Impact of Information Asymmetry on Return Volatility – Domestic and Cross-Country Evidence

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Abstract

This paper aimed at examining the impact of information asymmetry on return volatility in both domestic and cross-country stock market perspectives. For this purpose, secondary data were extracted from BSE 100 index as a domestic stock market index; the lbovespa, the leading stock index of the Brazilian stock market; IMOEX from the Russian stock market; SSE Composite Index of the Chinese stock market; and FTSE/JSE of the South African stock market for the period from January 2007 – December 2017. To assess the impact of information asymmetry on return volatility, the exponential generalized autoregressive conditional heteroskedasticity model (EGARCH) and Glosten, Jagannathan, and Runkle (GJR-GARCH) models were employed. Test results of GARCH family models showed the presence of information asymmetries in return volatility of all five stock market indices. GJR-GARCH model showed that negative shocks caused more volatility in return and EGARCH evidenced that positive shocks caused more volatility in return due to market anomalies that were experienced during the study period.

Keywords: cross-country evidence, information asymmetry, leverage effect, return volatility

JEL Classification: G11, G12, G14, G15, G17

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he efficient market hypothesis, popularized by Eugene Fama in his research paper in 1970, has been a matter of debate and conjecture ever since its introduction among researchers and investors around the world. Eugene Fama in his study explained that the price of any asset in a market must fully reflect all of its relevant available information (Fama, 1990). In the context of the capital markets, 'relevant information' refers to the information that may affect the potential cash flow of a business or the potential expectations of investors. The hypothesis slackly advocates that past data cannot be used to estimate the future trend of prices in the market, and a strong market has current market prices reflecting all the inside, market, and non-market information; thus, no one party has complete access to all relevant information. This would result in incessant excess volatility in asset returns.

Asymmetric information or information failure transpires when one party in a transaction or a contract holds greater knowledge than the counter party. Let us consider a transaction between a buyer and a seller, in which the seller of an underlying asset holds better knowledge about the asset than the buyer and vice versa. In almost all kinds of economic transactions or contracts, one can observe information asymmetry. In other words, it is a provision in which market participants involved in a transaction possess diverse information that affects the

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transaction in terms of decision making. Information that is circulated asymmetrically among market participants can be classified as ex-ante (pre-contractual of the transaction) or ex-post (post-contractual of the transaction) that will influence economic behaviour and functions of the market (Arnott, Greenwald, & Stiglitz, 1993).

Asymmetric information results in three kinds of impact on economic transactions or contracts, that is, adverse selection, moral hazard, and monitoring cost. These impacts may cause volatility in asset returns in the market and also in price fluctuations. In the context of the stock market, if an individual participant in the market possesses private or insider information of positive news with a lofty indication about a company or market or economy before others access to it, he/she can buy new securities and be able to gain anomalous returns from his/her investment in the security. On the other hand, when he/she gets private information with a stumpy indication, he/she will sell his/her holdings in the company before the news is disclosed to the public, which may result in the subsequent downfall of the security price. Karolyi (2001) opined that the presence of intense volatility in the security market weakens the expediency of security prices as an indication of the intrinsic value of a firm, a notion that is the crux to the hypothesis of informational efficiency of markets. Hence, the availability of information in the stock market indicates their potential importance as indicators of the current stock market activity on the one hand, and a potential source of information regarding the underlying fundamentals and, thus, the future behaviour of the stock market on the other (Mutalib, 2011).

Investment decisions of retail investors are mainly based on the available information in the market. Based on the available information, they analyze and assess investment avenues and take decisions. The presence of information asymmetry in the market will affect the decisions, and thereby, the transactions. It was evidenced in a study that retail investors gathered clues from institutional investors before investing and did not conduct any sort of analysis while entering the primary market, which also created effects of information asymmetry like adverse selection (Deepak & Gowda, 2014). Volatility clustering and asymmetrical features are important stylized facts in the markets. Modelling volatility clustering and asymmetric effect using conditional heteroskedasticity models gives an insight into what kind of news influences the returns of instruments. A study was conducted to model both the stylized facts in the Indian commodity and financial futures market and proved that bad news created more volatility compared to good news (Kaur & Singh, 2019).

Profile of Stock Indices

A brief profile of five stock indices selected for and used in this paper is presented below:

Ibovespa

The Ibovespa, established in 1968, is the leading stock index of the Brazilian stock market. It consists of about 50 of the largest and most liquid stocks trading on the Sao Paulo exchange. This index is also termed as Total Return Index symbolizing not only the return earned on each stock every year, but also designates which stock's dividends were reinvested and not distributed to the shareholders. The index was constructed based on the weighted average capitalization method. Individual stocks are weighted and this weighted average of all-around 50 stocks forms the Ibovespa index. The inclusion criteria requires stocks to satisfy certain conditions. One of these conditions is the active trading in at least 95% of the trading sessions in what they refer to as their previous three 'portfolio cycles.' Also, for the same period, these stocks should have contributed at least 0.1% of the total value of trading on cash equity markets (Bovespa Index Methodology, 2014).

IMOEX

The Moscow Stock Exchange, also called the IMOEX, is a collection of 50 prime liquid and biggest market cap stocks in the Russian economy. The base value of the index is 100 and it was initially calculated on September 22,

1997. This index is also characterized as a total return index and is computed before the 15th of the month, which is chosen for the recalculation to determine the constituent stocks of the index. A stock which has to be included in the index should have a Free Float factor of at least 10% and during six months before the revaluation of the index, it should have traded for at least 90% of the trading days (Moscow Exchange, 2019).

S&P BSE 100

This index consists of 100 large and midcap stocks, which are considered to be the largest and most liquid stocks. The base year and the base value of the index, when it was constructed, are 1983–84 and 58, respectively. This index was constructed under the weighted average capitalization methodology in which stocks that are part of the index are judged and ranked based on the weights which would be assigned as per their free-float market capitalization. The number of non-trading days is also taken into account, and approximately 250 trading days per annum are considered. Over this period, the median of all monthly medians of the value of that stock traded every day is also calculated (Asia Index Pvt. Ltd., 2018). It is a price movement index, not a total return index, unlike other indices mentioned here of different countries. There is a bi-annual rebalancing that happens at an interval of six months and for the companies which have been listed less than six months ago regarding the rebalancing date, then data points referred for the purpose are taken from the date of listing (Asia Index Pvt. Ltd., 2018). The eligibility criteria for stocks require them to have an annualized traded value of at least ₹ 10 billion. If stocks have ₹ 8 billion of the annualized traded value, then they should satisfy other criteria. Along with this criterion, all stocks included in the index should not have more than five non-trading days before six months of the rebalancing date.

SSE Composite Index

Shanghai Stock Exchange's Composite Index comprises of all 'A' shares and 'B' class shares which trade on the exchange. It was launched in the year 1991 and uses the total market capitalization of individual stocks and their price movements to be weighted (Shanghai Stock Exchange, n.d.). It is considered to be one of the most volatile exchanges in the world as there are shreds of evidence of constant government intervention with circuit breakers in place because the young stock markets often take a hit and plunge very frequently and in great numbers within very short periods (Chen, 2017).

FTSE/JSE Top 40

The FTSE/JSE Top 40 index was launched in 2002 and belongs to the FTSE/JSE all share index universe. It consists of topmost 40 shares in South Africa which are ranked based on their market value as per the FTSE/JSE All Share index (FTSE/JSE Top 40 Index – FTSE Russell, 2018). The base year is considered to be 2002 as well. The base value is 10300.31. All stocks in the index are weighted based on free-float market capitalization of the company they represent.

The main factor that motivated us to conduct this study with BRICS nations is that the BRICS nations together contribute to about 40% of the world population (The World Bank, 2017) and if counted in U.S. trillion dollars, then their respective GDP current prices were: Brazil: 2.14, Russia: 1.72, India: 2.85, China: 14.09, and South Africa: 0.37 (The World Bank, 2018). These figures are evidence enough that these five economies are developing at a pace that would match up soon with the developed nations' economies. Four out of these five countries, Brazil, Russia, India, and China are members of the G-20 group of nations, which is a team of developing and developed nations who come together to discuss the world economic, financial, and social growth.

To apprehend the impact of information asymmetry on the return volatility of stock markets of BRICS nations,

EGARCH and GJR-GARCH models are employed. The Exponential GARCH (EGARCH) model introduced by Nelson (1991) expresses the logarithmic feature of the conditional volatility that is used to identify asymmetric effects in financial time series. Further, Zakoian (1994) propounded the Threshold GARCH (TGARCH) model to determine the nexus between return on investment asset and its asymmetric volatility. Later, this model was extended by Glosten, Jagannathan, and Runkle (1993), and therefore, the model is also called the GJR model.

Objective of the Study

This paper aims at examining the presence/impact of information asymmetry in return volatility of both domestic and cross-country stock market indices by applying GARCH family models.

Data and Statistics

To investigate the impact of information asymmetry on return volatility of stock market indices from BRICS nations, financial time series were used, that is, daily closing prices of five indices for a period of 10 years, that is, from January 2007 - December 2017 were selected. From the closing prices of five market indices, the continuously compounded daily returns are calculated by taking the natural logarithm of the current day's price divided by the previous day's price during the study period.

Methodology

Description of Basic Statistics

To explain the distributional properties of return series during the period of study, a few descriptive statistics parameters such as mean, standard deviation, kurtosis, and Jarque – Bera statistics were calculated. Further, to check autocorrelation and volatility clustering, the correlogram test (autocorrelation and partial autocorrelation) was conducted. Since GARCH methods are stationary processes, it is important to make sure that the return series are stationary. A stationary time series can be defined as its statistical properties, that is, mean, variance, and autocorrelation are stable over time, and to check stationarity, the Augmented Dicky – Fuller test was applied. To employ GARCH family models, one should ensure that the residuals are confirming heteroskadasticity on the data set for which Lagrange multiplier (LM) test for ARCH effects propounded by Engle (1982) was applied.

Model Specifications

(1) GARCH Processes: GARCH (1,1) model proposed by Bollerslev (1986) is capable of explaining the volatility clustering and leptokurtic property of the time series data, but is incapable of explaining the presence of leverage effect and asymmetric volatility in the financial time series. Hence, EGARCH and GJR-GARCH models are employed to achieve the study objective.

\$\infty\$ Exponential GARCH: EGARCH model apprehends asymmetric response of time-varying variance to various shocks and, in the meanwhile, ensures that the variance is always affirmative. It was developed by Nelson in the year 1991 with the following specification:

The left-hand side is the log of the conditional variance. The coefficient γ is known as the asymmetry or

leverage term. The presence of leverage effects can be tested by the hypothesis that, $\gamma < 0$. The impact is symmetric if $\gamma \neq 0$. Higher-order EGARCH models can be specified similarly. EGARCH (p, q) is as follows:

$$Ln(\sigma_t^2) = \omega + \sum_{i=1}^p \beta_i Ln(\sigma_{t-i}^2) + \sum_{i=1}^q \alpha_i \left\{ \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| - \sqrt{\frac{2}{\pi}} \right\} - \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}}$$
(2)

♦ *GJR-GARCH Model*: The generalized specification of the GJR-GARCH for the conditional variance developed by Glosten et al. (1993) and Zakoian (1994) is given by:

$$\sigma_{t}^{2} = \omega + \alpha_{1} \varepsilon_{t-1}^{2} + \gamma d_{t-1} \varepsilon_{t-1}^{2} + \beta_{1} \sigma_{t-1}^{2} \qquad(3)$$

where,

 γ is known as the asymmetry or leverage parameter and d_{i-1} is a dummy variable. Under the GJR-GARCH model, the good news ($\varepsilon_{i-1} > 0$) and the bad new ($\varepsilon_{i-1} < 0$) shave a differential effect on the conditional variance. Good news has an impact of α_i , while bad news has an impact on $\alpha_i + \gamma_i$. Hence, if γ is significant and positive, negative shocks have a larger effect on σ_i^2 than the positive shocks. In the general specification of this model, GJR-GARCH (p,q), the conditional variance equation is specified as follows:

$$\sigma_{t}^{2} = \omega + \sum_{i=1}^{q} + (\alpha_{i} + \gamma_{i} d_{i-1}) \varepsilon_{i-1}^{2} + \sum_{i=1}^{p} \beta_{i} \sigma_{i-i}^{2} \qquad \dots (4)$$

Parameters and variables used in the above GARCH family model equations are explained in Table 1.

Table 1. Parameters and Variables Defined on the Basis of Conditional Volatility Models

Parameters and Variables	Description			
Ln	Natural logarithm			
σ^{2}	Conditional; volatility			
$\operatorname{Ln}(\sigma_{t}^{2})$	Log conditional volatility			
ω	Constant			
α_{ν}	ARCH term. That measures the symmetric			
	effects of the past on present volatility.			
ϵ^2_{t-1}	ARCHterm,squarederrortermattimet			
β_i	Parameter to measure volatility persistence			
σ^2_{t-1}	GARCH term			
\mathbf{E}_{t-1}	Lagged error term			
γ_i	Gamma or asymmetry or leverage effect coefficient			
$\left rac{oldsymbol{arepsilon}_{t-i}}{oldsymbol{\sigma}_{t-i}} ight $	Absolute value of standardized residuals			

Analysis and Results

In the light of the above theoretical framework, an attempt is made here to analyze and present the results under five heads.

Descriptive Statistics for Price and Return Series of Indices

The results of a few descriptive statistics computed based on the price and return statistics of five indices for 10 years are presented in Table 2.

Table 2 presents the distributional properties of price and return series of the selected stock market indices. As presented in Table 2, mean returns of all five indices are positive with high standard deviation when compared with mean return, indicating that all stock market indices are providing high average returns, but these returns are subject to high risk/volatility. Kurtosis values are greater than 3 (except for the FTSE Index), which indicates both prices and return series have a heavier tail than a standard normal deviation, and therefore, the price-return series are non-normally distributed. Jarque – Bera statistics are greater than 1.96 and statistically significant at the 5% level of significance. Therefore, the null hypothesis of normality is rejected.

Table 2. Descriptive Statistics for Price and Return Series of Indices

Parameters		Mean	Std. Dev.	Kurtosis	JB Stat	<i>P</i> -value	Observations
BOVESPA Index	Price	4.752432	0.068311	3.42397	202.94	0.0000	2677
	Return	0.000168	0.017599	9.19820	4285.31	0.0000	2677
BSE Index	Price	3.783433	0.134798	3.07185	47.55	0.0000	2677
	Return	0.000411	0.014405	13.28475	11799.80	0.0000	2677
FTSE Index	Price	4.519752	0.128959	1.89952	155.88	0.0000	2677
	Return	0.000267	0.013354	6.77089	1588.31	0.0000	2677
MOEX Index	Price	3.179513	0.108771	7.07381	3149.77	0.0000	2677
	Return	0.000562	0.020210	28.89932	74822.11	0.0000	2677
SHANGAI Index	Price	3.452032	0.107457	3.12840	158.02	0.0000	2677
	Return	0.000438	0.017258	7.26260	2203.15	0.0000	2677

Test for Stationarity

Augmented Dickey – Fuller (ADF) test was applied in order to examine whether the price and return series are stationary or not. The results of the test are presented in Table 3.

Table 3. Results of Stationarity (ADF Test)

Series		TAU value	<i>P</i> -value
BOVESPA	Price	-53.52095	0.0001
	Return	-53.53022	0.0001
MOEX	Price	-51.34337	0.0001
	Return	-51.35250	0.0001
BSE	Price	-47.90276	0.0001
	Return	-47.91058	0.0001
SHANGAI	Price	-50.76207	0.0001
	Return	-50.77126	0.0001
FTSE JSE	Price	-51.93161	0.0001
	Return	-51.93747	0.0001
Test critical	1% level	-3.432538	
values	5% level	-2.862392	
	10% level	-2.567268	

TAU values or *t*-statistics of Augmented Dickey – Fuller test are greater than the test critical values at 1%, 5%, and 10% levels of significance and the *p*-values are also significant, and therefore, the data set is stationary. Price series of all five exchanges are stationary at 1st difference, and for the return series, we get stationarity at the level. This is further understood from the price and return series of all the market indices during the study period as depicted in the Appendix Figure A1 and Appendix Figure A2.

Test for Heteroscedasticity

Table 4 shows the results for the ARCH - LM test applied to examine whether the data set is heteroskedastic or homoscedastic. It may be noted here that testing for the presence of heteroscedasticity is essential before applying the GARCH family models.

From the results of the ARCH - LM test (Table 4), it is evidenced that both Prob.(*F*-Statistic) and Prob. (Chi-square) values are statistically significant at the 5% level of significance, and therefore, the null hypothesis of homoscedasticity is rejected.

Table 4. Results for Heteroskedasticity (ARCH - LM Test)

Series		Prob. (F-Statistic)	Prob. (Chi-square)
BOVESPA	Price and Return	0.0000	0.0000
MOEX	Price and Return	0.0000	0.0000
BSE	Price and Return	0.0000	0.0000
SHANGAI	Price and Return	0.0000	0.0000
FTSE JSE	Price and Return	0.0000	0.0000

Test Results of GJR - GARCH

In order to capture the information asymmetries in the return volatility series, two models are used. They are GJR - GARCH (1,1) and EGARCH (1,1). ' γ ' (Gamma) examines the asymmetric effect in both GJR - GARCH (1,1) and EGARCH (1,1) models. GJR - GARCH (1,1) model is used to test for evidence of asymmetric volatility in the returns volatility data series of all five indices. The results of the same are presented in Table 5.

Table 5. Results of GJR - GARCH Model

Series	α	β	γ
BOVESPA	0.028059	0.121571	0.890177
	(0.0000)*	(0.0000)*	(0.0000)*
MOEX	0.045197	0.100756	0.903842
	(0.0000)*	(0.0000)*	(0.0000)*
BSE	0.005308	0.156896	0.922889
	(0.0000)*	(0.0000)*	(0.0000)*
SHANGAI	0.017314	0.087555	0.944917
	(0.0000)*	(0.0000)*	(0.0000)*
FTSE JSE	0.008993	0.170284	0.916508
	(0.0000)*	(0.0000)*	(0.0000)*

Note. Figures in parentheses are *p*-values;

^{*} denotes significant at 5%.

It is inferred from Table 5 that the result of the coefficient's leverage effect (γ) is positive and significant at the 5% level as the 'p' values are less than 0.05. The results establish that negative shocks or bad news have a larger effect on the volatility than the positive shocks or good news and also confirms the presence of asymmetries in return volatility series in all five stock market indices.

Test Results of EGARCH

Table 6 presents the results of the EGARCH model test for capturing information asymmetries or leverage effect in return volatility series of all five stock market indices.

Table 6. Results of EGARCH Model

Series	ω	α	β	γ	
BOVESPA	-0.214371	0.143091	-0.085075	0.987161	
	(0.0000)*	(0.0000)*	(0.0000)*	(0.0000)*	
MOEX	-0.000803	0.201187	-0.056822	0.992151	
	(0.0000)*	(0.0000)*	(0.0000)*	(0.0000)*	
BSE	-0.160107	0.142650	-0.111149	0.993807	
	(0.0000)*	(0.0000)*	(0.0000)*	(0.0000)*	
SHANGAI	-0.152523	0.129333	-0.045417	0.993074	
	(0.0000)*	(0.0000)*	(0.0000)*	(0.0000)*	
FTSE JSE	-0.295993	0.250949	-0.134320	0.984712	
	(0.0000)*	(0.0000)*	(0.0000)*	(0.0000)*	

Note. Figures in parentheses are p - values;

It is evidenced that ARCH (α) and GARCH parameters (β) are smaller than 1 (Table 6), stating that the conditional variance of return series is not volatile and there is no increase or decrease in prices, but a steady movement is observed. The estimated coefficients are statistically significant at the 5% level as 'p' value is less than 0.05. Gamma (γ) indicates the information asymmetries or leverage coefficient. As per the model philosophy, negative signs of γ are expected to prove the presence of asymmetries in the return volatility, but we get positive signs for all market indices. Negative leverage indicates that high negative returns are followed by higher volatility than the positive ones. However, it does not have to be the case in each market and in all time periods, and thus, is affected by the presence of some market anomalies. The positive signs of γ values are not completely rejecting that there are no asymmetries in the market, but instead, these explain the presumptions of EMH of the positive correlation between past returns and future returns.

Conclusion

An attempt is made in this paper to examine the presence of information asymmetry in the return volatility series of five stock market indices both from domestic and foreign countries, specifically BRICS nations. The daily closing prices of all these stock indices were collected for a period of 10 years starting from January 2007 – December 2017. To examine information asymmetries in the return volatility, GJR-GARCH and EGARCH models are employed. Before applying these two models, we confirm the unit root test with ADF, autoregressive conditional heteroskadasticity with the help of ARCH - LM models. The results of GJR-GARCH and EGARCH confirm the presence of information asymmetries in the return volatility of all five market indices.

^{*} denotes significant at 5%.

Results of GJR-GARCH in terms of gamma (γ) are positive and significant at the 5% level of significance, which further proves that negative shocks are causing more volatility in return than the positive shocks. However, in the case of EGARCH results, the gamma (γ) as a parameter to test asymmetry or leverage effect, we expected negative signs instead of positive signs with significance. On the contrary, we get a positive sign to test asymmetry or leverage effect, which means that there is a presence of information asymmetry or the leverage effect but in opposite direction, that is, rather than negative shocks, positive shocks will cause more volatility in return. This is because of market anomalies; specifically, the crisis affected the markets during the study period.

Research Implications

In the background of technical analysis and EMH, historical information about patterns and trends in asset price and trading volume will guide the investment decisions in the market. With respect to technical analysis, financial analysts and investment advisors can develop strategies pertaining to buy and sell recommendations by examining the past trends and patterns to formulate efficient investment classes for their clients. Since the efficiency of the market is based on the flow of information, sometimes, a private set of information is not accessed by all the market participants, and even if they are able to, then there are possibilities of manipulation of information which, in turn, creates information asymmetry and thereby affects the contract parties' positions. Hence, it is advised that market regulators need to mitigate the manipulation of market information, and this may significantly influence the determination of market dynamics by participants. Investors should be able to analyze and assess the negative and positive shocks in the market and its impact on the asset portfolio and particularly on return volatility.

Limitations of the Study and Scope for Further Research

The investment decisions of market participants are influenced by multiple factors. The expected return and the variations in the expected rate of return can be one of the factors that influence decisions. It is not necessarily only the expected rate of return and its volatility which influences the decisions as assumed in conditional volatility models. Similar to domestic factors, global factors will also have an impact on investment decisions. However, conditional volatility models are not assuming international economic and political factors, which result in volatility in the expected return. This research article aimed to capture the presence of information asymmetry on the basis of conditional volatility models' assumptions. The conditional volatility models (both symmetric and asymmetric models) perform better only in stable market conditions, but the selected markets in this study lacked this. Further, the current study dealt only with the price and return volatility but did not consider trading activity; hence, future research may include these aspects while modelling the information asymmetry in the markets.

Authors' Contribution

Mr. Shabarisha N. visualized the idea and developed quantitative design to undertake the empirical study. Shabarisha N. extracted research papers of high repute, filtered these based on keywords, and generated concepts relevant to the study design. Prof. J. Madegowda verified the analytical methods and supervised the study. The numerical computations were done by Shabarisha N. using EVIEWS 8. Shabarisha N. wrote the manuscript in consultation with Prof. J. Madegowda.

Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest, or non-financial interest in the subject matter, or materials discussed in this manuscript.

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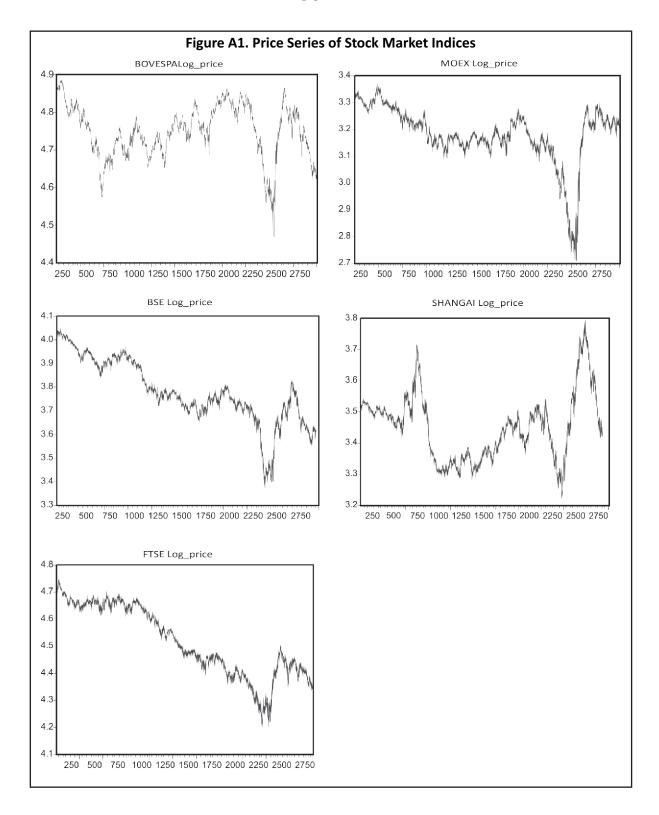
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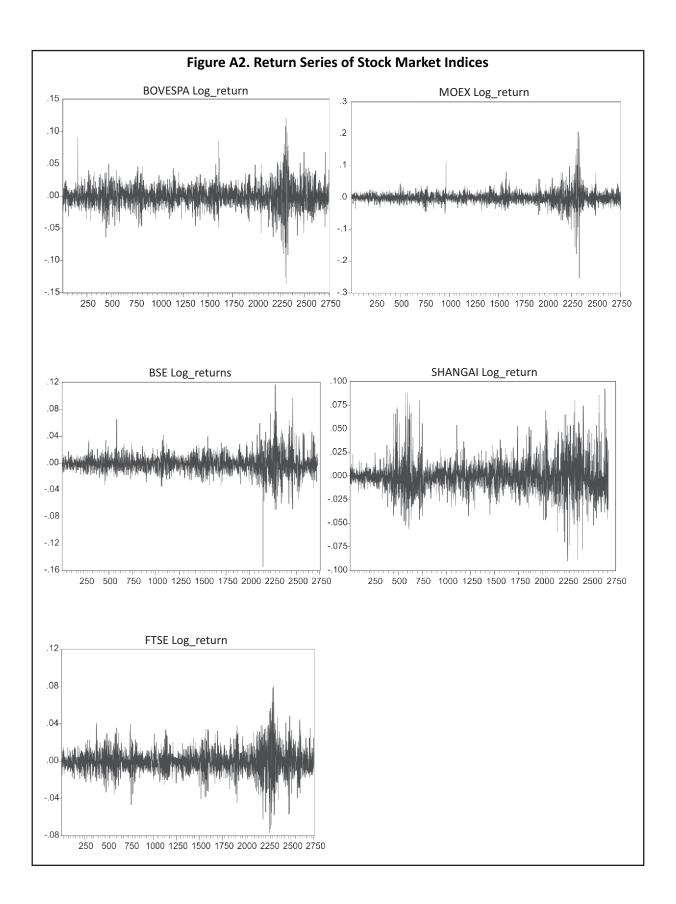
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Appendix





About the Authors

Mr. Shabarisha N. is currently an Assistant Professor in the School of Business and Management at Christ (Deemed to be University), Bangalore and is pursuing Ph.D. from Kuvempu University in the area of information asymmetry and options pricing. Mr. Shabarisha N. has attended many national and international conferences and has written research papers on empirical asset pricing and volatility modelling.

Prof. J. Madegowda is currently a Professor and Dean (Academic) in the Akshara Institute of Management Studies, Shivamogga, Karnataka. Prior to the current position, he was Professor and Chairman in the Department of Commerce, Kuvempu University. Prof. J. Madegowda has published 20 books and more than 75 research papers in journals of repute. Prof. Madegowda has also served Kuvempu University as its Finance Officer and Vice-Chancellor for a few months. He has also served as a member of different bodies of Kuvempu University such as Academic Council, Senate, Syndicate Finance Committee, etc.