Do Global stock market cues matter in forecasting stock returns in developed and developing markets?

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Abstract

Financial markets all over the world have witnessed growing integration within as well as across boundaries, spurred by deregulation, globalization and advances in information technology. However, none of the researches have investigated the trading profitability of models that employed the financial market integration information as input variables especially in the case of day trading. Moreover traditional methods employed linear correlation techniques to study the market integration though it is strongly believed that their relationship could be nonlinear.

This paper examines the usefulness of international stock market price transmission information (global cues) in day trading in developed and emerging stock markets. The study investigates the performance of global stock market cues in forecasting stock prices using Support Vector Regression for seven global markets – US (Dow Jones Industrial Average, S&P500), UK (FTSE -100), India (Nifty), Singapore (Straits Times Index), Hong Kong (Hang Seng Index), China (Shanghai Stock Composite) over the period 1999-2011. The empirical analysis shows that hit ratio of the models with other market cues outperform forecast models based merely on Auto-regressive past lags and technical indicators. Shanghai stock index movement was predicted best by Hang Seng Index opening price with a hit ratio of 57.69, while, Hang Seng Index by previous day's S&P500 closing price (54.34), FTSE by previous day's S&P500 closing price (57.94), Straits Times Index by previous day's Dow Jones closing price (54.44), Nifty by HSI opening price (60), S&P500 by STI closing price (55.31) and DJIA by HSI closing price (55.22) and Nifty was found to be the most predictable stock index. The study provides evidence that stock markets across the globe are integrated and that information on price transmissions across markets can induce arbitrage opportunities even in day trading.

Keywords: *Stock Market Indices, Technical indicators, Global Market Cues, Support Vector Machine, Forecasting.*

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1. Introduction

In a stock trading system, forecasting is the most important activity that helps us to judge the market risk and grab scarce opportunities. However, financial time series are inherently noisy, nonstationary and chaotic (Yaser and Atiya, 1996) considering forecasting financial series as one of the most difficult tasks receiving significant research contribution in the past.

Financial market integration encompasses a complex interplay of various factors such as policy initiatives, structure and growth of financial intermediaries/markets, organic linkages among market participants and the preference of investors for financial instruments. While assessing the integration of financial markets, it would also be useful to know the trading implications of this information. Many factors such as political events, global economic conditions, and market expectations influence financial markets and the interaction of these factors is complex, making financial market prediction even more difficult.

Globally, there is more interest and research on emerging market data due to the rapid growth and potential opportunities for investors. Since the establishment of stock exchanges such as Shanghai Stock Exchange (SSE) and National Stock Exchange (NSE), the financial markets in Asia have attracted considerable global investments. However, the influence of Asian stock markets on other markets is unknown and not empirically examined.

Harvey (1995) had found that emerging market returns are more likely to be influenced by local information than developed markets and emerging market behaviour may be unique. Though emerging market returns are found to be generally more predictable than developed market returns, not much work has been done to evolve models integrating emerging markets.

Most of the financial market integration studies have dealt with correlation testing and theoretical causal analysis (Balios and Xanthakis (2003); Masih, and Masih (1997);Awokuse *et al*. (2009)). However, none of the past studies have tried to exploit their application in real time trading by empirically testing the effectiveness of market cues obtained from these integrated markets. Moreover, most of the previous studies on the financial integration of emerging stock markets have used linear modelling tools (De Santis and Imrohoroglu (1997); Gérard *et al.* (2003); Phylaktis and Ravazzolo (2004); Bekaert *et al*. (2005)) which limits the financial integration dynamics to be linear and continuous and the speed of information transfer to be constant over time.

Though Madaleno and Pinho (2012) show that stock markets are not rapidly transmitting information to other markets, they suggest that the information transmission across markets have a significant time delay, which provides opportunities for arbitrage. Meric *et al* (2012), Masih and Masih (2001), Balios and Xanthakis (2003) examine long run information transmission across markets. Li and Chen (2009) show that the intraday returns of dually listed Chinese stocks are significantly influenced by the transmission of information from New York to Hong Kong. However, there is lack of analysis on instantaneous price transmission of information across markets, which is of utmost importance to speculation and traders. Moreover, there is no evidence on the use of market integration cues in forecasting stock prices or global cues for generating trading signals.

Hence, in this study we demonstrate the possibility of developing robust forecasting models for financial time series using global market cues as indicators by means of advanced predictive modeling tools.

2. Literature Review

With globalization, the global integration of markets has been a popular area for research. Several studies have been done to examine the interlinkage and causal effect of various stock markets. Masih and Masih (2001) examined the dynamic linkage patterns among major international stock price indices (US, UK, Japan, Germany, Hong Kong, Taiwan, Australia, South Korea, Singapore) using VECM and VAR. The sample used comprised monthly averaged stock price indexes from January 1982 to June 1994. They conclude that the linkage between the markets is not mutually exclusive of each other and significant short-run linkages appear to run among them.

McGuire and Martijn (2003) investigated the extent to which spreads on emerging market sovereign debt react to forces that are common across markets. The research found that common forces account for, on average, one third of the total variation in the daily movement of each spread for the emerging market issuers.

Balios and Xanthakis (2003) performed a bivariate and multivariate Granger Causality test for the stock indices of UK, Germany, France, Spain, Italy, the US and Japan on daily data for the period 2 January 1995 to 31 August 2001 to study the short run dynamics of the indices. The US market was found to be the leading indicator in the world and the most influential index in the European Union was the FTSE 100.

Madaleno and Pinho, (2012) analyzed the time-varying pattern of price shock transmission, exploring stock market linkages using continuous time wavelet methodology. The study uses Coherence Morlet test for correlation analysis between the stock market indices (US, UK, JP, Brazil). The results showed that innovations in the US and UK stock markets are not rapidly transmitted to other markets and geographically and economically closer countries exhibit higher levels of market linkages.

Awokuse *et al*. (2009) investigated the interdependence of Asian, Japan, US and UK markets using cointegration technique. The authors found evidence for an increase in international stock market integration as a result of the 1997 Asian Financial crisis. The results indicate that the relations among indices were strong but not homogeneous across. However, local phenomena were felt more in these markets and that there seems to be no quick transmission through markets around the world.

Meric *et al.* (2012) found that the contemporaneous co-movements of Asian stock markets have become closer and portfolio diversification benefits with Asian stock markets have diminished over time during the January 1, 2001-January 1, 2011 period. The study also revealed that the Singapore, Indian, and Japanese stock markets are the most influential stock markets and the Philippine and South Korean stock markets are the least influential stock markets in Asia. The Japanese, Singapore, and New Zealand stock markets are the least affected stock markets and the Shanghai, Australian, and South Korean stock markets are the most affected stock markets by the movements in the other Asian stock markets.

Though evidence of integration of markets have been empirically tested, little attempt has been made to capture the effect of interaction in trading models developed by various authors. Li and Chen (2009) examine the information transmission mechanism between HKSE and NYSE for 7 Chinese stocks which are dually listed in HKSE and NYSE using seemingly unrelated regression. The authors concluded that the intraday returns of the Chinese stocks were influenced by HSI than DJIA and the transmission of price information is from New York to Hong kong. The study also helps in understanding the channel of transmission of information that makes the exchanges dependant on each other.

Tripathi and Shruti (2010) examined the integration of the Indian stock market with the stock market of Japan, UK, US and China over the period 1st January 1998 to 31st October 2008 using Engle - Granger co-integration test and Granger's causality Test. The results showed that the Indian stock market is not integrated with any of these markets except US.

Sharma and Bodla (2010) reviewed the past research on Indian stock market linkages with the global markets. The review showed that exhaustive analysis was done in the past on US stock market's influence and majority of the studies suggested that the market integration has increased significantly over the years. The review shows that there is a need to study the interdependence between the Indian stock market and other Asian developing countries especially with the advent of growing trade associations such as SAARC.

Madaleno and Pinho (2012) and Awokuse *et al*. (2009) suggest that the information transmission across markets had a significant time delay, which provide arbitrage opportunities. Though long run information transmission across markets has been studied in detail previously by Meric *et al. (*2012), Masih and Masih (2001) and Balios and Xanthakis (2003), there is lack of analysis on instantaneous price transmissions across the markets, which is of primary importance to speculators and day traders.

Thus the literature shows that there is lack of empirical work on testing the effectiveness of global market cues in predicting stock market prices and also none of the authors have clearly established the usefulness of such market integration cues in forecasting of daily stock prices.

3. Forecasting methodology

3.1 Data and Sample

The study is empirically tested using the historical daily prices of 7 major indices in the world: SCI (Shanghai Stock Composite Index, Shanghai), HSI (Hang Seng Index, Hong Kong), STI (Straits Times Index, Singapore), FTSE 100 (London Stock Exchange), S&P CNX Nifty (National Stock Exchange, India), S&P500 (US) and DowJones (New York Stock Exchange, US).

Each series spans from 1st December, 1997, to 1st November, 2011, totalling 3,700 trading days. First 500 observations are utilized for pilot studies for tuning the prediction model. The rest of the data is divided equally into 32 datasets each of 100 trading days for testing. Each dataset is tested after training the model for the previous 400 days. The division amounts to approximately 20 per cent of the data being retained for out-of-sample validations.

3.2 Experimental Model: Choice of Input Variables

Most of the previous researchers have employed multivariate input. Several studies have examined the cross-sectional relationship between stock index and macroeconomic variables. The potential macroeconomic input variables which are used in forecasting models include term structure of interest rates (TS), short-term interest rate (ST), long-term interest rate (LT), consumer price index (CPI), industrial production (IP), government consumption (GC), private consumption (PC), gross national product (GNP) and gross domestic product (GDP) .

Fama and Schwert (1977), Rozeff (1984), Keim and Stambaugh (1986), Campbell (1987), Fama and Bliss (1987), and Fama and French (1988, 1989) found that macroeconomic variables such as short-term interest rates, expected inflation, dividend yields, yield spreads between long- and short-term government bonds, yield spreads between low- and high-grade bonds, lagged price–earnings ratios, and lagged returns have some power to predict stock returns using time-series analysis. However, as most macro economic data is aggregated at monthly or quarterly frequency, they cannot be used in daily returns forecasting models.

Technical analysis employs models and trading rules based on price and volume transformations, such as the relative strength index, moving averages, regressions, inter-market and intra-market price correlations, business cycles, stock market cycles or, classically, through recognition of chart patterns. In most of the earlier studies, past lagged returns and technical indicators have been used as input to the neural network models. Technical analysis is widely used among traders and financial professionals and is very often used by active day traders, market makers and pit traders, though it was widely dismissed by academics in the 1960s and 1970s. Brock *et al.* (1992), Osler (2000), Neely and Paul (2001) and Taylor and Allen (1992) have suggested that technical trading rules might lead to consistent returns.

Previous studies have mostly used a unique combination of technical indicators.Cheng *et al*, 2009 used Moving Average, Stochastics (%K), Stochastics (%D), Stochastics slow (%D), Larry's William indicator, RSI (relative strength index), BIAS momentum indicator, 10 day psychological line , A ratio and B ratio as the indicator variables in their hybrid Self Organized Feature Mapping- Support Vector Regresion model for stock market forecasting.

Tay and Cao (2001) tested the ability of relative difference in percentage of price and an exponential moving average variation as expanatory variables in financial forecasting.

Stephan Schulmeister, (2009) investigated the profitability of stock forecasting models using Moving Average, Momentum and RSI variations as the key technical indicators. The empirical results showed that the profitability of stock trading had gradually shifted from daily data to data of increasingly high frequencies.

The most used combination of technical indicators are – Stochastics (%K), Stochastics (%D), Stochastics slow (%D), Momentum indicator, ROC, Larry's William indicator, A/D Oscillator, Disparity 5-day, 10-day, price oscillator (OSCP), CCI (commodity channel index), RSI (relative strength index). [(Kim, K.J and Han.I, 2000), (Kim K.J, 2003), (Kumar, M. and M. Thenmozhi, 2005), (Kim K.J, 2006)]. This study also incorporates moving average and exponential moving average along with the technical indicators. The descriptions of initially selected attributes are presented in Table1.

Kumar, M. and M. Thenmozhi (2009) have used the more conventional input variables of the stock index's past lags for the one day ahead closing price forecasts using Hybrid ARIMA -Support Vector Machines and Hybrid ARIMA – Neural Networks techniques. There are several studies which use the past lags as predictors and model using ARIMA and GARCH techniques.

However, the use of global cues for daily stock price predictions has been very scarce. Research in this area has been limited to market integration analysis and has not been extended to developing Market Cues based trading models and testing their profitability. Moreover, market integration has always been tested with US market as a base reference and this study is intended to explore the influence of other large markets such as Singapore, Hong Kong, and Shanghai on trading.

3.3 Choice of forecasting model

Traditionally, the autoregressive integrated moving average (ARIMA) model has been one of the most widely used linear models in time series forecasting. However, the ARIMA model cannot easily capture the nonlinear patterns. Support vector machines (SVMs), a novel neural network technique, have been successfully applied in solving nonlinear regression estimation problems.

Poon and Granger (2003), provide an exhaustive survey of the research in this area in the last 20 years. The survey found that among the time series models, there was no clear winner between the historical volatility models (including random walk, historical averages, ARIMA, and various forms of exponential smoothing) and GARCH-type models (including ARCH and its various extensions), but both classes of models outperform the stochastic volatility model.

Core techniques used in financial time series forecasting are

a. Simple Exponential Smoothing (Muth, 1960)
b. Linear Regression, Multiple Linear Regression
c. Auto Regressive Integrated Moving Average models (Box and Jenkins, 1970)
d. Autoregressive Conditional Heteroscedastic (ARCH)/ Generalized ARCH (GARCH) models (Engle,1982, 1987, 1994)
e. K-Nearest Neighborhood method(K-NN) (Kotsiantis, 2007)
f. Decision Trees (Tsai and Wang, 2009) (Kotsiantis, 2007)
g. Discriminant analysis (Linear/Quadratic) - (Phichhang Ou, Hengshen, 2009) investigated the performance of ten different data mining techniques including discriminant analysis, NN's, Naïve Bayes classifier, K-NN and the SVM in predicting the Hang-Seng index movement direction and showed that SVM outperformed other models.
h. Stochastic analysis (Closed –form formulae)

i. Markov Chain- (Deju Zhang, Xiaomin Zhang, 2009) studied the related properties of Markov process and established a Markov chain mathematical model for the stock market trend forecasting. Being a probabilistic forecasting technique, the method might work well in a trending market, but would fail miserably when applied to day trading strategies.

ii. Bayesian Classification using kernels - (Phichhang Ou, Hengshen, 2009) used the Gaussian radial basis function for extending Bayesian models for linear estimators to non-linear situations.

i. Neural networks - (Steven, Narciso, 1999) developed guidelines for the design of artificial neural networks and tested empirically various ANN models in forecasting exchange rates.
j. Support Vector Networks - SVM algorithm invented by Vladimir Vapnik, is a set of related supervised learning methods that analyze data and recognize patterns, used for classification and regression analysis. The modified Soft Margin method was proposed by (Corinna Cortes, Vladimir Vapnik, 1995).

Machine learning techniques such as neural networks have been used extensively for developing trading rules. These approaches have allowed dynamic trading strategies but are more like a black box, with little or no possibility to understand its internal behaviour. (Friedman, 2003). Simulation, meta-heuristic methods on the other hand do not provide the flexibility to adapt their trading behaviour to the changing market conditions. A large amount of literature on such trading strategies finds very mixed results on profitability (Krause, 2009).

The support vector machine (SVM), a supervised learning algorithm, was developed by Vapnik and his colleagues (1990). Many traditional neural network models had implemented the empirical risk minimization principle which seeks to minimize the misclassification error or deviation from correct solution of the training data. SVM implements the structural risk minimization principle where the model searches to minimize an upper bound of the generalization error. Also, the solution of SVM may be global optimum while other neural network models may tend to fall into a local optimal solution. Thus over-fitting is unlikely to occur with SVM.

Kumar and Thenmozhi, (2005) and Kumar and Thenmozhi (2012) compared the performances of two advanced forecasting tools, Support Vector Machines and Random Forest in predicting the Stock Index Movement and found that the SVM had better results than Random Forest while both significantly outperformed other techniques such as ARIMA, Artificial Neural Networks (ANN) and Linear Discriminant Analysis.

Kim (2003) found that SVMs outperformed back-propagation neural networks and case-based reasoning when used to forecast the daily Korea composite stock price index (KOSPI). Cao and Tay, (2003) used SVM, a multilayer back-propagation (BP) neural network and a regularized radial basis function (RBF) neural network to predict five real futures contracts collated from the Chicago Mercantile Market. Results showed that the SVM and the regularized RBF neural network were comparable and both significantly outperformed the BP neural network. Shin *et al*., (2005) demonstrated that the accuracy and generalization performance of SVM is better than back-propagation neural networks.

Kumar and Thenmozhi, (2009), Kim (2003), Phichhang Ou and Hengshan Wang (2009), Cao (2003) show that Support Vector Machine (SVM) outperforms Artificial Neural Networks (ANN) and ARIMA in forecasting stock indices. This study employs the non linear extension of the SVM which can distinguish noise from measurement error in forecasting stock indices.

3.4 Model development using Support Vector Machine

The SVMs belong to a family of generalized linear classifiers and can be interpreted as an extension of the perceptron. The support vector machine constructs a hyperplane or set of hyperplanes in a high dimensional space, which can be used for classification and regression. The hyperplane intuitively separates the space into two halves. The distance of the hyperplanes to the nearest data points of any class is known as the functional margin. A good classification separation can be achieved by maximizing the distance between the hyperplanes and the training data points of any class. In general the larger the margin, the lower is the generalization error of the classifier. A special property is that they simultaneously minimize the empirical classification error and maximize the geometric margin and hence they are also known as maximum margin classifiers.

Another key property of SVM is that training SVM is equivalent to solving a linearly constrained quadratic programming problem so that the solution of SVM is always unique and globally optimal, unlike neural networks training which requires nonlinear optimization with the danger of getting stuck at local minima. Vast applications of SVM to forecasting problems have been reported recently. In most cases, the degree of accuracy and the acceptability of certain forecasts are measured by the estimates' deviations from the observed values. A comparison of the SVM to other classifiers has been made by Meyer *et al.* (2003) and show that the mathematical model to identify the maximal margin in Support Vector Machines gives it a thrust over other classification and regression techniques which do not guarantee optimal solutions. Based on the structured risk minimization (SRM) principle, SVMs seek to minimize an upper bound of the generalization error instead of the empirical error as in other neural networks. Additionally, the SVMs models generate the regress function by applying a set of high dimensional linear functions.

The Figure 3.1 shows the Maximum Margin Classification method used in the Support Vector Machine.

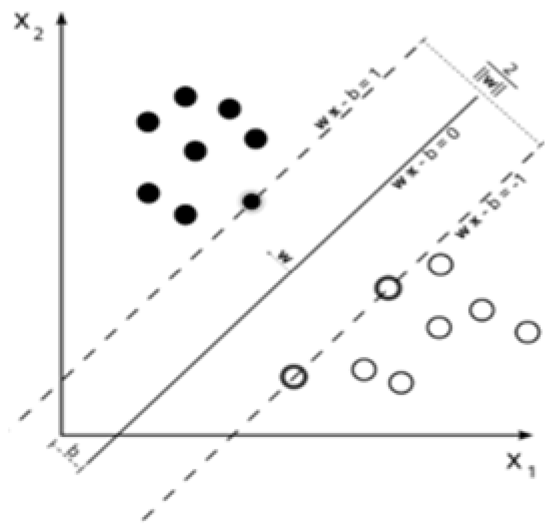

Fig 1 – Maximum Margin Classification

The SVM regression function is formulated as follows

$$y = w\Phi(x) + b \tag{1}$$

Where $\Phi(x)$ is called the feature, which is nonlinear mapped from the input space *x*. The coefficients *w* and *b* are estimated by minimizing

$$R(C) = C\left(\frac{1}{N}\right)\sum_{i=1}^{N} L_\varepsilon(d_i, y_i) + \left(\frac{1}{2}\right)\|w\|^2 \tag{2}$$

$$L_\varepsilon(d, y) = \begin{cases} |d-y| - \varepsilon, & |d-y| \geq \varepsilon \\ 0, & otherwise \end{cases} \tag{3}$$

where both C and ε are prescribed parameters. The first term L_ε *(d, y)* is called the ε -intensive loss function. The d_i is the actual stock price in the i^{th} period. This function indicates that errors below ε are not penalized. The term $C\left(\frac{1}{N}\right)\sum_{i=1}^{N} L_\varepsilon(d_i, y_i)$ is the empirical error. The second term,$\left(\frac{1}{2}\right)\|w\|^2$ measures the flatness of the function. C evaluates the trade-off between the empirical risk and the flatness of the model. Introducing the positive slack variables ζ and ζ^*, which represent the distance from the actual values to the corresponding boundary values of ε -tube, Eq. (2) is transformed to the following constrained formation:

Minimize :

$$R(w,\zeta,\zeta *) = C^* \left(\frac{1}{N}\right)\sum_{i=1}^{N}(\zeta_i, \zeta_i^*) + \left(\frac{1}{2}\right) ww^T \tag{4}$$

Subjected to:

$$w\Phi(x_i) + b_i - d_i \leq \varepsilon + \zeta_i^* \tag{5}$$

$$d_i - w\Phi(x_i) - b_i \leq \varepsilon + \zeta_i^* \tag{6}$$

$$\zeta_i, \zeta_i^* \geq 0 \tag{7}$$

$$i = 1,2, \ldots . N.$$

Finally, introducing Lagrangian multipliers and maximizing the dual function of Eq. (4), changes Eq. (4) to the following form:

$$R\ (\alpha_i - \alpha_i^*) = \sum_{i=1}^{N} d_i(\alpha_i - \alpha_i^*) - \varepsilon \sum_{i=1}^{N}(\alpha_i - \alpha_i^*) - (1/2)\sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i - \alpha_i^*) * \left(\alpha_j - \alpha_j^*\right) K(x_i, x_j) \quad (8)$$

With constraints,

$$\sum_{i=1}^{N}(\alpha_i - \alpha_i^*) = 0 \tag{9}$$

$$0 \leq \alpha_i \leq C \tag{10}$$

$$0 \leq \alpha_i^* \leq C \tag{11}$$

$$i = 1,2, \ldots . N.$$

Where α_i, α_i^* are called Lagrangian multipliers. Based on the Karush–Kuhn–Tucker (KKT) conditions of quadratic programming, only a certain number of coefficients $(\alpha_i - \alpha_i^*)$ in Eq. (8) will assume non-zero values.

The data points associated with them have approximation errors equal to or larger than ε and are referred to as support vectors. These are the data points lying on or outside the ε -bound of the decision function. According to Eq. (8), it is evident that support vectors are the only elements of the data points that are used in determining the decision function as the coefficients $(\alpha_i - \alpha_i^*)$ of other data points are all equal to zero. Generally, the larger the ε, the fewer the number of support vectors and thus the sparser the representation of the solution. However, a larger ε can also depreciate the approximation accuracy placed on the training points. In this sense, ε is a trade-off between the sparseness of the representation and closeness to the data.

And they satisfy the inequalities

$$\alpha_i * \alpha_i^* = 0 \tag{12}$$

$$f(x, \alpha, \alpha^*) = \sum_{i=1}^{N} (\alpha_j - \alpha_i^*) \, K(x, x_i) + b. \tag{13}$$

Here $K(x, x_i)$ is called the kernel function. The value of the kernel is equal to the inner product of the two vectors x_i and x_j the feature space Φ (x_i) and Φ(x_j) such that $K(x_i, x_j) = \Phi(x_i) * \Phi(x_j)$. The Kernel trick in machine learning is a technique to write a nonlinear operator as a linear one in a space of higher dimension.

The original optimal hyperplane algorithm proposed by Vapnik in 1963 was a linear classifier. Bernhard Boser, Isabelle Guyon and Vapnik, (1997) later developed nonlinear classifiers by applying the kernel trick to maximum-margin hyperplanes. In the proposed algorithm every dot product is replaced by a nonlinear kernel function. This allows the algorithm to fit the maximum-margin hyperplane in a transformed feature space. The transformation may be nonlinear and the transformed space is high dimensional. Hence even if the classifier is a hyperplane in the high-dimensional feature space, the original input space may be nonlinear.

The typical examples of kernel function are the polynomial kernel K(x, y) = (x * y + 1)d and the Gaussian kernel $K(x, y) = \exp(-1/\delta^2(x - y)^2)$ where d is the degree of polynomial kernel and δ^2 is the bandwidth of the Gaussian kernel. Kim (2003) found that the polynomial function kernel function takes very long time for the training of SVM and provides worse results than the Gaussian radial basis function in empirical tests. This study uses the Gaussian radial basis function as the kernel function of SVMs. Tay and Cao (2001) have shown that the upper bound C (regularization constant) and the kernel parameter δ2 play an important role in the performance of SVMs. Improper selection of these two parameters can cause the model to over fit or the under fit the data (Chapelle *et al.* 2002). As there are no set guidelines to determine the parameters of SVM, this study varies the parameters to select optimal values for the best prediction performance.

3.5 Measures of Performance

Traditionally, financial forecasting models have been evaluated using statistical measures such as root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) (Moustafa Ahmed, 2011). Earlier studies measured the degree of accuracy and acceptability of forecasting model, by the estimate's deviations from the observed values. Less importance was given to turning-point forecast capability using sign and direction test. Directional accuracy measures the degree to which the forecast correctly predicts the direction of change in the actual stock returns, where global cues can prove to be effective predictors. The most commonly used non-statistical performance metric is the

Hit Ratio that measures the percentage of correct predictions of the model. Another measure, Annual rate of return deals with the trading profitability of the model.

3.6 Evaluating using Trading Strategy

For the practitioners in financial market, forecasting methods based on minimizing forecast error may not be adequate to design effective trading strategies. Trading strategies that are driven by a certain forecast with a small forecast error may not be as profitable as strategies guided by an accurate prediction of the direction of movement. [Leung *et al* (2000)]. Performance indicators, such as past trading returns and risk-adjusted returns, have been used for ex-post assessment of Hedge funds trading. In this study, we emphasize the evaluation of the performance of forecasting models using directional accuracy and trading returns.

The robustness of the forecast models using past lags and other market cues are validated by simulating trades using a simple trading strategy. The trading decisions are made based on the forecasts provided by the model. Market entry is made during the market opening and the trade is exited at the market closing price. If the prediction model forecasts a positive closing return a buy order is executed at the market opening price and a sell order is executed at the market closing price. Conversely, when the model predicts negative returns, a short sell trade is performed similarly.

3.7 Experimental Steps

The following steps are used in developing the SVM forecast Models.

1. The Log (logarithm) returns of stock index closing prices are used to obtain Log returns as they retain the stationarity characteristics of the time series. The stock index opening and closing returns are used as global cues for other markets.
2. Appropriate explanatory variables such as past lags, global cues and technical indicators are built into the SVM model.
3. Appropriate generalization constant and kernel parameters for the SVM models are chosen through trial and error method.
4. The performance of the models is compared using hit ratio and best model for forecasting is identified for each market.
5. The chosen models are further evaluated for trading performance for a simple trading strategy using simulation.

4. Experimental Results

4.1 Experiment

This study investigates the performance of three kinds of predictors – technical indicators, autoregressive past lags and global stock market cues in forecasting 7 stock indices. The log returns of the stock prices are used to maintain stationarity in time series analysis. Autocorrelation tests were performed to identify the number of past lags to be used in the autoregressive model. Test data over a period of 12 years from 8^{th} August, 1999, to 1^{st} November is split into 32 equal samples for better training of the model. All the data required for the analysis was obtained from Yahoo Finance database. The model uses

80% of the data for training and 20% for testing. The model was built in C++ using Visual Studio Version6.0, and the Support Vector Regression forecasts were obtained using SVM-Light Version V6.02 package.

The performance of the models are compared across 7 major indices in the world: SCI (Shanghai Stock Composite Index, China), HSI (Hang Seng Index, Hong Kong), FTSE 100 (UK), STI (Straits Times Index, Singapore), Nifty (India), S&P500 (US) and Dow Jones (US) using hit ratio.

4.2 SVM forecast model using Technical Indicators

Table 2 shows the performance of the SVM in predicting the daily closing price of the 7 stock indices using technical indicators as the input variables. Hit ratio is the ratio of the number of correct predictions to the total number of predictions. The trading returns shown in Table 2 is the sum of negative and positive returns obtained from a simple trading simulation experiment conducted during the study. Detailed explanation of the experiment provided later in the paper. Table 2 also provides the results obtained from a random walk model.

From Table 2, we can infer that a high hit ratio can be transformed into profitable trades, with SCI having the highest hit ratio among the stock indices. Moreover, the predicted values have varied widely across the different markets. Though the technical indicators model has outperformed the random walk model in majority of the markets based on Hit ratio, trading returns generated by the random walk model is higher than the technical indicators model in most of the markets.

4.3 Effect of Autoregressive Lags in predicting the Markets:

Table 3 and Table 4 report the average Hit ratio and RMSE values respectively of the forecast models using only previous closing returns. The Hit ratio and RMSE values are the average values obtained across 32 test samples.

SCI: Past lags play an important role in forecasting the SCI closing price. The 3 day lagged closing prices were the most contributing followed by the 4 day lagged closing prices.

HSI: The previous closing returns did not have much effect on the predictive performances of the various models tested in forecasting the daily closing price of HSI.

FTSE: The models with 1 lag showed a slight advantage over the other models with more lags.

STI, Nifty, S&P 500, and DJIA: The analysis did not show any significant variation in the forecasting performances of the models with respect to the number of past auto-lags used.

4.4 Effect of Cues in predicting the Markets:

The consolidated Hit ratio and RMSE values for the forecast models using previous closing returns and other global market cues are shown in Table 5 and Table 6 respectively.

SCI: Hang-Seng Index which opens 10 minutes earlier than Shanghai Stock Composite Index sets the tone for its closing price. However, the previous day’s closing prices of S&P500 and DJIA are also equally proficient in predicting the SCI closing price. The effect of cues is not very significant as models with and without global indicators as independent variables have produced very similar Hit Ratio and RMSE values.

HSI: The American stock markets *(S&P 500 and DJIA)* seem to have higher Predictive power in forecasting the daily closing price of Hang-Seng Index. The previous day's S&P500 closing price is the best predictor among the tested global cues while Nifty is most insignificant in prediction.

FTSE: The previous day's closing prices of the developed American stock indices, S&P500 and DJIA fare well in predicting the daily closing price of FTSE 100. The previous day's S&P500 closing price is the best predictor among the tested global cues. HSI opening price also performs reasonably well in the FTSE closing price prediction. The Chinese SCI and the Indian Nifty indices are insignificant as independent variables with minimal effect.

STI: The previous day's closing prices of developed markets namely American (S&P 500 and DJIA) and London (FTSE 100) markets show better predictive power in forecasting STI daily closing price.

Nifty: The opening price of the Hang-Seng Index drives the day's market sentiments in the Indian stock market. The high 60% Hit Rate in predicting the Nifty closing price shows the significant difference that inclusion of global cues as predictors can make compared to past lags or other technical indicators. The Chinese and London stock markets were comparatively insignificant in predicting Nifty movement.

S&P 500: The day's closing prices of STI, Hang-Seng Index and Nifty perform reasonably well in predicting the closing price of S&P500 (Hit Ratios close to 55%)

DJIA: Forecasting models for DJIA showed very similar results to that of predicting S&P500, its American counterpart with HSI, Nifty and STI proving to be significant cues.

4.5 Effect of the Time-lag of the Cues in predicting the Markets:

Figure 2 shows the overlapping of trading hours of various markets across the world. The axis in the Fig 2 is the co-ordinated universal time (UTC).

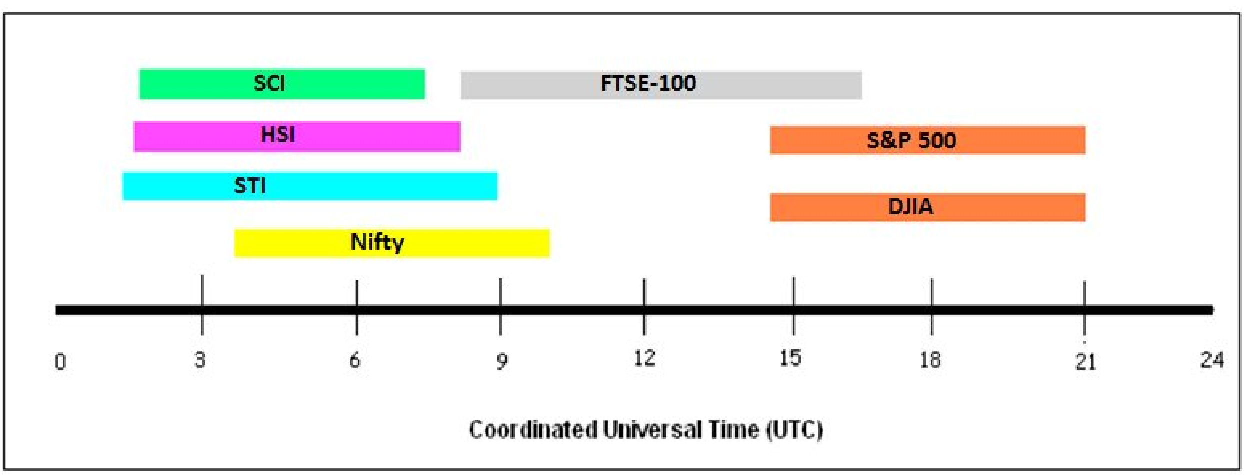

Fig 2: Opening and closing times for stock exchanges worldwide

SCI: For SCI, though stock markets around the world appear to take their cues from the US market, the opening market moves in the Hang-Seng Index which starts trading 10 minutes earlier has shown better predictive power compared to the other cues. A possible reason could be that the opening Hang-Seng Index price also captures the overnight global developments unlike the previous day's US Market closing prices. However, the effect of Hang-Seng cues is not significantly high compared to other cues.

HSI, STI: Supporting the popular belief of taking cues from the American markets' previous day's closing prices, S&P500 and DJIA closing prices emerge as better indicators. A probable reason is that HSE and SGX are one of the earliest opening global markets and therefore rely on the American markets' closing moves, the then latest available information.

FTSE: The previous day's closing prices of the developed American stock indices, S&P500 and DJIA fare well in predicting the daily closing price of FTSE 100. The closely linked market structures of the European and American exchanges, the large number of companies listed on both the stock exchanges and the inter market trading participation could be possible reasons for strong performance of the American indices as predictors.

Nifty: Earlier researches have shown the predictability of Indian markets using lagged closing price of S&P 500 and the results have confirm the same. However, the most contemporaneous price, namely, HSI opening price outruns other cues by a significant margin.

S&P 500, DJIA: The day's closing prices of STI, HIS and Nifty perform well in predicting the closing price of S&P500 showing that the availability of new information has an important role in stock price prediction.

4.6 Comparison of Models

The various models developed are compared using hit ratio which is a good measure of turning point forecast capability. Moreover, the RMSE values did not provide clear differentiation between the models. Out of all the indices considered, Nifty is the most predictable index with the highest hit ratio, while STI and DJIA are the least predictable stock market indices. Of the predictors, S&P500 is the best predictor performing well in predicting almost all the tested market indices, while SCI is the least significant, probably showing a staunch difference in the market structure. Except for SCI, other markets showed almost insignificant effect of the lagged returns (autoregressive lags) in improving the predictive capabilities of the models. However, a very meek decrease in the predictive powers was noted with the inclusion of more number of autoregressive historical lags, probably indicating that older data contained more noise than predictive powers.

This study examined the extent to which information on past prices, technical indicators and global market cues affect the stock price. The time of availability of the cues had the most noticeable effect on performance of the models (see Fig 2). All the markets in general showed a tendency to be influenced by the latest available global information which probably reflected more relevant information rather than older data.

The inclusion of global cues as predictors has had a profound effect in improving the performance of the forecasting models. All markets have shown better predictability with global cues thus validating the popular belief that the large markets in general are integrated with other global exchanges. The study has proven that markets do react to global cues and any event occurring in the global scenario (macroeconomic or country specific) affect various markets.

4.7 Validation by Trading Simulations

The validation is done through a trading simulation using past lags and other market cues. The trading experiment was carried with an initial investment of 100 currency units and using a simple trading strategy. Market entry is made during the market opening and the trade is exited at the market closing price. If the prediction model forecasts a positive closing return a buy order is executed at the market opening price and a sell order is executed at the market closing price. Conversely, when the model predicts negative returns, a short sell trade is performed similarly. The trading decision was taken based on the forecasts provided by the model being tested.

The trading experiment results shown in Table 7 follow suit with the hit ratio performance of the models. Nifty is the most predictable among the seven indices and yielded the highest trading returns. A consistent pattern that we could notice from the trading results is that the models with one autoregressive lag have performed better than the models with more number of autoregressive lags, again a probable indication that all the relevant information is carried by the most recent data.

Stock Markets have become more integrated with its global counterparts and its reaction is in tandem with that seen globally. Stock exchanges are now crossing national boundaries to extend their service areas and this has led to cross-border integration. Stock exchanges have also begun to offer cross-border trading to facilitate overseas investment options for investors. This has not only increased the appeal of the stock exchange for investors but also attracted more volumes. Exchanges regularly solicit companies outside their home territory and encourage them to list on their exchange. Adding to this, global competition has put pressure on corporations to seek capital outside their home country.

Experts have argued that stock markets are influenced by many inter related factors including the global economic, political, and even psychological factors. These factors interact with each other in a complex fashion and hence it is difficult to find the exact set of factors that determine the behaviour of stock markets (Tilakaratne, 2004). But these factors could be reflected on the price indices on global markets (Tilakaratne *et al.* 2007).

The expanding presence of globally operating businesses makes understanding the similarities and differences between national practices of securities market regulation vital for key stakeholders, including regulators, market operators, issuers and investors. In addition, recent trends of demutualization and international mergers between exchanges are changing the framework of capital markets and necessitating adaptive regulatory regimes.

Global trading cycle has overlapping markets that provide round the clock trading opportunities for global investors. Also overlapping markets enable them to compete directly with other markets in other time zones. Regulation hence has also become an increasingly overlapping and collaborative endeavour between and among the global stock exchanges and various regulatory institutions.

5. Contribution

1. The study brings out the importance of information transmission across markets in generating daily forecasts. This may help regulators in understanding the interaction behaviour of the global stock markets.
2. The model has been developed using real time data covering all economic cycles – growth, maturity and recession.
3. We study the influence of Asian markets compared to developed markets on stock price forecasting.
4. The paper also makes contributions at the methodological level. Unlike the existing literature we provide a dynamic framework for developing profitable trading strategies from the forecasting cues, clearly bringing out the trading implications of various forecast indicators.
5. The model is appropriate for algorithmic trading strategies that focus on taking profits from price differentials between two or more paired markets.

6. Conclusion

In this study, an attempt has been made to examine the dynamic relationships between the global stock indices. Our study focuses more on trading profitability of the global cues than just testing their relationship using conventional linear techniques and correlation ratios. The goals of the study were to compare the performance of trading models that used – Technical indicators, past lags, past lags with global cues.

The support vector machine (SVM) regression which is a state of art regression technique is applied to predict the daily closing prices. The test data of over 12 years is split into 32 equal test samples to check the consistency and robustness of the models being tested. Out-of-sample performances of the two models were evaluated using RMSE and Hit ratio. The best forecasting models in each market were further tested on trading measures.

The research found that Global cues model significantly outperformed 1) Past lags model and 2) Technical indicators model in all the seven markets tested. Moreover the analysis results suggest that most recent market information is more productive than the aged data. The study testaments that stock markets across the globe are integrated and that information on price transmissions can induce arbitrage opportunities.

Finally, we can sum up with the following observations:

- The markets are well integrated and Indian market is no exception.
- As for the existence of any signals or patterns among the stock exchanges, it can safely be said that the markets do react to global cues and any happening in the global scenario be it macro-economic or country specific affect the various markets, that is global scenarios affect local market sentiments.
- Cues have performed overwhelmingly well compared to mere past lags as stock closing price predictors for all the 7 stock markets.
- The availability of new market information plays a vital role in determining the trading profits.

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Table 1: Description of Technical Indicators used in the study

The table gives a brief description of the various attributes adopted in the forecasting model based on technical indicators. All the indicators were built using log returns of the index prices.

Feature name	Description	Formula
MA	The most basic and widely used trend indicator, the simple moving average (MA) smoothes the period to period fluctuations within a raw data sample to reveal the average value at a given point in time. The indicator calculates the mean for a series of data contained within a specified range bounded by the present period and an earlier period.	$\mathrm{MA}(n)_t = \frac{1}{n} \times \sum_{i=t-n+1}^{t} C_i$
EMA	The exponential moving average (EMA) calculates a weighted mean for a series of data by adding a percentage of the most recent data to the previous value of the moving average. Rather than dropping the oldest data in the series to keep the data range constant as time advances, the smoothing constant causes the most recent data to be most heavily weighted and the oldest data to be least weighted. The exponential moving average is often preferred by technicians over the simple moving average for analyzing historically volatile markets.	$(P(i) - \overline{EMA_n(i)}) * K + \overline{EMA_n(i)}$
%K	Stochastic %K compares where a security's price closed relative to its price range over a given time period. Buy and sell signals are given when the faster %K crosses the slower %D or when either curve extends above or below specific threshold levels.	$\overline{\frac{C_t - LL_{t-n}}{HH_{t-n} - LL_{t-n}} \times 100,}$
%D	Stochastic %D is the moving average of %K.	$\frac{\sum_{i=0}^{n-1} \%K_{t-i}}{n}$
Slow %D	Stochastic slow %D is the moving average of %D.	$\frac{\sum_{i=0}^{n-1} \%D_{t-i}}{n}$
Moment um	It measures the amount by which a security's price has changed over a given time span.	$C_t - C_{t-4}$
ROC	Price rate-of-change. It displays the difference between the current price and the price n days ago.	$\frac{C_t}{C_{t-n}} \times 100$
Williams ' %R	Larry William's %R is a momentum indicator that measures overbought/oversold levels. Larry Williams depicts the exact negative inverse of the stochastic oscillator. The current period closing price is compared to the recent trading range to indicate overbought and oversold conditions. Large (small) negative values indicate oversold (overbought) conditions.	$\frac{H_n - C_t}{H_n - L_n} \times 100$

A/D Oscillator	Accumulation/distribution oscillator (A/D) is a momentum indicator that associates changes in price.	$\frac{H_t - C_{t-1}}{H_t - L_t}$
Disparity 5	5-day disparity is a measure of the distance of current price and the moving average of 5 days. Latest shift with respect to the previous 5 day trend.	$\frac{C_t}{MA_5} \times 100$
Disparity 10	10-day disparity is a measure of the distance of current price and the moving average of 10 days. Latest shift with respect to the previous 10 day trend.	$\frac{C_t}{MA_{10}} \times 100$
OSCP	Price oscillator (OSCP) displays the difference between two moving averages of a security's price. Helps to study the shift in the short term trend from long term trend.	$\frac{MA_5 - MA_{10}}{MA_5}$
CCI	Commodity channel index (CCI) measures the variation of a security's price from its statistical mean. It is used to detect beginning and ending market trends. CCI is used to look for divergences from the mean and to indicate overbought or oversold conditions.	$\frac{(M_t - SM_t)}{(0.015\, D_t)}$ where $M_t = (H_t + L_t + C_t)/3$; $SM_t = \frac{\sum_{i=1}^{n} M_{t-i+1}}{n}$, and $D_t = \frac{\sum_{i=1}^{n} \lvert M_{t-i+1} - SM_t \rvert}{n}$
RSI	Relative strength index (RSI) is a price momentum oscillator which measures price velocity by tracking positive and negative price changes from one period to the next. Incremental net positive and negative changes in closing price are tallied and smoothed by an exponential moving average, then a ratio between the smoothed positive and negative changes is constructed for the final RSI computation. RSI ranges from 0 to 100.	$100 - \frac{100}{1 + (\sum_{i=0}^{n-1} Up_{t-i}/n)/(\sum_{i=0}^{n-1} Dw_{t-i}/n)}$

Note: Ct is the closing price at time t, L_t the low price at time t, H_t the high price at time t and, MA_t the moving average of t days, LL_t and HH_t the lowest low and highest high in the last t days, respectively. UP_t means upward-price-change and DW_t means downward-price-change at time t.

Table 2: Performance of the Model using Technical Indicators

The table shows the hit ratio and trading returns obtained from the model based on technical indicators as the independent variables. Hit ratio is the ratio of the number of correct predictions to the total number of predictions. The returns column in Table 2 is the sum of negative and positive returns obtained from a simple trading simulation experiment conducted during the study. Detailed explanation of the trading experiment is provided in the section 4.7.

Indices	Technical Indicators		Random Walk	
	Hit Ratio	Returns	Hit Ratio	Returns
Shanghai Stock Composite Index	54.31	113.23	47.38	103.62
Hang Seng Index	49.19	93.71	51.22	109.49
Straits Times Index	51.09	100.40	51.06	102.62
FTSE-100	52.06	108.09	50.44	100.50
S&P CNX Nifty	50.00	101.85	49.31	98.45
S&P 500	50.50	94.1	48.97	96.40
Dow Jones Industrial Average	50.69	101.61	50.00	104.24

Table 3: Hit Ratio of the various models using previous closing returns

The table reports the average Hit ratio values of the forecast models using only previous closing returns. The Hit ratio values are the average values obtained across 32 test samples. The number of closing return lags used in the model is shown in column 1 and the corresponding markets are shown in the rest of the columns.

Closing Return Lags	Market						
	SCI	HSI	FTSE	STI	NIFTY	S&P500	DJIA
1	56.50	52.91	51.47	**52.06**	51.56	**52.59**	**51.94**
2	56.06	**53.16**	50.94	50.94	52.00	51.94	51.56
3	**57.38**	52.59	**51.69**	50.66	51.50	52.16	51.22
4	57.06	52.47	50.63	51.16	**52.66**	52.44	51.41

Table 4: RMSE values of the various models using previous closing returns

The table reports average RMSE values of the forecast models using only previous closing returns. The RMSE values are the average values obtained across 32 test samples. The number of closing return lags used in the model is shown in column 1 and the corresponding markets are shown in the rest of the columns.

Closing Return Lags	Market						
	SCI	HSI	FTSE	STI	NIFTY	S&P500	DJIA
1	0.0240	0.0174	**0.0181**	**0.0170**	0.0224	0.0189	**0.0175**
2	**0.0205**	**0.0172**	0.0182	0.0172	**0.0220**	**0.0181**	0.0176
3	0.0207	0.0172	0.0182	0.0171	0.0220	0.0182	0.0176
4	0.0206	0.0172	0.0183	0.0172	0.0221	0.0182	0.0176

Table 5: Hit Ratio of the various Models using Other Market Cues

The table reports the average Hit ratio results of the forecast models using previous closing returns and other global cues. The Hit ratio values are the average values obtained across 32 test samples. The market for which the forecast model is developed is shown in column1, the number of closing return lags used in the model is shown in column 2 and the other market cues used in the model are as shown in the column headers.

Market	Closing Return Lags	Other Market Cues used in the model													
		SCI		HSI		FTSE		STI		NIFTY		S&P500		DJIA	
		Closing	Opening	Closing	Opening	Closing	Opening	Closing	Opening	Closing	Opening	Closing	Opening	Closing	Opening
SCI	1	-	55.69	55.5	56.47	55.16	55.53	55.88	55.69	55.47	55.72	55.81	56.09	55.91	55.47
	2	-	56.13	55.75	56.22	55.72	56.31	55.19	56	55.81	55.66	56	56.09	55.84	55.72
	3	-	57.06	56.75	57.69	56.34	57.06	56.75	57.31	56.22	57.16	57.16	57.13	57.34	57.13
	4	-	56.34	56.34	56.69	56	56.31	56.75	57	55.84	56.56	56.78	56.34	56.72	56.66
HIS	1	52.88	53.75	-	52.81	53.22	52.06	52.78	53.5	51.69	51.75	53.5	53.22	53.5	52.22
	2	53.13	52.5	-	52.59	53.44	52.59	52.22	53.28	52.84	53.03	53.56	52.94	53.84	53.47
	3	52.66	52.69	-	52.47	53.25	53.16	52.53	52.38	52.09	52.59	54.34	53.03	53.28	52.97
	4	52.63	53.13	-	52.66	52.88	52.25	52.31	51.97	52.5	52.91	53.25	52.38	53.44	53.03
FTSE	1	51.56	53.28	51.13	56.06	-	51.91	51.63	55.47	52.25	52.5	57.94	51.44	57.34	51.31
	2	51.66	51.72	51.06	57	-	52.19	51.59	55.31	51.06	53.16	56.94	52.28	56.34	50.84
	3	52.13	51.66	51.03	55.66	-	52.44	50.25	54.63	51.06	52.78	56.84	50.31	56.38	51.47
	4	51.75	52.06	51.53	56.56	-	50.81	51.31	53.38	51.88	52.25	56.38	51.56	56.03	50.84
STI	1	51.56	51.72	51.59	51.03	53.41	52.34	-	51.47	51.31	51.31	53.53	52.16	53.28	52.09
	2	51.59	51.97	51.53	51.13	52.03	51.25	-	51.19	51.53	51.13	53.88	50.97	53.13	51.31
	3	51.28	51.44	51.53	51.53	52.47	51.59	-	51.19	51.03	51.03	53.66	51.06	54.44	51.22
	4	52.09	51.28	52.16	51.47	52.78	51.13	-	51.44	51.06	51.66	54	51.5	53.03	51.94
NIFTY	1	52.59	52.91	52.53	59.06	54.53	52.78	52.09	55.75	-	52.22	56.94	52.41	55.84	51.97
	2	52.16	53.72	52.41	60.00	52.94	52.63	52.28	54.38	-	52.66	57.13	51.81	55.59	52.34
	3	52.5	54	53.31	58.88	53.34	52.03	51.97	54.5	-	53	56.59	52.5	55.44	53.22
	4	52.72	53.09	52.84	58.63	53.84	52.53	52.19	54.84	-	52.44	56.69	52.13	55.25	52.69
S&P 500	1	51.91	51.75	54.44	52.22	53.25	52.81	55.31	53	54	52.41	-	53.16	52.97	53.06
	2	51.47	52.41	54.75	52.16	51.84	51.91	55.06	52	53.41	52.31	-	52.09	52.41	52.38

	3	52.13	52.88	54.63	53.19	52.16	52.16	54.03	52.09	53.63	52.31	-	52.34	52.25	52.19
	4	51.84	52.78	54.66	52.28	52.56	52.63	54.91	52.5	53.63	52.38	-	52.38	52.59	52.97
DJIA	1	50.94	52.75	55.22	53.03	52.09	52.22	54.72	51.72	54.94	51.56	51.88	53.06	-	51.5
	2	50.97	51.94	54.44	51.34	51.72	51.22	53.81	52.16	53.47	51.28	52	52.16	-	51.53
	3	51.28	51.91	54.44	51.47	51.63	51.13	54.13	51.56	53.28	51.47	50.94	52.5	-	51.53
	4	51.13	51.28	54.38	51.25	50.78	51.03	53.75	50.81	53.41	51.53	52.03	53.06	-	51.31

Table 6: RMSE values of the various models using Other Market Cues

The table reports the average RMSE results of the forecast models using previous closing returns and other global cues. The RMSE values are the average values obtained across the 32 test samples. The market for which the forecast model is developed is shown in column1, the number of closing return lags used in the model is shown in column 2 and the other market cues used in the model are as shown in the column headers.

Market	Closing Return Lags	Other Market Cues used in the model													
		SCI		HSI		FTSE		STI		NIFTY		S&P500		DJIA	
		Closing	Opening	Closing	Opening	Closing	Opening	Closing	Opening	Closing	Opening	Closing	Opening	Closing	Opening
SCI	1	-	0.0205	0.0206	0.0207	0.0206	0.0242	0.0205	0.0205	0.0205	0.0206	0.0207	0.0205	0.0206	0.0206
	2	-	0.0207	0.0206	0.0205	0.0206	0.0206	0.0206	0.0206	0.0206	0.0206	0.0206	0.0205	0.0206	0.0207
	3	-	0.0206	0.0206	0.0207	0.0207	0.0205	0.0206	0.0206	0.0207	0.0206	0.0208	0.0205	0.0207	0.0206
	4	-	0.0206	0.0206	0.0206	0.0207	0.0205	0.0207	0.0205	0.0207	0.0207	0.0207	0.0207	0.0208	0.0207
HIS	1	0.0172	0.0172	-	0.0171	0.0172	0.0175	0.0172	0.0172	0.0172	0.0171	0.0172	0.0175	0.0171	0.0172
	2	0.0172	0.0172	-	0.0172	0.0172	0.0172	0.0173	0.0172	0.0172	0.0172	0.0171	0.0172	0.0172	0.0171
	3	0.0172	0.0172	-	0.0172	0.0172	0.0172	0.0173	0.0172	0.0173	0.0171	0.0173	0.0172	0.0172	0.0172
	4	0.0172	0.0172	-	0.0172	0.0173	0.0172	0.0172	0.0172	0.0172	0.0172	0.0172	0.0172	0.0172	0.0173
FTSE	1	0.0181	0.0181	0.0182	0.0181	-	0.0183	0.0181	0.0183	0.0181	0.0182	0.0182	0.0181	0.0182	0.0181
	2	0.0182	0.0182	0.0181	0.0183	-	0.0182	0.0182	0.0183	0.0181	0.0182	0.0182	0.0181	0.0183	0.0183
	3	0.0182	0.0182	0.0182	0.0183	-	0.0183	0.0183	0.0182	0.0183	0.0182	0.0182	0.0183	0.0183	0.0182
	4	0.0182	0.0183	0.0184	0.0183	-	0.0183	0.0183	0.0183	0.0182	0.0182	0.0182	0.0183	0.0183	0.0183

STI	1	0.0171	0.017	0.017	0.0171	0.0172	0.017	-	0.0171	0.0171	0.0169	0.0171	0.0171	0.0171	0.017
	2	0.0172	0.0171	0.0172	0.0171	0.0171	0.0171	-	0.0172	0.0172	0.0172	0.0171	0.017	0.0171	0.0171
	3	0.0172	0.0171	0.0172	0.017	0.0172	0.0172	-	0.0171	0.0172	0.0172	0.0172	0.0171	0.0171	0.0172
	4	0.0172	0.0171	0.0171	0.0171	0.0172	0.0171	-	0.0171	0.0172	0.0172	0.0173	0.0172	0.0172	0.0172
NIFTY	1	0.0219	0.022	0.022	0.0221	0.022	0.0224	0.022	0.0219	-	0.0221	0.022	0.022	0.0219	0.0221
	2	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.0221	-	0.022	0.0221	0.022	0.0219	0.0221
	3	0.0221	0.022	0.0221	0.022	0.022	0.022	0.0221	0.022	-	0.0221	0.022	0.0221	0.022	0.022
	4	0.022	0.022	0.0221	0.0219	0.0222	0.022	0.0221	0.0221	-	0.022	0.022	0.022	0.0221	0.022
S&P 500	1	0.0182	0.0183	0.0181	0.0182	0.0182	0.0182	0.0181	0.0181	0.0181	0.0181	-	0.0181	0.0182	0.0182
	2	0.0181	0.0182	0.0182	0.0182	0.0182	0.0182	0.0182	0.0182	0.0182	0.0181	-	0.0182	0.0182	0.0183
	3	0.0182	0.0182	0.0182	0.0182	0.0182	0.0182	0.0183	0.0183	0.0183	0.0182	-	0.0182	0.0182	0.0182
	4	0.0182	0.0183	0.0182	0.0182	0.0183	0.0183	0.0182	0.0182	0.0182	0.0182	-	0.0182	0.0181	0.0182
DJIA	1	0.0176	0.0175	0.0177	0.0175	0.0175	0.0178	0.0176	0.0175	0.0175	0.0175	0.0175	0.0174	-	0.0175
	2	0.0176	0.0176	0.0176	0.0176	0.0176	0.0176	0.0176	0.0175	0.0175	0.0176	0.0176	0.0176	-	0.0175
	3	0.0177	0.0177	0.0176	0.0177	0.0176	0.0176	0.0176	0.0176	0.0176	0.0176	0.0177	0.0177	-	0.0177
	4	0.0176	0.0177	0.0176	0.0177	0.0177	0.0177	0.0176	0.0177	0.0176	0.0176	0.0176	0.0177	-	0.0176

Table 7: Trading Returns of the various models from simulation

The table reports the average returns generated from the global cues and pasts lags model in the trading simulation. The test data period 8th August, 1999, to 1st November, 2011, is broken into 32 equal test samples of 100 trading days each. The average return over the 32 test periods is given as the test period returns in the table. The annualized returns are obtained by extrapolating the average test period returns for 250 trading days. The returns clearly indicate that foreign global market cues are excellent indicators of stock market indices.

Market	Lags	Returns for the test period		Annualized Returns	
		Without Cues	With Cues	Without Cues	With Cues
SCI	1	105.75	132.07	114.38	180.18
SCI	2	102.39	126.79	105.98	166.96
SCI	3	104.89	125.79	112.23	164.46
SCI	4	103.82	130.64	109.55	176.61
HSI	1	101.96	116.96	104.91	142.41
HSI	2	102.50	116.79	106.25	141.96
HSI	3	104.14	113.18	110.36	132.95
HSI	4	107.79	113.79	119.46	134.46
FTSE	1	106.25	124.07	115.63	160.18
FTSE	2	101.11	120.86	102.77	152.14
FTSE	3	100.54	117.79	101.34	144.46
FTSE	4	102.79	116.21	106.96	140.54
STI	1	105.43	141.79	113.57	204.46
STI	2	102.82	139.68	107.05	199.20
STI	3	104.96	137.36	112.41	193.39
STI	4	98.00	138.04	95.00	195.09
NIFTY	1	100.75	147.75	101.88	219.38
NIFTY	2	99.57	146.50	98.93	216.25
NIFTY	3	103.96	145.11	109.91	212.77
NIFTY	4	104.57	146.93	111.43	217.32
S&P500	1	103.82	114.39	109.55	135.98
S&P501	2	103.18	116.11	107.95	140.27
S&P502	3	101.29	116.82	103.21	142.05
S&P503	4	103.36	114.29	108.39	135.71
DJIA	1	106.82	123.21	117.05	158.04
DJIA	2	101.82	112.75	104.55	131.88
DJIA	3	101.00	115.57	102.50	138.93
DJIA	4	98.68	119.75	96.70	149.38