings suggest that the pure HAR model performs well, and it is difficult to surpass the pure HAR model in forecasting the VIX. In their study, for example, the pure HAR model shows the best one-step-ahead forecast results in terms of MSE and MAE losses. In contrast with their results, for the analysis on the VKOSPI, our chosen model, M6, clearly dominates the pure HAR model in our sample for forecasting all horizons.

For the within-sample estimation result, we confirm that Korea's stock market return is still redundant in forecasting future VKOSPI levels when other relevant covariates (the macroeconomic factors or the VIX) are included. The forecast errors (MSEs or MAEs) of M3 and M5 are similar. This is because they produce similar out-of-sample forecasts for all horizons, which implies that Korea's stock market return loses its forecasting ability for the VKOSPI when the macroeconomic factors are included. The forecast errors of M3 and M7 are also similar because each model produces similar forecasts for all horizons. The Korean stock market return does not make any significant contribution to forecasting the VKOSPI.

For the robustness check of our out-of-sample results, we conduct a pair-wise comparison based on the DMW tests for MSE/MAE values (see Table 7) and the SPA tests (Table 8). Following Muzzioli (2013), we undertake a pair-wise comparison among the models (M1-M7). The DMW test statistic is calculated for all possible pairs of the models. Panels A and B of Table 7 show the DMW test results based on the MSE and MAE, respectively. For the one-step-ahead out-of-sample forecasting, M4 outperforms M1-M3, M5, and M7, as does M6. This might be due to the fact that both M4 and M6 include the US stock market returns. However, for multi-step-ahead out-of-sample forecasting, M4 does not perform significantly better than the other models, and M6 still outperforms other models in many cases. This might be due to the inclusion of the (persistent) VIX index variable in M6. Table 8 reports the SPA *p*-values for forecasts compared to a forecast made by M6. The null hypothesis is that none of the other models (M1-M5 and M7) is better than the key model (M6). The *p*-value of the SPA test (consistent), SPA_c, is presented in bold. The *p*-values of the lower bound (SPA_l) and upper bound (SPA_u) are also reported. These *p*-values, reported in Table 8, show that we cannot reject the null hypothesis of the SPA regardless of the type of loss function. This finding implies that no competing model, among those considered, is significantly better than the key model, M6. In sum, Tables 7 and 8 also confirm our findings for out-of-sample results.

[Tables 7 and 8 here]

5 Conclusions

Using the modified HAR framework, we analyze the statistical properties of an emerging market volatility index, namely the VKOSPI. Previous studies focus on advanced markets and do not consider the influence of global market factors in predicting implied market volatility indices in emerging markets. Our empirical results show that that the statistical properties of the VKOSPI are well captured by the HAR framework and that Korea's macroeconomic variables can explain the VKOSPI dynamics. In particular, we find that US stock market return and implied volatility index of the US market play a key role in explaining the dynamics of the VKOSPI and predicting its future levels, and their explanatory power dominates that of domestic macro-finance variables. This underscores the importance of considering global information linkages when analyzing and modeling the implied volatility dynamics of financial variables, especially in emerging markets, which are subject to significant global shocks.

Considering that the VKOSPI reflects market sentiment and the risk perspective of the market's participants, our study, which uncovers the time-series properties of the VKOSPI and explains its dynamics, provides useful trading information for market practitioners. Based on the predicted implied volatility index in this study, investors may implement investment strategies regarding hedging, speculative short-term trading, and broad portfolio management. Our study, which is based on the Korean market and the KOSPI, can be extended to other emerging markets. Our findings may provide a useful yardstick for future researchers to compare and contrast their findings in the markets with those reported here for the Korean market.

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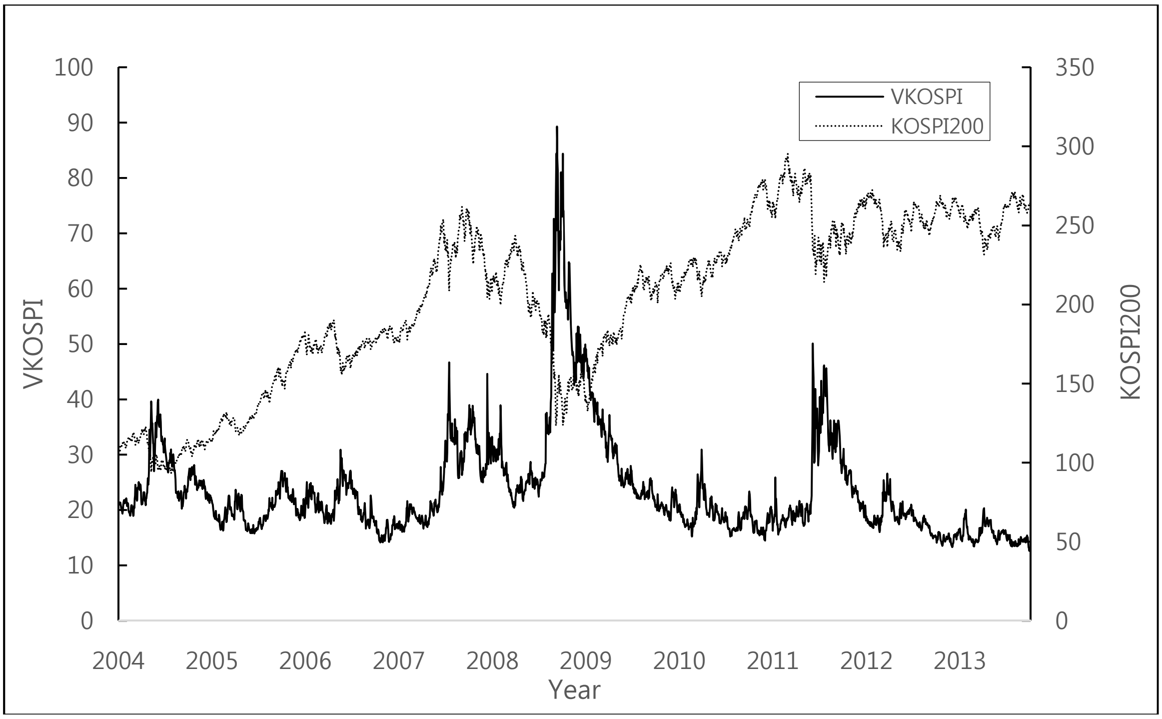
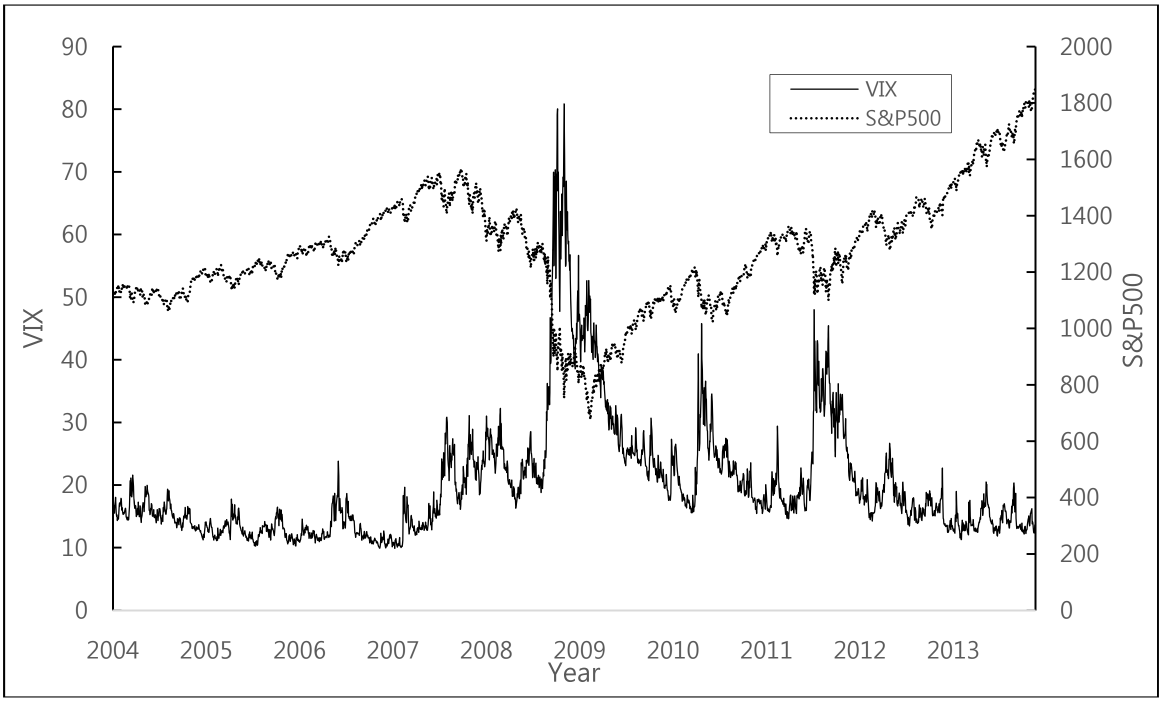
Figure 1: Time trends of stock market returns and implied volatility indices

Panel A. The KOSPI 200 and VKOSPI of the Korean market

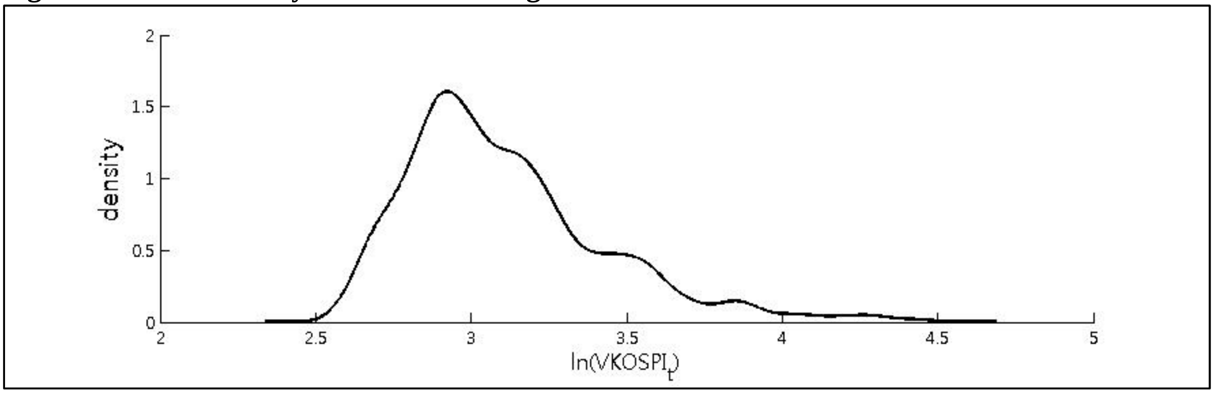


Panel B. The S&P 500 and VIX of the US market



Notes: The two panels in this figure show the time trends of the stock market returns and implied volatility indices for the Korean (Panel A) and US (Panel B) markets. In each panel, the left-hand vertical axis denotes the percentage value of each implied volatility index and the right-hand vertical axis denotes the level of each stock market index.

Figure 2: Kernel density estimate of the logarithm of the VKOSPI



Notes: This figure presents the kernel density estimate of the logarithm of the VKOSPI ($ln(VKOSPI_t)$). The Gaussian kernel function is used to estimate the kernel density.

Table 1: Trading volume by investor types

	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%

Notes: This table presents the trend in trading volumes of the KOSPI 200 options by three investor types, namely, domestic individuals (*Individuals*), domestic institutions (*Institutions*), and foreigners (*Foreigners*), during the sample period 2004-2013. The trading volume is presented in the number of options contracts (*No. of contracts*). Columns titled *Percent* present the proportion of the trading volume of each investor type in percentage values. Source: Korea Exchange (www.krx.co.kr).

Table 2: Descriptive statistics

	ln(*VKOSPI*)	*Ex*	*Interest*	*Rf*	*Term*	*ln*(*VIX*)	$Return^{US}$	$Return^{KOR}$
Mean	3.107	-0.004	3.718	4.630	0.619	2.919	0.000	0.000
Median	3.039	-0.027	3.540	5.320	0.400	2.842	0.001	0.001
Maximum	2.534	10.229	6.180	6.300	2.590	4.393	0.110	0.115
Minimum	4.492	-13.243	2.410	2.240	-1.480	2.292	-0.095	-0.109
Std. Dev.	0.323	0.796	1.006	1.353	0.769	0.396	0.013	0.015
Skewness	1.140	-0.749	0.606	-0.352	0.719	0.951	-0.258	-0.434
Kurtosis	4.579	52.035	2.229	1.504	2.675	3.712	14.126	8.896
Jarque–Bera	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ADF	0.044	0.000	0.383	0.809	0.236	0.012	0.000	0.000
PP	0.013	0.000	0.690	0.880	0.218	0.013	0.000	0.000
Estimates of d	0.824	0.015	1.012	0.960	1.003	0.744	-0.074	0.009

Notes: This table reports the descriptive statistics of all time-series variables used in this study. The sample period spans from March 26, 2004 to December 30, 2013, which includes 2,430 daily observations. We present the sample mean, median, minimum, maximum, standard deviation, skewness, and kurtosis values of the variables, as well as the p-values of the Jarque–Bera test for normality and of the Augmented Dickey–Fuller (*ADF*) and Phillips–Perron (*PP*) tests for unit roots. We also report the log–periodogram estimates for the memory parameter d (*Estimates of d*). *Ex* is the log return of the USD/KRW (US Dollar/Korean Won) exchange rate (a positive *Ex* value means that the Korean Won (KRW) appreciates). *Rf* denotes the 3-month certificate of deposit (CD) rate, which is a proxy for the risk-free rate. *Credit* is the yield difference between BBB and AA corporate bonds. *Term* is calculated as the difference between the yields on the 5-year government bonds and the 3-month CD rates. *ln*(*VIX*) is the logarithm of the VIX. $Return^{US}$ is the log return of the S&P 500 index, and $Return^{KOR}$ is the log return of the KOSPI 200 index.

Table 3: Estimation results of the pure HAR and HAR-X models: In-sample model fitness

	HAR	M1	M2	M3	M4	M5	M6	M7
y^{1}_{t-1}	0.916	0.900	0.885	0.863	0.887	0.893	0.867	0.882
	(27.65)	(37.95)	(38.14)	(27.01)	(41.90)	(36.44)	(41.74)	(24.22)
y^{5}_{t-1}	-0.067			0.101				0.082
	(-1.14)			(3.09)				(2.23)
y^{10}_{t-1}	0.188	0.092	0.099		0.099	0.091	0.094	
	(3.23)	(3.94)	(4.28)		(4.71)	(3.71)	(4.48)	
y^{22}_{t-1}	-0.047							
	(-1.62)							
Ex_{t-1}			0.004	0.004		0.005		0.005
			(2.27)	(2.18)		(2.46)		(2.49)
Rf_{t-1}			0.011		0.007	0.011	0.005	
			(3.63)		(2.53)	(3.63)	(4.01)	
$Credit_{t-1}$			0.005		0.004	0.005		
			(2.29)		(1.81)	(2.30)		
$Term_{t-1}$			0.003			0.003		
			(1.94)			(1.91)		
$ln(VIX_{t-1})$				0.027			0.025	0.027
				(5.66)			(4.74)	(5.71)
$Return^{US}_{t-1}$					-1.507		-1.430	
					(-9.02)		(-8.71)	
$Return^{KOR}_{t-1}$						0.135		0.163
						(1.13)		(1.27)
Adj. R^2	0.974	0.974	0.974	0.975	0.978	0.974	0.978	0.975

Notes: This table shows the in-sample fitness of the pure HAR model (HAR) and its extended HAR model (HAR-X) with exogenous variables (models M1-M7). y_t^h denotes the average value of the logarithm of the VKOSPI over the last h days. Ex_{t-1} is the log return of the USD/KRW (US Dollar/Korean Won) exchange rate at time t–1 (a positive *Ex* value means that the Korean Won (KRW) appreciates). *Rf* denotes the 3-month certificate of deposit (CD) rate, which is a proxy for the risk-free rate. *Credit* is the yield difference between BBB and AA corporate bonds. *Term* is calculated as the difference between the yields on the 5-year government bonds and the 3-month certificate of deposit (CD) rates. *ln*(*VIX*) is the logarithm of the VIX. $Return^{US}$ is the log return of the S&P 500 index, and $Return^{KOR}$ is the log return of the KOSPI 200 index. The table reports the least squares estimates of the coefficients, and their *t*-statistics provided in parentheses are based on heteroskedasticity-consistent standard errors. The last row shows the adjusted R^2 (*Adj.* R^2) for each model.

Table 4: Results of the subsample analysis for in-sample model fitness

Panel A: Precrisis period (2004-2006)

	HAR	M1	M2	M3	M4	M5	M6	M7
y^{1}_{t-1}	0.911	0.904	0.889	0.850	0.880	0.904	0.845	0.881
	(21.18)	(28.72)	(28.91)	(21.11)	(29.08)	(27.15)	(27.40)	(19.85)
y^{5}_{t-1}	-0.043			0.082				0.052
	(-0.49)			(2.00)				(1.17)
y^{10}_{t-1}	0.162	0.079	0.076		0.086	0.062	0.102	
	(1.71)	(2.49)	(2.28)		(2.68)	(1.74)	(3.34)	
y^{22}_{t-1}	-0.051							
	(-1.15)							
Ex_{t-1}			0.006	0.003		0.007		0.004
			(1.31)	(0.82)		(1.55)		(1.08)
Rf_{t-1}			0.019		0.017	0.020	-0.001	
			(1.65)		(1.59)	(1.68)	(-0.41)	
$Credit_{t-1}$			0.018		0.017	0.018		
			(1.88)		(1.87)	(1.90)		
$Term_{t-1}$			0.006			0.006		
			(1.52)			(1.43)		
$ln(VIX_{t-1})$				0.083			0.065	0.084
				(4.59)			(3.60)	(4.62)
$Return^{US}_{t-1}$					-1.782		-1.522	
					(-5.86)		(-4.92)	
$Return^{KOR}_{t-1}$						0.169		0.219
						(0.97)		(1.26)
$Adj.\ R^2$	0.948	0.948	0.948	0.949	0.951	0.948	0.952	0.949

Panel B. Crisis period (2007-2009)

	HAR	M1	M2	M3	M4	M5	M6	M7
y^{1}_{t-1}	0.813	0.876	0.851	0.747	0.863	0.862	0.788	0.763
	(14.38)	(22.73)	(23.26)	(14.11)	(24.21)	(21.87)	(21.66)	(12.71)
y^{5}_{t-1}	0.106			0.166				0.148
	(0.98)			(3.09)				(2.42)
y^{10}_{t-1}	0.144	0.113	0.133		0.122	0.122	0.106	
	(1.52)	(3.04)	(3.63)		(3.50)	(3.12)	(3.04)	
y^{22}_{t-1}	-0.076							
	(-1.57)							
Ex_{t-1}			0.003	0.004		0.005		0.005
			(1.59)	(1.78)		(1.67)		(1.82)
Rf_{t-1}			0.012		0.012	0.012	0.009	
			(1.74)		(1.67)	(1.75)	(3.98)	

	HAR	M1	M2	M3	M4	M5	M6	M7
$Credit_{t-1}$			0.009		0.008	0.009		
			(1.29)		(1.39)	(1.28)		
$Term_{t-1}$			-0.003			-0.003		
			(-0.41)			(-0.36)		
$ln(VIX_{t-1})$				0.066			0.082	0.067
				(4.98)			(4.58)	(5.01)
$Return^{US}{}_{t-1}$					-1.093		-0.906	
					(-5.03)		(-4.34)	
$Return^{KOR}{}_{t-1}$						0.149		0.134
						(0.77)		(0.66)
Adj. R^2	0.974	0.974	0.974	0.975	0.978	0.974	0.979	0.975

Panel C. Postcrisis period (2010-2013)

	HAR	M1	M2	M3	M4	M5	M6	M7
$y^1{}_{t-1}$	0.979	0.913	0.895	0.875	0.893	0.897	0.853	0.887
	(17.47)	(21.71)	(21.81)	(16.94)	(25.28)	(21.64)	(25.24)	(15.41)
$y^5{}_{t-1}$	-0.187			0.028				0.015
	(-2.06)			(0.52)				(0.25)
$y^{10}{}_{t-1}$	0.222	0.072	0.073		0.079	0.071	0.064	
	(2.28)	(1.74)	(1.73)		(2.23)	(1.65)	(1.79)	
$y^{22}{}_{t-1}$	-0.029							
	(-0.57)							
Ex_{t-1}			0.005	0.003		0.006		0.004
			(1.73)	(0.83)		(1.41)		(1.00)
Rf_{t-1}			0.012		0.010	0.013	0.019	
			(1.57)		(1.94)	(1.56)	(3.26)	
$Credit_{t-1}$			0.016		0.013	0.016		
			(1.11)		(2.15)	(1.07)		
$Term_{t-1}$			0.000			0.000		
			(0.08)			(0.09)		
$ln(VIX_{t-1})$				0.080			0.051	0.080
				(6.47)			(4.55)	(6.46)
$Return^{US}{}_{t-1}$					-2.385		-2.162	
					(-10.49)		(-9.96)	
$Return^{KOR}{}_{t-1}$						0.037		0.152
						(0.16)		(0.60)
Adj. R^2	0.956	0.956	0.956	0.958	0.967	0.956	0.967	0.958

Notes: Considering the effects of the global financial crisis, we divide our sample period into three subsamples, namely, the precrisis period (2004-2006), crisis period (2007-2009), and postcrisis period (2010-2013). This table shows the in-sample fitness of the pure HAR model (HAR) and extended HAR model (HAR-X) with exogenous variables (models M1-M7) for each subsample period. Panels A, B, and C present the results for the three subperiods, respectively. y_t^h denotes the average value of the logarithm of the VKOSPI over the last h days. Ex_{t-1} is the log return of the USD/KRW (US Dollar/Korean Won) exchange rate at time t–1 (a positive Ex value means that the Korean Won (KRW) appreciates). Rf denotes the 3-month certificate of deposit (CD) rate, which is a proxy for the risk-free rate. *Credit* is the yield difference between BBB and AA corporate bonds. *Term* is calculated as the difference between the yields on the 5-year government bonds and the 3-month CD rates. $ln(VIX)$ is the logarithm of the VIX. $Return^{US}$ is the log return of the S&P 500 index, and $Return^{KOR}$ is the log return of the KOSPI 200 index. The table reports the least squares estimates of the coefficients, and their t-statistics provided in parentheses are based on heteroskedasticity-consistent standard errors. The last row shows the adjusted R^2 ($Adj.\ R^2$) for each model.

Table 5: In-sample fitting evaluations of the HAR-X models (M1-M7)

Panel A. MSEs and MAEs of the HAR-X models

	MSE	*MAE*
M1	0.00271	0.0365
M2	0.00268	0.0365
M3	0.00267	0.0368
M4	0.00231	0.0342
M5	0.00268	0.0365
M6	**0.00229**	**0.0341**
M7	0.00267	0.0367

Panel B. Pair-wise comparisons of the Diebold-Mariano and West (DMW) tests

		M2	M3	M4	M5	M6	M7
MSE							
	M1	1.53	1.21	3.95***	1.61	4.05***	1.33
	M2		0.42	4.09***	0.68	4.23***	0.60
	M3			4.31***	-0.29	4.52***	0.77
	M4				-4.07	2.22**	-4.29***
	M5					4.20***	0.48
	M6						-4.49***
MAE							
	M1	0.14	-1.28	5.82***	0.65	5.86***	-0.96
	M2		-1.34	6.16***	2.02**	6.25***	-1.03
	M3			6.42***	1.67*	6.83***	1.44
	M4				-5.95***	0.72	-6.27***
	M5					6.04***	-1.41
	M6						-6.65***

Notes: This table shows in-sample fitting performance of the HAR-X model with exogenous variables (models M1-M7). The loss functions used are the mean squared errors (*MSE*) and mean absolute errors (*MAE*). Panel A reports the MSEs and MAEs of each model. Panel B reports the pair-wise comparison of the Diebold-Mariano and West (DMW) tests. *, **, and *** signify rejection of the null hypothesis of equal predictability at 10%, 5%, and 1%, respectively. The DMW test statistic is calculated from the distance between M6 (the key model) and the remaining models.

Table 6: Out-of-sample forecast evaluations of the HAR-X models (M1-M7)

		MSE	*DMW*	*MAE*	*DMW*
1-step					
	M1	0.00285	2.90***	0.0368	3.34***
	M2	0.00284	3.08***	0.0370	3.62***
	M3	0.00281	3.51***	0.0384	7.21***
	M4	0.00240	1.49	0.0343	-0.74
	M5	0.00284	3.12***	0.0370	3.59***
	M6	0.00234		0.0346	
	M7	0.00281	3.59***	0.0384	7.16***
5-step					
	M1	0.01108	2.40**	0.0749	2.72***
	M2	0.01064	1.55	0.0731	1.16
	M3	0.01108	4.05***	0.0761	4.63***
	M4	0.01049	1.26	0.0735	1.38
	M5	0.01067	1.62	0.0733	1.28
	M6	0.01017		0.0718	
	M7	0.01112	4.25***	0.0764	4.92***
10-step					
	M1	0.01749	2.21**	0.0939	2.17**
	M2	0.01625	0.74	0.0932	1.40
	M3	0.01753	3.63***	0.0975	4.24***
	M4	0.01642	1.01	0.0948	2.09**
	M5	0.01623	0.71	0.0930	1.34
	M6	0.01580		0.0904	
	M7	0.01755	3.62***	0.0975	4.17***
22-step					
	M1	0.03646	2.71***	0.1351	3.17***
	M2	0.03129	0.07	0.1339	1.66*
	M3	0.03664	4.83***	0.1438	5.03***
	M4	0.03252	0.53	0.1396	2.76***
	M5	0.03130	0.07	0.1338	1.64
	M6	0.03113		0.1258	
	M7	0.03671	4.83***	0.1442	5.10***

Notes: This table shows the out-of-sample forecasting performance of the HAR models with exogenous variables (HAR-X models, M1-M7). *MSE* and *MAE* denote the mean squared errors and mean absolute errors, respectively. *DMW* presents the Diebold-Mariano and West test statistics, which are calculated from the distance between M6 (the key model) and the remaining models. *, **, and *** signify the rejection of the null hypothesis of equal predictability at 10%, 5%, and 1%, respectively.

Table 7: The Diebold-Mariano and West (DMW) tests: Pair-wise comparisons

Panel A. Pair-wise comparisons: MSEs

		M2	M3	M4	M5	M6	M7
1-step							
	M1	0.26	0.53	2.69***	0.18	2.90***	0.51
	M2		0.52	2.87***	-0.41	3.08***	0.48
	M3			2.95***	-0.56	3.51***	-0.29
	M4				-2.92***	1.49	-3.03***
	M5					3.12***	0.53
	M6						-3.59***
5-step							
	M1	1.45	0.01	1.52	1.36	2.40**	-0.08
	M2		-1.41	0.90	-1.04	1.55	-1.52
	M3			1.88*	1.30	4.05***	-1.14
	M4				-1.03	1.26	-1.99**
	M5					1.62	-1.43
	M6						-4.25***
10-step							
	M1	1.39	-0.05	1.05	1.41	2.21**	-0.07
	M2		-1.87*	-0.54	0.40	0.74	-1.87*
	M3			1.46	1.92*	3.63***	-0.43
	M4				0.58	1.01	-1.47
	M5					0.71	-1.93*
	M6						-3.62***
22-step							
	M1	1.27	-0.08	0.94	1.24	2.71***	-0.11
	M2		-1.96**	-1.53	-0.04	0.07	-2.06**
	M3			1.44	1.90*	4.83***	-0.32
	M4				1.52	0.53	-1.52
	M5					0.07	-2.01**
	M6						-4.83***

Panel B. Pair-wise comparisons: MAEs

		M2	M3	M4	M5	M6	M7
1-step							
	M1	-0.89	-2.89***	4.47***	-0.84	3.34***	-2.95***
	M2		-2.67***	4.99***	0.23	3.62***	-2.71***
	M3			6.35***	2.67***	7.21***	-0.46
	M4				-4.96***	-0.74	-6.37***
	M5					3.59***	-2.73***
	M6						-7.16***

5-step							
	M1	1.69*	-0.88	1.12	1.55	2.72***	-1.11
	M2		-2.23**	-0.64	-1.38	1.16	-2.46**
	M3			1.71*	2.10**	4.63***	-2.72***
	M4				0.39	1.38	-1.91*
	M5					1.28	-2.34**
	M6						-4.92***
10-step							
	M1	0.37	-1.80*	-0.38	0.42	2.17**	-1.76*
	M2		-1.97**	-1.52	0.74	1.40	-1.93*
	M3			1.10	2.03**	4.24***	0.26
	M4				1.59	2.09**	-1.07
	M5					1.34	-1.99**
	M6						-4.17***
22-step							
	M1	0.21	-2.60***	-0.74	0.22	3.17***	-2.66***
	M2		-1.93*	-2.34**	0.24	1.66*	-2.02**
	M3			0.78	1.93*	5.03***	-1.10
	M4				2.38**	2.76***	-0.85
	M5					1.64	-2.02**
	M6						-5.10***

Notes: To carry out the pair-wise comparisons among the HAR-X models (M1-M7), this table reports the DMW test statistics for each pair of forecasts. The DMW test statistic is calculated from the distance between M6 (the key model) and the remaining models (M1 to M5, and M7). The loss functions used are the mean squared errors (MSEs) and mean absolute errors (MAEs). Panels A and B show the pair-wise comparison results based on the MSEs and MAEs, respectively. *, **, and *** signify rejection of the null hypothesis of equal predictability at 10%, 5%, and 1%, respectively.

Table 8: Tests for superior predictive ability (SPA)

		Results evaluated using *MSE*			Results evaluated using *MAE*		
		SPA_l	SPA_c	SPA_u	SPA_l	SPA_c	SPA_u
1-step							
	SPA *p*-values	0.540	**0.955**	0.998	0.218	**0.218**	0.448
5-step							
	SPA *p*-values	0.572	**0.960**	0.996	0.548	**0.943**	0.996
10-step							
	SPA *p*-values	0.545	**0.868**	0.987	0.553	**0.949**	0.998
22-step							
	SPA *p*-values	0.494	**0.576**	0.948	0.520	**0.520**	1.000

Notes: The table reports the *p*-values of the SPA tests for forecasts compared to a forecast by M6. The null hypothesis is that none of the other models (M1 to M5, and M7) are better than the key model (M6). The *p*-value of the SPA test (consistent), SPA_c, is in bold type. The *p*-values of the lower bound (SPA_l) and upper bound (SPA_u) are also reported. We run the 10,000 bootstrap replications to calculate the *p*-values. The dependence parameter, q, is set to 0.25.