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DOES INDIAN ADR STOCKS UNCERTAINTY SHOCK PLAY IMPORTANT ROLES IN THE MOBILITY OF US STOCK MARKET?

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Abstract *The study focuses on the selection of Indian ADR (American depository receipts) equities for the mobility of the US stock market, which are listed on the US stock exchange. This study evaluated the dynamic link between Indian ADR and the US stock market utilising VAR Granger Causality/Block Exogeneity Wald Tests, followed by variance decomposition and impulse response. The NYSE (New York Stock Exchange) is used as a proxy variable for the US stock market. The research gathered data with the goal of having a data range of twenty years. The data range of less than twenty years was excluded from the investigation, and the study was completed with seven Indian ADR variables out of fourteen Indian ADR variables. Daily time-series data for seven Indian ADR variables listed in the US market have been gathered from 2001 to 2021. The result verifies that NYSE is caused by WIT (Wipro Limited), HDB (HDFC Bank Limited), and SIFY (Sify Technologies Limited), and it confirms that NYSE is also causing RDY (Dr. Reddy's Laboratories Limited) and SIFY, respectively. As a result, the bivariate causation between SIFY and NYSE is confirmed SIFY is the Indian ADR that is contributing to the NYSE's mobility among all Indian ADRs listed on the foreign stock exchange. IBN (ICICI Bank Ltd.) and WIT are contributing to the variance decomposition of NYSE, and this is a highly significant variation in NYSE when compared to other variables. The SIFY's asymmetric influence on the NYSE is represented by the impulse response function.*

Keywords: *Indian ADR, NYSE, VAR Granger Causality/Block Exogeneity Wald Tests, Variance Decomposition, Impulse Response, American Depository Receipt*

JEL Classification: *G15, G17*

INTRODUCTION

An ADR is a commodity offered by US registered monetary institution to national investors like a replacement for the immediate possession of foreign company shares. An ADR can symbolise one or more stocks of a non-US company, or a proportion of a stock (Bhatiya, 2014). Throughout the last 2 decades, as businesses in emerging nations have cultivated a more holistic view, ADR have become ubiquitous means for international corporations to obtain money. The earnings on ADRs are totally reliant on underpinning equity as well as foreign fluctuations, further they trade close to parity with their local counterparts (Gupta, 2010). (Madhavan & Ray, 2016) ADRs are negotiable securities offered by non-U.S. corporations as well as traded on US stock exchanges, providing an opportunity for worldwide exposure for American buyers. Rule 144 A, Level-I, II, and III are various forms of ADR accessible on the market. The currency trading volume of ADRs increased by 36 percent on an annualised rate between 1997-98, as per New York Bank, main depository of ADRs in the United States. At the same time, the New York Stock Exchange (NYSE) dollar trading volume (except ADRs) increased by 32 percent. Arbitrage activity in Indian ADRs is regulated by the Indian government. ADRs can be redeemed for underlying shares, but they can only be created from underlying shares in the primary market with approval from the Indian government granted to the corporation. According to (Kadapakkam & Misra, 2003), premiums on Indian ADRs cannot be arbitraged away in secondary markets. American depository receipts (ADRs) continue to be the major methods utilised by businesses in emerging economies to list internationally. However, there is a dearth of research in emerging markets regarding the aftermath performance of ADR issuances.

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(Adami et al., 2023) analysed how operating performance of the firms changed after ADR issuances and the findings indicate that ADRs have comparatively superior short-term purchasees and hold abnormal returns and they eventually produce positive abnormal returns. (Wadhwa, 2015) examined the impact of trading behaviour by foreign portfolio investors on the Indian stock markets and proposed that appropriate foreign investment policies for the Indian stock markets should be designed and overseen by the government and economists. (Khalid & Habib, 2016) examined how different macroeconomic factors affect the Indian stock market and found that stock returns are significantly impacted negatively solely by exchange rates while money supply, inflation, industrial production, interest rates, and oil prices have a big influence on the stock market. (Samet et al., 2023) discovered that institutional investors make larger investments in standalone ADRs, or ADRs without underlying stocks listed in the home market. The volume of ADR transactions in 1998 was $563 Billion[1]. According to (Bin et al., 2003), ADR yields are susceptible to fluctuations in (a) the US trade, (b) the underpinning home stock markets, as well as (c) the equivalent foreign exchange market. Similarly, we incorporated equivalent elements into our adaptive structural model. Using monthly data, (Rohilla et al., 2023) examined the long-term relationship between investor sentiment and the volatility of the Indian stock market from 2010 to 2021 and determined that, over time, volatility is negative when sentiment is positive and vice versa. (Lins & Strickland, 2000) discovered that having accessibility to global financial markets is a substantial advantage of a US stock market listing, particularly for developing market companies. Most of the ADR research suggests that pairing ADRs with the US market or additional assets can minimise risk while maintaining projected benefits (Officier & Hoffmeister, 1987; Wahab & Khandwala, 1993).

The current paper focuses on the selection of Indian ADR (American depository receipts) equities for the mobility of the US stock market, which are listed on the US stock exchange. This study evaluated the dynamic link between Indian ADR and the US stock market utilising VAR Granger Causality/Block Exogeneity Wald Tests, followed by variance decomposition and impulse response.

LITERATURE REVIEW

Numerous research has been conducted on ADRs and US stock market along with the Indian stock market. (Choi & Kim, 2000) investigated ADRs from 1990 to 1996 and found that they can be advantageous in a person's portfolio for diversification of risk, with developing markets, ADRs providing the optimum opportunity. (Kim et al., 2000) use the VECM to scrutinise static price links among the price of an American Depository Receipt and the price of an underlying stock. (Alaganar & Bhar, 2001) explored whether arbitrage possibilities exist amongst ADRs and their underlying equities in established marketplace, whereas (Rabinovitch et al., 2003) consider the problem in developing economies. (Arnold et al., 2002) surveyed regarding the variability of ADRs in conditions of trade in United States, trade in its native territories, as well as the variability in the rate of exchange amid the United States with ADRs' home country. Their findings showed that the standard deviation (σ) of profit of ADRs is non considerably divergent as of standard deviation of return of its underlying native nation's equities. (Gorman et al., 2004) contrast the ex-dividend day investment gains coupled with trade velocity of external equities traded as ADRs in U.S. stock markets to ex-day yields in addition to the quantity of paired sample of U.S. equities. Researchers enable us to see if changes in payment of dividend methods and/or foreign money risk have an impact on ADRs equity returns and trade velocity on ex-dividend day. (Chung et al., 2007) to explore the dynamic price connection among both ADRs and their underlying equities use the criterion VECM in research. (Chen et al., 2011) investigated whether American Depositary Receipts (ADRs) have a detrimental impact on the underlying local index (LD) for the Japanese market.

(Kabir et al., 2011) determined if ADRs may provide diversified advantages to U.S. investors beyond what can be obtained by buying directly in nation indexes. Their data demonstrate that ADRs and country indexes were interchangeable in the industrialised world in the late 1990s, but traders needed to finance both ADRs as well as country indexes in Latin America and just ADRs in Asia in recent years. (Kumar et al., 2011) investigated the impact of global competition for order flows on the local market as a result of six Indian enterprises registering American Depository Receipts (ADRs) on the NYSE. The study (Visalakshmi & Lakshmi, 2013) showed that the values of Indian ADRs and their underlying securities, as well as the Indian and U.S. market indexes, have a long run cointegrating connection. The divergence from long-run equilibration and lagged variations of all, impact the ADR portfolio's short-term fluctuations. (Wang et al., 2013) examined how trading location influences the equity returns of China-backed American Depository Receipts (ADRs) traded in the US. If International Financial Markets are interconnected, stock prices should be influenced only by fundamentals; otherwise, stock prices may be influenced by trading locations and investor emotion. According to the report, China ADR results are influenced more by US market volatility than by Chinese market returns. (Wu, 2013) detected a positive holiday effect

[1]Data on trading volume is obtained from the ADR segment of the Bank of New York's website. Retrieved from http: www.bankofny.com:adr

during the CNY (Chinese National Holidays) season using all Chinese ADRs completed from 1993-2011, however, this influence becomes statistically negligible when adjusted or modified for US returns. Conversely, Chinese ADRs had much greater mean returns in the week leading up to the festival than in the remaining year, but lower mean returns in the week after holiday. From a non-linear univariate aspect (Madhavan & Ray, 2016) assessed at the effectiveness of level II/III Indian ADRs and its underlying equities operating in Mumbai (Maharashtra). The findings show that the measure of effectiveness of all U.S./Indian securities studied in the study is varied, necessitating a grading mechanism in each trading platform. (Tripathi & Kumar, 2014) in order to analyse the issue of sectoral efficiency of the Indian stock market, the following tests are used: variance ratio test, unit root tests, Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS). The overall performance of the Indian stock market appears to be lackluster, but several sectors within it have performed well, particularly over the course of the study period. (Bhatnagar & Khan, 2015) examined the impact of global currency value on the monthly yield on ADR from 2004 to 2013 and found that Forex earnings have a substantial relationship with ADR returns, but the ADR returns are not a major predictor of Forex returns. (Gupta et al., 2016) examined that oil prices and economic growth lead ADR prices in the near run, but ADR prices foretell changes in the money supply in India. The same demonstrate that in the long-run, economic development boosts ADR returns favourably in Brazil and China but adversely in Russia and India.

According to the experimental findings, the equity market in the United States is more competitive than the capital market in India. The effectiveness of all ADRs, its underlying stocks, and now both countries' market has varied (Singh & Chakraborty, 2017). Although, compared to their underlying equities, variation in efficacy of Indian ADRs is greater, implying that a stock listed on stock indexes from various nations may exhibit varying rates of efficiency development depending upon market maturity. (Li et al., 2019) looked at foreign companies' decisions to list on ADRs exchanges in the United States. ADR firms listed in hot years do much worse in terms of operating and stock performance than those listed in cold years. Foreign companies reveal more information than comparable U.S. companies, according to (Chowdhary et al., 2021), notably in the social and the environment Corporate Social Responsibility (CSR) components. Additionally, they discovered conclusive proof, as a result of foreign firms' greater CSR revelation, overseas equities have lower idiosyncratic volatility, better liquidity, and higher institutional ownership than other comparable U.S. stocks. Domestic liquidity for both established and emerging market enterprises dramatically rises after a US cross listing, according to research by (Ghaffar et al., 2022). The preventive, primary, transitional, and extensive impacts on domestic liquidity are all noticeably favourable for businesses in emerging economies.

According to (Kumar, 2023), premiums are adversely correlated with underlying stock returns while Indian ADR returns are closely linked to underlying market returns. This analysis demonstrates that Indian ADR premiums are considerably and favorably related to investor to buy demand using an order imbalance of small and total trades of ADRs. (Aharon et al., 2022) studied the effect of Robinhood investors' activity on the volatility of 382 American depository receipts (ADRs) from 33 different nations revealed that their participation increases the volatility of cross-listed securities. They claimed that their findings had significant ramifications for various market and government policy makers as well as domestic companies thinking about cross listing their equities. Another study, by (Aharon et al., 2022), looked at the effect of COVID-19 related government involvement on the liquidity and volatility of 387 ADRs from 34 different countries and found the closures, limitations, and restraint health measures put in place during the pandemic's outbreak period appeared to worsen the ADRs' liquidity and stability. (Grossmann et al., 2024) to investigate the relationship between societal secrecy and IPO underpricing, a study that looks at 350 Level III ADR IPOs from thirty-five countries between 1990 and 2020 discovered that ADR IPO underpricing is lower for ADRs from high secrecy nations.

RESEARCH METHODOLOGY

The dynamic relationship between Indian ADR and the underlying stock is well known in the Indian stock market. The ADR stands for American Depository Receipt, which allows Indian equities to be traded on American stock exchanges. Several research on Depository Receipts (DRs) have found that trading on the DR in the foreign market has an impact on the stock, price, volatility, and volume in the home country. Similarly, will Indian ADRs are influencing the US stock market and do they have the dynamic relationship. This is the strong reason to conduct this research. The research is going to help various groups and individuals who are interested in the equity research and interested in the foreign investment. The study period is from July 2001 to April 2021. The dataset is on a daily basis. The data is collected from the yahoo finance website. Firstly, we have taken the 14-variable dataset of Indian ADR listed in US market, but we have drop down the 7 Indian ADR variables due to the limited time series dataset. We have taken twenty years as a base to collect the data. Finally, we have chosen seven Indian ADR variables to test the US market mobility. The proxy variable for US market is NYSE. The model will take into account Indian ADR's greater and

more significant contribution to the US stock market in terms of price, volume, and volatility. For improved time series analysis results, all the variables used in the study are transformed to the logged version.

Model Specification

The VAR model equation is written for every variable, which is explaining the dynamic relationship with its own lag variable and the other equation model variables. The VAR system is employed to investigate the dynamic relationship, which is, exist between the series variables. The VAR model system is also going to check the impact of random disturbance on the variables of the system (Table 1). The VAR model is as follows:

$$Y_t = A_1 Y_{t-1} + \ldots\ldots\ldots\ldots + A_p Y_{t-p} + B X_t + e_t$$

Table 1

Description of Variables	NYSE	New York Stock Exchange
	HDB	HDFC Bank Limited
	IBN	ICICI Bank Limited
	INFY	Infosys Limited
	RDY	Dr. Reddy's Laboratories Limited
	REDFY	Rediff.com India Limited
	SIFY	Sify Technologies Limited
	WIT	Wipro Limited

The process of VAR model equations is written as follows:

$$D(LN\_NYSE)_t = \alpha_1 + \beta_{11}D(LN\_IBN)_{t-1} + \beta_{12}D(LN\_WIT)_{t-1} + \beta_{13}D(LN\_RDY)_{t-1} + \beta_{14}D(LN\_INFY)_{t-1} + \beta_{15}D(LN\_NYSE)_{t-1} + \beta_{16}D(LN\_HDB)_{t-1} + \beta_{17}D(LN\_SIFY)_{t-1} + \beta_{18}D(LN\_REDFY)_{t-1} + \varepsilon_t \quad \text{(Equation 1)}$$

$$D(LN\_IBN) = \alpha_2 + \beta_{21}D(LN\_IBN) + \beta_{22}D(LN\_WIT) + \beta_{23}D(LN\_RDY) + \beta_{24}D(LN\_INFY) + \beta_{25}D(LN\_NYSE) + \beta_{26}D(LN\_HDB) + \beta_{27}D(LN\_SIFY) + \beta_{28}D(LN\_REDFY) + \varepsilon_t \quad \text{(Equation 2)}$$

$$D(LN\_WIT) = \alpha_3 + \beta_{31}D(LN\_IBN) + \beta_{32}D(LN\_WIT) + \beta_{33}D(LN\_RDY) + \beta_{34}D(LN\_INFY) + \beta_{35}D(LN\_NYSE) + \beta_{36}D(LN\_HDB) + \beta_{37}D(LN\_SIFY) + \beta_{38}D(LN\_REDFY) + \varepsilon_t \quad \text{(Equation 3)}$$

$$D(LN\_RDY) = \alpha_4 + \beta_{41}D(LN\_IBN) + \beta_{42}D(LN\_WIT) + \beta_{43}D(LN\_RDY) + \beta_{44}D(LN\_INFY) + \beta_{45}D(LN\_NYSE) + \beta_{46}D(LN\_HDB) + \beta_{47}D(LN\_SIFY) + \beta_{48}D(LN\_REDFY) + \varepsilon_t \quad \text{(Equation 4)}$$

$$D(LN\_INFY) = \alpha_5 + \beta_{51}D(LN\_IBN) + \beta_{52}D(LN\_WIT) + \beta_{53}D(LN\_RDY) + \beta_{54}D(LN\_INFY) + \beta_{55}D(LN\_NYSE) + \beta_{56}D(LN\_HDB) + \beta_{57}D(LN\_SIFY) + \beta_{58}D(LN\_REDFY) + \varepsilon_t \quad \text{(Equation 5)}$$

$$D(LN\_HDB) = \alpha_6 + \beta_{61}D(LN\_IBN) + \beta_{62}D(LN\_WIT) + \beta_{63}D(LN\_RDY) + \beta_{64}D(LN\_INFY) + \beta_{65}D(LN\_NYSE) + \beta_{66}D(LN\_HDB) + \beta_{67}D(LN\_SIFY) + \beta_{68}D(LN\_REDFY) + \varepsilon_t \quad \text{(Equation 6)}$$

$$D(LN\_SIFY) = \alpha_7 + \beta_{71}D(LN\_IBN) + \beta_{72}D(LN\_WIT) + \beta_{73}D(LN\_RDY) + \beta_{74}D(LN\_INFY) + \beta_{75}D(LN\_NYSE) + \beta_{76}D(LN\_HDB) + \beta_{77}D(LN\_SIFY) + \beta_{78}D(LN\_REDFY) + \varepsilon_t \quad \text{(Equation 7)}$$

$$D(LN\_REDFY) = \alpha_8 + \beta_{81}D(LN\_IBN) + \beta_{82}D(LN\_WIT) + \beta_{83}D(LN\_RDY) + \beta_{84}D(LN\_INFY) + \beta_{85}D(LN\_NYSE) + \beta_{86}D(LN\_HDB) + \beta_{87}D(LN\_SIFY) + \beta_{88}D(LN\_REDFY) + \varepsilon_t \quad \text{(Equation 8)}$$

Unit Root Analysis

The majority of financial time series are non-stationary time series or random walks with unit root in their original form, based on the current literary work. As a result, before using any econometric method, we checked for the presence of a unit root in the selected time series variables. We conducted the investigation to determine the dynamic connections between the series. A unit root existence in the chosen series can lead to erroneous conclusions in the analysis. The time series data stationarity is determined by applying the ADF test. At level, the time series data is non-stationary. Therefore, we have adopted the first difference to make the data stationary. Data become stationary at first difference (see Table 2).

The response of ADF test has allowed us to test the VAR approach among the eight variables to test the causality. All the specified time series are assumed to be endogenous

variables in the VAR techniques. Each endogenous variable in the model is explained using both its own lagged values and the lagged values of the other endogenous variable in the model. Generally, exogenous variables are not considered in the VAR model. Here we have eight endogenous variables in the study such as log NYSE, log IBN, log WIT, log HDB, log INFY, log RDY, log SIFY, and log REDFY with no exogenous variables.

Table 2: Augmented Dickey-Fuller

	Level (5%)			First Difference (5%)		
	Test Statistic	**C.V.**	**P.V.**	**Test Statistic**	**C.V.**	**P.V.**
ln_NYSE	-0.6775	-2.8619	0.8504	-77.511	-2.8619	0.0001
ln_HDB	-1.0722	-2.8619	0.7288	-77.197	-2.8619	0.0001
ln_IBN	-2.0892	-2.8619	0.2492	-73.551	-2.8619	0.0001
ln_INFY	-1.4916	-2.8619	0.5380	-71.436	-2.8619	0.0001
ln_RDY	-0.9007	-2.8619	0.7886	-73.114	-2.8619	0.0001
ln_REDFY	-1.1088	-2.8619	0.7146	-25.348	-2.8619	0.0000
ln_SIFY	-2.6236	-2.8619	0.0882	-54.139	-2.8619	0.0001
ln_WIT	-2.0390	-2.8619	0.2701	-74.667	-2.8619	0.0001

Table 3: VAR Lag Exclusion Wald Tests

Chi-Squared Test Statistics for Lag Exclusion									
	D(LN_IBN)	**D(LN_ WIT)**	**D(LN_ RDY)**	**D(LN_ INFY)**	**D(LN_ NYSE)**	**D(LN_HDB)**	**D(LN_SIFY)**	**D(LN_ REDFY)**	**Joint**
Lag 1	16.73136 [0.0330]	42.08532 [0.0000]	38.83061 [0.0000]	45.80899 [0.0000]	57.22695 [0.0000]	50.79181 [0.0000]	134.4749 [0.0000]	1124.504 [0.0000]	1615.02 [0.0000]
Lag 2	11.42428 [0.1788]	8.010211 [0.4325]	16.45414 [0.0363]	16.38496 [0.0372]	9.187235 [0.3267]	23.64458 [0.0026]	35.42373 [0.0000]	280.3309 [0.0000]	438.9473 [0.0000]
Lag 3	15.75166 [0.0461]	13.48850 [0.0961]	10.15056 [0.2546]	18.91245 [0.0153]	9.998660 [0.2651]	17.62930 [0.0242]	20.59581 [0.0083]	144.7283 [0.0000]	274.3285 [0.0000]
Lag 4	3.072155 [0.9297]	19.41187 [0.0128]	3.502604 [0.8990]	19.17065 [0.0140]	29.93962 [0.0002]	14.28117 [0.0747]	10.26430 [0.2470]	150.2207 [0.0000]	257.5279 [0.0000]
Lag 5	9.622611 [0.2925]	8.875186 [0.3529]	26.86777 [0.0007]	8.323778 [0.4025]	8.635446 [0.3740]	10.07745 [0.2596]	7.374493 [0.4968]	80.02223 [0.0000]	157.7956 [0.0000]
Lag 6	19.16475 [0.0140]	15.19413 [0.0555]	5.459171 [0.7076]	19.16805 [0.0140]	13.76618 [0.0881]	22.55005 [0.0040]	22.43372 [0.0042]	9.447456 [0.3060]	139.2121 [0.0000]
Lag 7	14.71078 [0.0650]	11.80290 [0.1602]	22.90761 [0.0035]	16.97926 [0.0303]	23.12452 [0.0032]	28.58302 [0.0004]	23.45334 [0.0028]	7.139323 [0.5217]	154.8503 [0.0000]
Lag 8	14.12272 [0.0786]	6.260529 [0.6181]	4.706558 [0.7884]	9.203938 [0.3254]	4.343288 [0.8249]	15.64451 [0.0478]	12.88395 [0.1159]	10.87098 [0.2091]	96.62524 [0.0053]
Lag 9	16.37654 [0.0373]	31.75345 [0.0001]	18.31147 [0.0190]	28.51402 [0.0004]	16.21070 [0.0395]	18.55945 [0.0174]	8.511580 [0.3852]	51.54118 [0.0000]	156.8426 [0.0000]
Lag10	22.71006 [0.0038]	10.41953 [0.2368]	3.149519 [0.9246]	14.86909 [0.0617]	7.313668 [0.5032]	14.76890 [0.0638]	4.130631 [0.8451]	4.950358 [0.7629]	73.37193 [0.1978]
df	8	8	8	8	8	8	8	8	64

To estimate the optimum lag value, we have applied the VAR lag exclusion Wald tests to obtain the right lag length. The result of the VAR lag exclusion Wald tests suggested us the six-lag length. We can see in the above result (Table 3) that up to six joint lag lengths the value is declining and after that it has an increasing and decreasing sequence. It means that we cannot reject it up to the six-lag length. In lag 1, all variable values are showing significant results followed by lag 2 is five significant values, lag 3 is five significant values, lag 4 are four significant values, lag 5 with two significant values, and lag 6 with four significant values.

We hypothesised that if one variable in a time series is "Granger Causes" to the other time series variables, the coefficient of the lagged values of the former time series must be significant because the VAR technique evaluates many variables at once. However, to investigate multivariate causation in a VAR technique, we needed to determine the appropriate number of lags. The following indicators were used to make this decision and after the analyses, the selections of the optimum lag of the eight selected time series, as shown in Table 3.

Finalising the lag length, the next step is to employ the VAR Granger Causality/ Block Exogeneity Wald Test. The result of the test is shown in Table 4. The outcome of the VAR Granger Causality/ Block Exogeneity Wald test revealed the presence of a significant multivariate causal link within the specified time series NYSE, IBN, WIT, HDB, INFY, RDY, SIFY, and REDFY.

If we see the result, the lagged value of log WIT, log HDB, and log SIFY is significant and affecting the daily value of log NYSE. The log SIFY is highly significant out of the three significant variables. It means that log NYSE is largely caused by the log SIFY Indian ADR as per the result. So here, this represents the highest mobility in the NYSE value. If we see the other results, lagged valued of the log HDB and log SIFY is significant and explaining the changes in the value of log IBN. Similarly, log IBN, log INFY, log HDB causing to log WIT and log IBN, log NYSE, log HDB, log SIFY causing to log RDY and log HDB, log SIFY, log REDFY causing to log INFY and log IBN, log SIFY causing to log HDB and log IBN, log NYSE, log REDFY causing to log SIFY, and log SIFY causing to log REDFY.

The results confirm that log NYSE is caused by the log WIT, log HDB, log SIFY and it is also confirming that log NYSE is causing log RDY and log SIFY. Therefore, it confirms the bivariate causality between log SIFY and log NYSE. Log SIFY is the Indian ADR, which is contributing to the mobility of log NYSE among all the Indian ADR listed in the foreign stock market.

Table 4: VAR Granger Causality/Block Exogeneity Wald Tests

D V : D(ln_IBN)			
Excluded	**Chi-sq**	**Df**	**Prob.**
D(LN_WIT)	7.980732	6	0.2395
D(LN_RDY)	4.628057	6	0.5923
D(LN_INFY)	3.804746	6	0.7031
D(LN_NYSE)	6.192105	6	0.4020
D(LN_HDB)	14.51574	6	0.0244
D(LN_SIFY)	14.83289	6	0.0216
D(LN_REDFY)	5.601641	6	0.4693
All	64.15724	42	0.0154

D V : D(ln_WIT)			
Excluded	**Chi-sq**	**Df**	**Prob.**
D(LN_IBN)	14.50701	6	0.0245
D(LN_RDY)	11.53742	6	0.0731
D(LN_INFY)	33.59868	6	0.0000
D(LN_NYSE)	5.090492	6	0.5323
D(LN_HDB)	19.88208	6	0.0029
D(LN_SIFY)	7.750476	6	0.2570
D(LN_REDFY)	5.465520	6	0.4856
All	102.0913	42	0.0000

D V : D(ln_RDY)			
Excluded	**Chi-sq**	**Df**	**Prob.**
D(LN_IBN)	25.05982	6	0.0003
D(LN_WIT)	7.551019	6	0.2729
D(LN_INFY)	11.22397	6	0.0817
D(LN_NYSE)	19.48342	6	0.0034
D(LN_HDB)	21.12817	6	0.0017
D(LN_SIFY)	18.42382	6	0.0053
D(LN_REDFY)	8.171327	6	0.2258
All	106.4021	42	0.0000

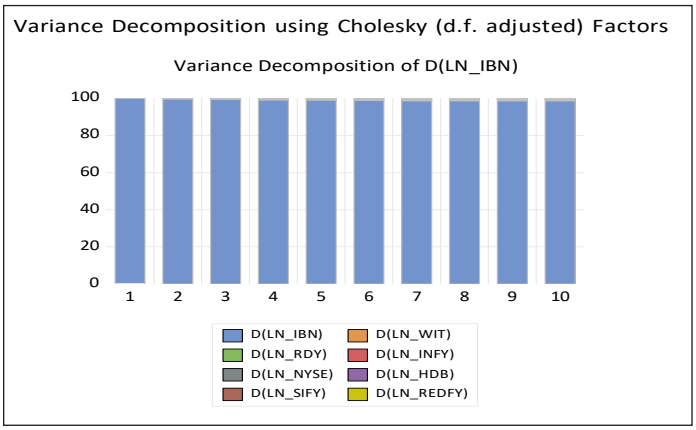
D V : D(ln_HDB)			
Excluded	**Chi-sq**	**Df**	**Prob.**
D(LN_IBN)	28.33285	6	0.0001
D(LN_WIT)	8.837558	6	0.1829
D(LN_RDY)	2.855567	6	0.8267
D(LN_INFY)	6.565448	6	0.3629
D(LN_NYSE)	12.07890	6	0.0602
D(LN_SIFY)	12.82409	6	0.0459
D(LN_REDFY)	2.341908	6	0.8857
All	76.69987	42	0.0009

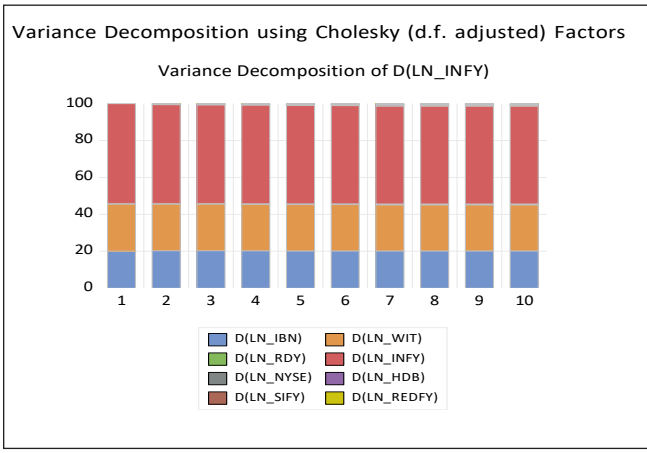
D V : D(ln_INFY)			
Excluded	**Chi-sq**	**Df**	**Prob.**
D(LN_IBN)	8.948238	6	0.1765
D(LN_WIT)	7.732993	6	0.2583
D(LN_RDY)	4.196605	6	0.6501
D(LN_NYSE)	12.16361	6	0.0584
D(LN_HDB)	24.90958	6	0.0004
D(LN_SIFY)	13.62401	6	0.0341
D(LN_REDFY)	14.38288	6	0.0256
All	116.6586	42	0.0000

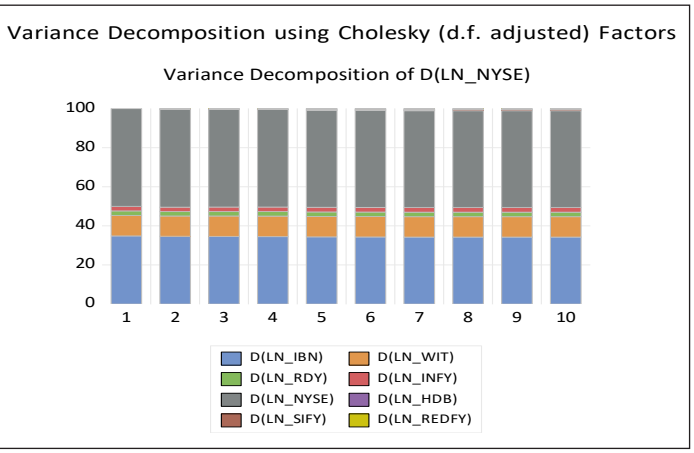
D V : D(ln_SIFY)			
Excluded	**Chi-sq**	**Df**	**Prob.**
D(LN_IBN)	13.04419	6	0.0423
D(LN_WIT)	11.08001	6	0.0859
D(LN_RDY)	11.67176	6	0.0697
D(LN_INFY)	6.894852	6	0.3307
D(LN_NYSE)	19.67735	6	0.0032
D(LN_HDB)	5.095233	6	0.5317
D(LN_REDFY)	19.00575	6	0.0042
All	176.0046	42	0.0000

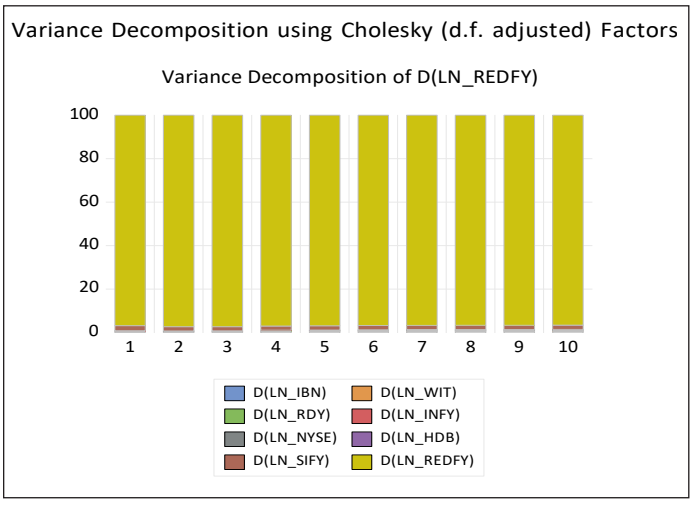
D V : D(ln_NYSE)			
Excluded	**Chi-sq**	**Df**	**Prob.**
D(LN_IBN)	5.653600	6	0.4631
D(LN_WIT)	14.96713	6	0.0205
D(LN_RDY)	3.501464	6	0.7438
D(LN_INFY)	6.205846	6	0.4005
D(LN_HDB)	15.68213	6	0.0156
D(LN_SIFY)	24.69767	6	0.0004
D(LN_REDFY)	12.16771	6	0.0583
All	80.45495	42	0.0003

D V : D(ln_REDFY)			
Excluded	**Chi-sq**	**Df**	**Prob.**
D(LN_IBN)	4.300007	6	0.6361
D(LN_WIT)	3.758762	6	0.7093
D(LN_RDY)	5.453684	6	0.4871
D(LN_INFY)	5.653607	6	0.4631
D(LN_NYSE)	9.423475	6	0.1511
D(LN_HDB)	7.526922	6	0.2748
D(LN_SIFY)	42.45348	6	0.0000
All	129.0244	42	0.0000









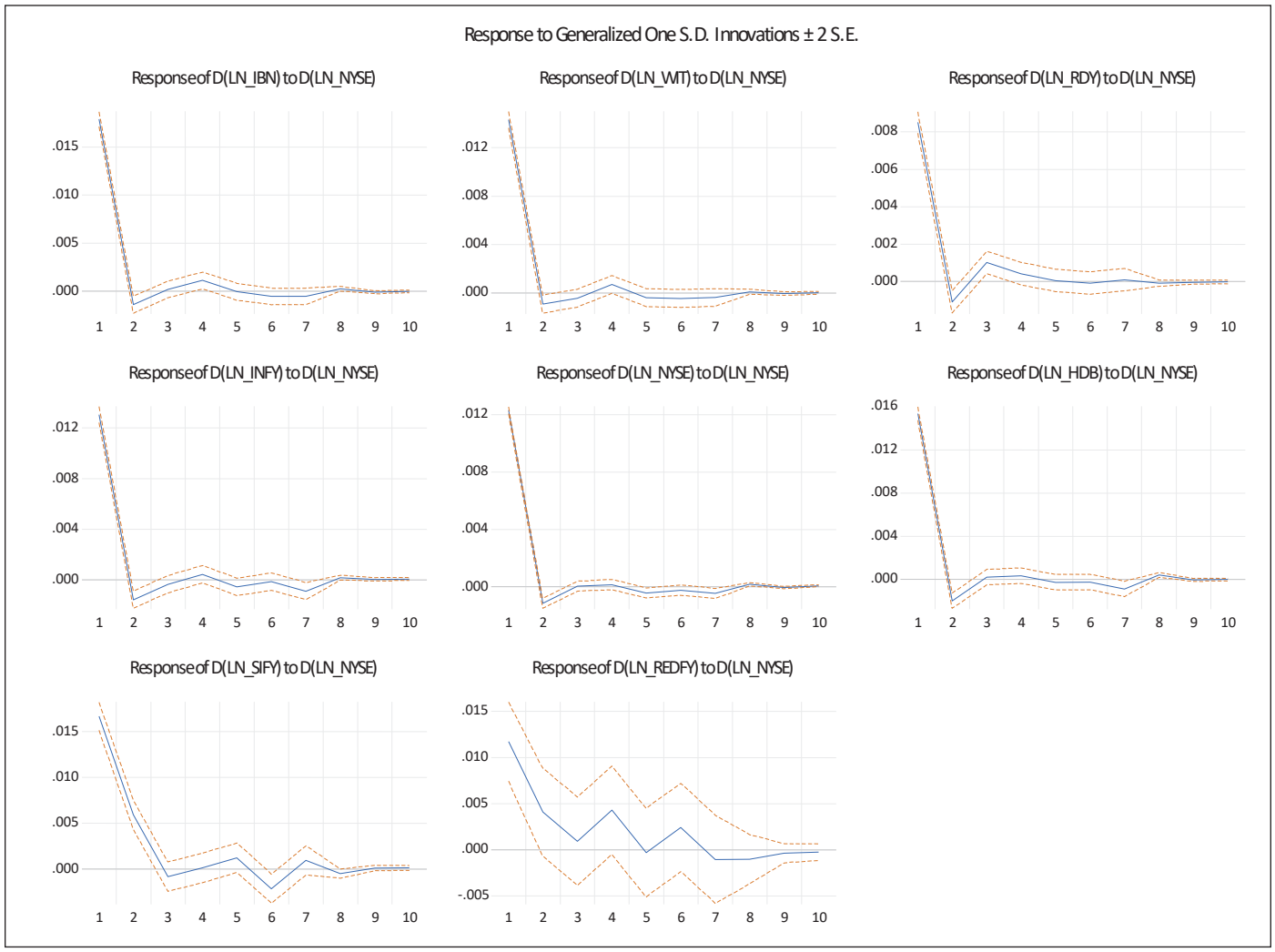
Graph 1: Variance Decomposition

Table 5: Variance Decomposition

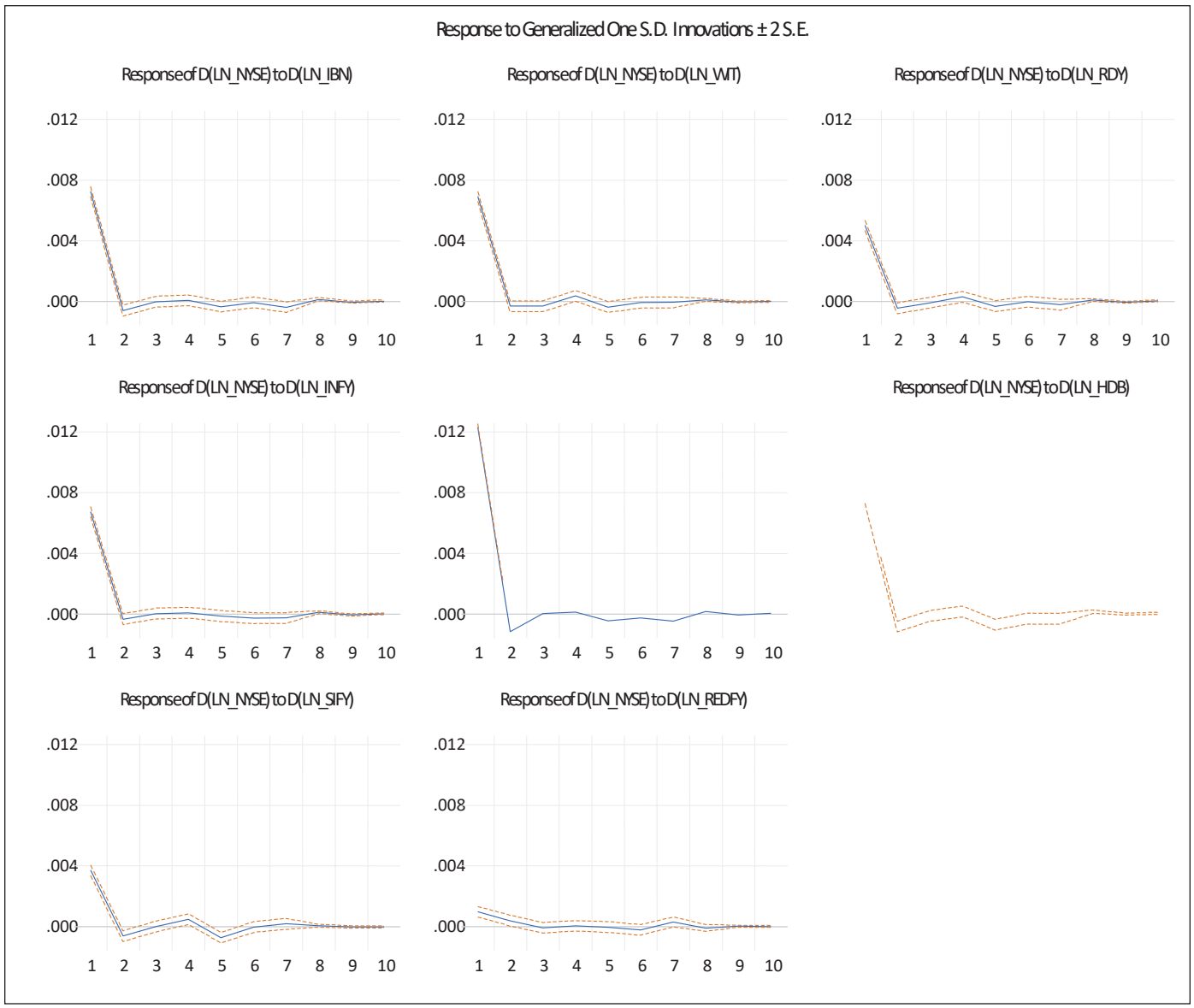
	D(LN_IBN)	(LN_WIT)	(LN_RDY)	(LN_INFY)	(LN_NYSE)	(LN_HDB)	(LN_SIFY)	(LN_REDFY)
D(LN_IBN)	98.70913	0.307207	0.110558	0.068528	0.130007	0.265764	0.296326	0.112480
(LN_WIT)	21.97352	76.15468	0.335965	0.614875	0.168876	0.427362	0.227795	0.096925
(LN_RDY)	13.16949	3.173146	81.97488	0.166226	0.579463	0.416421	0.342707	0.177669
(LN_INFY)	20.18888	24.99335	0.429501	53.02811	0.299064	0.494483	0.271479	0.295128
(LN_NYSE)	34.27539	10.42115	2.301283	2.431003	4946713	0.329506	0.507240	0.267295
(LN_HDB)	48.29568	4.106455	0.664514	0.249137	3.501260	42.89087	0.245709	0.046373
(LN_SIFY)	5.917891	4.101555	0.339045	0.529577	1.950515	0.194739	86.61518	0.351496
(LN_REDFY)	0.547152	0.298526	0.091300	0.177845	0.208501	0.159707	1.957182	96.55979

The variance decomposition function provides a slightly different approach to investigating the dynamics of a VAR system. The variance decomposition shows how much of the variation in endogenous variables' movements is due to their own lagged shocks vs. shock from the system's remaining variables' lagged movements.

The result of variance decomposition is presented in the above Graph 1 and Table 5. The graph of variance decomposition of IBN is indicating that it is highly significant with its own contribution. Followed by WIT, where the IBN is contributing 21.97 and the highest variance in the behaviour is explained by its own contribution of 76.15 percent. Next is RDY, the results indicate that 13.16 percent variance in the behaviour of RDY is defined by the daily value of IBN and 81.97 percent variance is explained by its own daily innovation shock. Similarly, in case of INFY, IBN and WIT are contributing 20.18 & 24.99 respectively. Its own daily lag value is significant and representing highest variance in the behaviour is explained by its own contribution of 53.02 percent. In the variance decomposition of NYSE, IBN is contributing 34.37, WIT is contributing 10.42, and the highly significant variation in NYSE is defined by its contribution of 49.46 through its own innovation. The variance decomposition of HDB, it indicates that 48.29 percent of variance in the behaviour of the daily HDB value is defined by the contribution of IBN. The larger contribution by its own shock is defined by the value 42.89. In the variance decomposition of SIFY, NYSE is contributing 1.95 only, and the 86.61 percent variance is defined by its own daily innovation shock. The last variance decomposition of REDFY is contributing 96.55 percent by its own daily innovation shock. The NYSE is only defining 0.20 percent variance in the REDFY, which is very low. The highest variance contribution is caused by the two variables such as IBN and WIT to NYSE.



Graph 2: Impulse Response



Graph 3: Impulse Response

A one standard deviation shock to x generates significant increases (decreases) in y for 'm' periods (defined by the length of period for which the SE bands are above 0 in the event of an increase or below 0 in the event of a decrease), after which the effect diminishes is the interpretation of impulse response function. The rise peaks in period k. This interpretation aligns well with goals such as "how x affects y", when the largest impact is felt, and how the effect last. Here a one SD shock of innovation to NYSE initially has declining impact on IBN, WIT, RDY, INFY, HDB, SIFY, and REDFY in periods 2 and 3 and remains in the negative region. From period 2nd the response gradually starts increase and comes into a positive region for IBN, WIT, RDY, and SIFY. Only SIFY responses were negative and then positive from period 5th to 7th. The shock to NYSE will have asymmetric impacts on the SIFY (Graph 2).

In the graph 3, one SD shock of innovation to SIFY initially has a decline impact on NYSE in the period 2 and then from 2nd period it starts moving to the positive region from period 2nd to 4th period. Again, decline and stayed in the negative region until the shock impact disappears. This represents the asymmetric impacts on the NYSE. Almost similar response recoded in the case of WIT, initially it has declined and stayed in the negative region. After the period, it has moved in the positive region between 3rd to 4th periods. Then again came down to negative territory and stayed there until to the disappearance of shock. The rest of the variable's response on the one SD shock of innovation to NYSE is initially negative

till to the 2nd period stage and stayed almost between zero to negative till to the disappear of the shock.

CONCLUSION AND IMPLICATION OF THE STUDY

The research examined on the mobility of the US market by using the listed Indian ADR in US stock market and confirmed the nexus between the US market and the Indian ADR. Various tests such as VAR Granger Causality/Block Exogeneity Wald Tests, variance decomposition and impulse response has been incorporated. The proxy variable for US market is NYSE. The result of VAR Granger Causality/Block Exogeneity Wald Test was applied on the time series data (2001-2021), and it explains the bivariate causality between SIFY and NYSE. On the other hand, one-way causality is confirmed where NYSE is caused by WIT and HDB. The two variables IBN and WIT contribution are the highest in the variance of NYSE. One standard shock of innovation to SIFY is representing the asymmetric impacts on the NYSE. This is because of the behaviour of the SIFY, initially it is decline and then came into positive region for a few periods and then again declined to a negative zone. Then one standard innovation shock disappeared. This shows the asymmetric behaviour. Hence, SIFY, WIT and HDB contributing to the mobility of the stock market (NYSE). This can be helpful for the international investor and for the domestic investor (India).

Several research on Depository Receipts have demonstrated their effect on the home country's stock market prices, volatility, and volume. In this study, we examined the dynamic interaction between Indian ADR and the US stock market in this study. Foreign corporations and US investors who invest in ADRs and in the US market. This is where research is crucial and beneficial to both investors. The study also implied the impact of Indian ADR volatility on the US market and to observe the reaction of the US market to changes in Indian ADR pricing. This relation is also beneficial for the Indian Domestic Investors. The study will help the US investor decide their trade volume and strategy in the short run due to the changes in the Indian ADR price.

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