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ANALYZING THE LINKAGE OF CAPITAL MARKET TO ECONOMIC TRENDS IN LONG-RUN AND SHORT-RUN TIME SERIES IN INDIAN PHARMACEUTICAL COMPANIES

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ABSTRACT

In the financial markets, where macroeconomic parameters demonstrate the performance of an economy, stock return variation draws attention to market uncertainty and shifting expectations on industry/company performance. This study looks into the stock return variation of 25 Indian pharmaceutical businesses and macroeconomic factors such as Inflation, Interest rate and IIP before and after the COVID-19 pandemic that erupted in November 2019 using the Granger Causality test and Johansen Co-integration test to study the short-run and long-run interlinkage. The study aids in gaining a better knowledge of the interdependence of stock volatility and macroeconomic conditions to make better investment decisions.

Keywords: Share Return, Inflation, Industrial Production, Interest Rate, Granger Causality Test, Johansen Co-Integration Test

1. INTRODUCTION

- To understand the movement of share price volatility, inflation, policy repo rate and production index before and after the COVID-19 pandemic.
- To investigate the interlinkage between share price fluctuations with the selected macroeconomic indicators in the short-run and long-run before and after the COVID-19 pandemic.

Stock returns show the gains or losses investors endure when holding a company's shares over a specified period. This has an important effect on market performance. Understanding returns provides an important perspective on the workings of capital markets as creators of capital and wealth and accelerators of prosperity. Good stock performance indicates the presence of effective markets where all market players including people with different risk aversion levels can allocate their assets prudently towards their financial goals. This in turn encourages creativity, competition as well and business expansion hence faster economic development.

Inadequate markets are characterized by quite too much speculation, unequal returns among investor classes, and underperformance by listed firms; which hamper capital flows decreasingly trust by investors leading to low participation. Equities returns exceedingly provide indispensable knowledge on the country's investor environment, corporate health and whether the capital market ecosystem is viable or not. They are influenced by the primary sociopolitical environment and other large administrative variables. This is particularly important for India which has witnessed incredible growth in its shareholding culture for individual investors since there has been a constant rise in market capitalization over the last few years. Nevertheless, Indian markets are still shallow relative to other parts of the world where the total value of equities did not exceed 100% of GDP in 2019. On the other hand, volatility remained higher than among developed counterparts.

The stock markets and other economic sectors have been greatly disrupted during the coronavirus crisis. The pharmaceutical industry in India has had a unique response to the pandemic (Chavarkar & Nayak, 2022)1. The world health issue has been accompanied by greater demand for drugs and associated benefits accruing to the industry. Consequently, there was heightened interest and fluctuations in volatility in India's stock exchange particularly within the pharmaceutical sector. Moreover, an investigation was conducted concerning how the COVID-19 pandemic was related to stock return variations in the Indian pharmaceutical sector; thus, this led to varying macroeconomic variables along with the pandemic (Behera & Rath, 2021)2. This study discovered that various worldwide economic factors like inflation rates, and borrowing costs among others do considerably influence on stock returns of India's pharmaceutical firms (Sharma, 202)3. This article uses the Granger Causality test and Johansen Co-integration test to analyze short-term interrelations between stock return variations for 25 S&P BSE listed pharmaceutical companies and economic indexes such as inflation rates, borrowing costs as well as Industrial Performance Index in India before and after COVID-19. With the selected macroeconomic indicators, a Consumer Price Index (CPIIR) and Policy Repo Rate (PRRLIR) represent the concepts of an inflation rate and lending rate, respectively. The interaction of selected independent variables such as CPIIR and PRRLIR with share return variations (SRV); as well as behaviour trends in SRV with CPIIR, PRRLIR and IPI before and after COVID-19 are examined in the paper. The findings from this research indicate different roles that country-specific and global variables play in predicting return on equity for India's markets. This implies that the practical application of empirical relationships can guide investors as well as national policymakers to make rational choices. There exist economic fundamentals in this study that impact different markets' return volatility hence it is upon the investors to consider these factors while improving their portfolios 'efficiency.

2. LITERATURE REVIEW

The relationship between stock returns and macroeconomic conditions has been examined in many studies. Naka (1998)4 used VECM to discover the existence of a cointegrating relationship between selected economic indicators and the Indian stock market. Ratanapakorn (2007)5 discovered that stock prices in the U.S. go upwards with low long-term lending rates but downward with high money supply, industrial production index, inflation, currency rate, and short-term interest rates;

on the other hand, such macroeconomic factors as inflation, currency rate, GDP, earnings, and company growth rates do not affect equity prices worth mentioning in short.

Al-Jafari (2011)6 found a significant association between genuine economic advancement and stock market valuations has been unearthed in both immature and developed economies, however, the latter recorded stronger linkage. Kuwornu (2011)7 and Owusu-Nantwi (2011)8 discovered a strong link between market returns and price increases, Kuwornu pointed out that the key factors were exchange rates and movements in T-bill yields. Naik (2012)9 discovered that the BSE Sensex significantly correlated with various economic factors among which it was positively associated with both money supply and industrial production while having a negative relationship with inflation. Further investigation on this relationship was carried out by Ali (2015)10 in Nigeria which revealed a bi-directional association between the volatility of stock markets and various macroeconomic indicators together with a significant influence coming from broad money supply and the nominal effective exchange rate. The conclusions of this exploration pointed to a complicated and varied correlation between stock returns and economic indicators. Analysts have, therefore, discovered a downside association between stock return volatility and inflation. (Feng-yun 200411, Albulescu 201612, Valcarcel 201213), whereas other studies found an encouraging relationship (Solnik 198314, Mousa 201215, Boucher 200416, Al-Abbadi 201717). B. Ewing (2008)18 reveals that output volatility varies from era to era and that levels of volatility can typically be quantified in most cases, while overstated outputs result in more significant ups and downs of volatility compared with understatement or underestimates.

3. METHODS

The paper is entirely based on an analytical study of the behaviour and relationship between share market rates (SRV) and macroeconomic indicators such as inflation rate (CPI_IR), policy repo rate (PRR_LIR), and industrial output index (IPI) over 8 years from November 2015 to October 2019 (Pre-COVID-19) and November 2019 to October 2023 (Post-COVID-19). The data was obtained from the BSE website and the RBI Statistical Database. A subset of 49,525 daily observations of the share price of 25 Indian BSE-listed healthcare companies that topped in terms of market capitalization throughout the study period was used to arrive at the monthly share price volatility using the formula,

$$\sigma\,(m) = \sigma\,(d) * \sqrt{N}$$

where, σ (m) = monthly fluctuation of the stock

σ (d) = Standard deviation of the everyday returns

N = No. of trading days in a month (between 21 to 23 days)

To analyze the interlinkage between SRV, CPI_IR, PRR_LIR and IPI in short-run and long-run dynamics, 1344 monthly observations of the dependent and independent variables are employed in the study. First, to test the hypothesis, Ha0: Selected Macroeconomic indicators do not Granger cause Share price fluctuation in the short run, the unit root test is conducted to test the stationarity and the Granger Causality test and Exogeneity test are employed. Second, to test the hypothesis, Hb0: Selected Macroeconomic indicators do not have any active co-integration with the

Share price fluctuation in the long term, the Johansen Co-integration test is used on the study data and the model is tested using VECM model specification,

$$\Delta SRV_n = c + \pi SRV_{n-1} + \Gamma 1 \Delta SRV_{n-1} + \Gamma 2 \Delta CPI\_IR_{n-1} + \Gamma 3 \Delta PRR\_LIR_{n-1} + \Gamma 4 \Delta IPI_{n-1} + \boldsymbol{\varepsilon} n$$

where,

ΔSRV_n = First difference of share price fluctuations; π = Coefficient matrix indicating long-run dynamics; SRV_{n-1} = Lagged level term; Γx = Coefficient matrices indicating the short-run dynamics; ΔSRV_{n-1} = First difference of lagged share price fluctuations; ΔCPI_IR_{n-1} = First difference of lagged consumer price index; ΔPRR_LIR_{n-1} = First difference of lagged policy repo rate; ΔIPI_{n-1} = First difference of lagged Industrial Output Index; c = Constant and $\boldsymbol{\varepsilon}$n = Error Term

4. EMPIRICAL RESULTS AND DISCUSSION

Trend analyses and statistical descriptions are utilized to better understand the changes and characteristics of SRV, CPI_IR, PRR_LIR, and IPI before and following COVID-19.

Chart 1

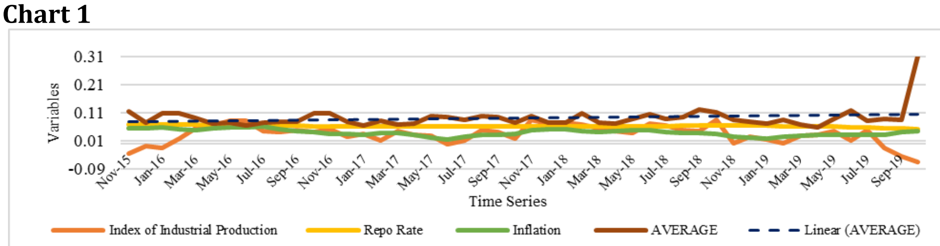


Chart 1 (a) Movement of SRV, CPI_IR, PRR_LIR and IPI - Pre COVID-19 (Nov 2015 - Oct 2019)
Source RBI Statistics, Yahoo Finance [21][22]

Chart 2

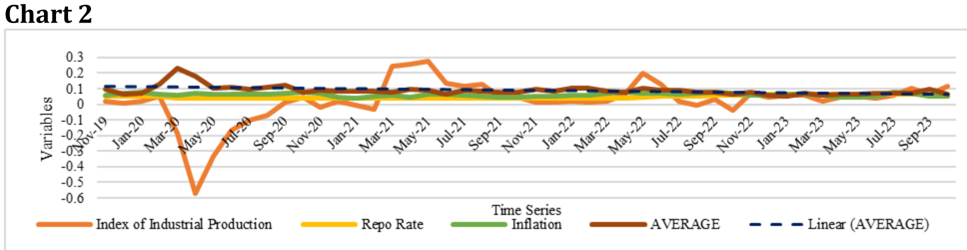


Chart 2 (b) Movement of SRV, CPI_IR, PRR_LIR and IPI -Post COVID-19 (Nov 2019 - Oct 2023)
Source RBI Statistics, Yahoo Finance [21][22]

Charts 6.1 (a) and 6.1(b) show that the IPI changes more than other parameters after COVID-19 than before COVID-19, with a sharp drop shortly following the pandemic's onset. The SRV trend path shows a gradual increase before the global epidemic, followed by a large decline during the post-pandemic

Table 1

Table 1 Descriptive Statistics of SRV, CPI_IR, PRR_LIR and IPI

	Pre COVID-19 Period				Post COVID-19 Period			
	Mean	Maximum	Minimum	Std. Dev	Mean	Maximum	Minimum	Std.Dev

SRV	0.0917	0.3118	0.0589	0.036	0.0887	0.2311	0.0536	0.0303
CPI_IR	0.0395	0.0607	0.0146	0.0117	0.0605	0.0779	0.0406	0.0106
PRR_LIR	- 0.0054	0.0417	-0.0608	0.0190	0.0059	0.1136	-0.2233	0.0450
IPI	0.0332	0.0854	-0.0663	0.0337	0.0236	0.2760	-0.5730	0.1361

Source Calculated Data

Table 6.1 reveals that, except CPI_IR (0.0605), every variable has a smaller central tendency in the post-COVID-19 period. Furthermore, PRR_LIR and IPI (0.0450, 0.1361) show a larger deviation than CPI_IR and SRV in the post-COVID-19 era than in the pre-COVID.

Table 2

Table 2 Augmented Dickey-Fuller Test on the SRV, CPI_IR, PRR_LIR and IPI

	Pre-COVID-19 period				Post-COVID-19 period			
Variable	**At Level**		**At First Difference**		**At Level**		**At First Difference**	
	Intercept	**Trend & Intercept**	**Intercept**	**Trend & Intercept**	**Intercept**	**Trend & Intercept**	**Intercept**	**Trend &Intercept**
SRV	-2.3401	-2.3744	-4.3009	-4.4275	-2.5054	-4.0428	-6.8403	-6.7885
	-0.1641	-0.3876	(0.0013) *	(0.0050) *	-0.1209	(0.0138) *	(0.0000) *	(0.0000) *
CPI_IR	-2.6433	-2.5131	-4.7855	-4.8829	-3.8475	-3.8395	-6.8561	-6.7766
	-0.0919	-0.3207	(0.0003) *	(0.0014) *	(0.0049) *	(0.0231) *	(0.0000) *	(0.0000) *
PRR_LIR	-2.3408	-2.4812	-18.9626	-18.7763	-2.5419	-2.9177	-8.6425	-8.5421
	(0.1640)	(0.3356) *	(0.0001) *	(0.0000) *	(0.1127)	(0.1668)	(.0000) *	(.0000) *
IPI	-2.7204	-2.9095	-8.8416	-9.3049	-2.6489	-2.9472	-6.2078	-6.141
	-0.0782	-0.1689	(0.0000) *	(0.0000) *	-0.0907	-0.1578	(0.0000) *	(0.0000) *

Note * p-value significant at 5% level

Source Calculated Data

Table 6.2 uses the Augmented Dickey-Fuller test to recognize the stationary trends of the study variables (SRV, CPI_IR, PRR_LIR, and IPI). Before COVID-19, none of the variables were stationary at levels. However, in the first difference, all of the parameters are stationary because their significance values are less than 0.05. In the time frame following COVID-19, SRV and CPI_IR stabilize at their respective levels, although PRR_LIR and IPI must initially diverge. COVID has influenced the statistical properties of SRV and CPI_IR, resulting in a mean return in post-COVID-19 terms, even at the level. The first difference renders the parameters constant in both times. Because all variables are not stable at the level, the VECM model is best suited for testing the long-run interaction of variables. Further VAR Lag length Criteria are applied to the endogenous variables that include SRV, CPI_IR, PRR_LIR, and IPI, as well as the exogenous parameter 'c', in both the pre-COVID and post-COVID periods, to identify the lag length that yields the greatest quality fit and predictive power. Various statistical criteria are employed such as the LR test sequential statistic (LR), final prediction error (FPE), Akaike Criterion (AIC), Schwarz Criterion (SC) and Hannan-Quinn Criterion (HQ).

Table 3

Table 3 Var Lag Order Selection Criteria

Lag	Log L	LR	FPE	AIC	SC	HQ
Pre COVID period (Nov 2015 – Oct 2019)						
0	435.9948	NA	3.49e-14	-19.63613	-19.47393	-19.57598

1	488.7698	93.55568	6.58e-15	-21.30772	-20.49672*	-21.00696
2	510.2606	34.18991*	5.22e-15*	-21.55730*	-20.09751	-21.01594*
3	522.5288	17.28698	6.50e-15	-21.38767	-19.27908	-20.60571
4	541.3073	23.04633	6.31e-15	-21.51397	-18.75658	-20.4914
Post COVID period (Nov 2019 – Oct 2023)						
0	347.7293	NA	1.93E-12	-15.62406	-15.46186	-15.56391
1	394.1389	82.27143*	4.85e-13*	-17.00631*	-16.19532*	-16.70556*
2	407.6582	21.5081	5.54E-13	-16.89356	-15.43376	-16.3522
3	419.9119	17.26654	6.90E-13	-16.72327	-14.61468	-15.9413
4	430.0344	12.42302	9.93E-13	-16.45611	-13.69872	-15.43354

Source Calculated Data

According to Table 6.3, the findings suggest that model testing prior to COVID-19 should be performed for two statistical lags with respect to AIC, SC as well as LR-test, whereas one statistical lag based on the LR test, FPE criterion, AIC, SC, and HQ after COVID-19 shall evaluate the model.

Table 4

Table 4 Granger Causality Test During Pre-COVID and Post-COVID Period

Null Hypothesis	Pre-COVID Period	Column1	Post COVID Period	Column2
	F-Statistic	Prob.	F-Statistic	Prob.
PRR_LIR does not Granger Cause SRV	2.95429	0.0633	0.97196	0.3296
SRV does not Granger Cause PRR_LIR	0.43801	0.6483	0.35284	0.5556
IPI does not Granger Cause SRV	4.98553	**0.0115***	0.59341	0.4452
SRV does not Granger Cause IPI	0.45631	0.6368	25.5999	**0.0000***
CPI_IR does not Granger Cause SRV	0.44622	0.6431	0.75996	0.3881
SRV does not Granger Cause CPI_IR	2.41974	0.1015	2.52521	0.1192
IPI does not Granger Cause PRR_LIR	2.34917	0.1082	0.00971	0.9219
PRR_LIR does not Granger Cause IPI	3.94585	**0.0271***	10.4153	**0.0024***
CPI_IR does not Granger Cause PRR_LIR	1.87720	0.1659	0.51307	0.4776
PRR_LIR does not Granger Cause CPI_IR	0.42451	0.6569	0.35130	0.5564
CPI_IR does not Granger Cause IPI	1.95263	0.1549	0.00306	0.9561
IPI does not Granger Cause CPI_IR	1.50145	0.2348	0.43496	0.5130

Note * p-value significant at 5% level

Source Calculated Data

Before and after the epidemic of COVID-19, the Granger causality test was employed to explore the causal connections between SRV, IPI, CPIIR, and PRRLIR in short-run dynamics. According to Table 6.4, the hypothesis that IPI causes SRV is confirmed during the pre-coronavirus time since p-values are below .05, which reveals a one-way link from IPI to SRV. The post-COVID period shows a reversed association between SRV and IPI. The null postulate that SRV does not affect IPI is rejected (p-value <0.05). PRR_LIR impacts IPI across both study periods. In short-run dynamics, SRV, IPI, and PRR_LIR all show a substantial link.

Table 5

Table 5 VEC Residual Serial Correlation LM Test

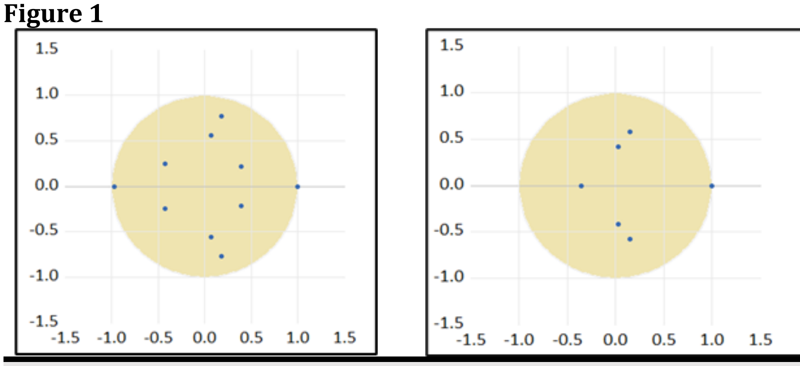
Lag	LRE* stat	df	Prob.	Rao F-Stat	D	Prob.2
Pre-COVID Period (Nov 2015 – Oct 2019)						
Null hypothesis: No serial correlation at lag h						
1	23.07589	16	0.1117	1.513589	(16, 86.2)	0.1134
2	24.06885	16	0.0880	1.587510	(16, 86.2)	0.0895
Null hypothesis: No serial correlation at lags 1 to h						
1	23.07589	16	0.1117	1.513589	(16, 86.2)	0.1134
2	45.05766	32	0.0627	1.507143	(32, 90.1)	0.0678
Post COVID Period (Nov 2019 – Oct 2023)						
Null hypothesis: No serial correlation at lag h						
1	9.960401	16	0.8687	0.607658	(16,86.2)	0.8697
Null hypothesis: No serial correlation at lags 1 to h						
1	9.960401	16	0.8687	0.607658	(16, 86.2)	0.8697

Note pre-COVID at 2 lag and post-COVID at 1 lag (VAR Lag Length Criteria)

Source Calculated Data

The VEC Residual Serial Correlation test is used to determine the presence of autocorrelation among data at lags 2 and 1 for the pre-COVID and post-COVID periods, respectively. The findings presented in Table 6.5 show that the p-value for the Lag 1 LRE stat, the Lag 2 LRE stat, and the combined Lags 1 and 2 LRE test is greater than 0.05. Thus, both null hypotheses are considered valid, leading to no sign of residual serial association, which satisfies the validity assumptions for the computed VECM during both research periods.

Figure 1



a) Pre-COVID-19 – Inverse Roots   b) Post COVID-19 – Inverse Roots

Source Calculated Data

From Fig. 6.6 (a) and (b), during the pre-COVID, 3-unit roots are present at modulus =1 and the remaining 8-unit roots are bounded between 0.44 and 0.96 (moduli <1), no root lies outside the unit circle (modulus >1) at lag 2. During the post-COVID, at lag 1 as recommended by VAR Lag Length Criteria, 3-unit roots at modulus = 1 and 4 roots at moduli < 1 (between 0.354 to 0.594) and no root outside the circle was confirmed. From the result, it is clear that the VEC specification satisfies the stability condition check test based on the inverse root of characteristic polynomial during both the pre-COVID and post-COVID periods. The study used the Johansen Co-integration test to look at the long-term relationship between the selected variables SRV, IPI, CPIIR and PRRLIR post COVID-19.

Table 6

Table 6 (a) Johansen Co-Integration Test on SRV, CPI_IR, PRR_LIR and IPI Before the COVID-19 Outbreak

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical value	Prob.	Max-Eigen Statistic	0.05 Critical value	Prob.
None	0.418768	46.67766	47.85613	0.0642	24.95984	27.58434	0.1045
At most 1	0.226171	21.71782	29.79707	0.3145	11.79461	21.13162	0.5681
At most 2	0.182268	9.923211	15.49471	0.2867	9.256132	14.26460	0.2655
At most 3	0.014397	0.667079	3.841465	0.4141	0.667079	3.841465	0.4141
1 Cointegrating Equation(s):			**Log-likelihood**		**521.1526**		
Normalized co-integrating coefficients (standard error in parentheses)				**Adjustment Coefficients (standard error in parentheses)**			
SRV	**IPI**	**CPI_IR**	**PRR_LIR**	**D(SRV)**	**D(IPI)**	**D(CPI_IR)**	**D(PRR_LIR)**
1.000000	1.675247 (0.36421)	-1.480812 (0.79519)	-2.444024 (0.73247)	-0.250357 (0.11240)	-0.261559 (0.07872)	-0.000148 (0.01612)	0.107823 (0.05663)
2 Cointegrating Equation(s):			**Log Likelihood**		**527.0499**		
Normalized co-integrating coefficients (standard error in parentheses)				**Adjustment Coefficients (standard error in parentheses)**			
SRV	**IPI**	**CPI_IR**	**PRR_LIR**	**D(SRV)**	**D(IPI)**	**D(CPI_IR)**	**D(PRR_LIR)**
1.000000	0.000000	-2.346478 (1.58914)	5.214130 (1.54311)	-0.525946 (0.16375)	-0.189178 (0.12055)	0.002219 (0.02487)	-0.024437 (0.08297)
0.000000	1.000000	0.516739 (1.14571)	-4.571357 (1.11252)	-0.582245 (0.19243)	-0.395409 (0.14166)	0.001151 (0.02923)	1.102483 (0.09750)
3 Cointegrating Equation(s):			**Log Likelihood**		**531.6780**		
Normalized co-integrating coefficients (standard error in parentheses)				**Adjustment Coefficients (standard error in parentheses)**			
SRV	**IPI**	**CPI_IR**	**PRR_LIR**	**D(SRV)**	**D(IPI)**	**D(CPI_IR)**	**D(PRR_LIR)**
1.000000	0.000000	0.000000	4.982441 (1.44448)	-0.586764 (0.17625)	-0.166794 (0.13069)	-0.023260 (0.02499)	0.023045 (0.08810)
0.000000	1.000000	0.000000	-4.520334 (1.05746)	-0.632870 (0.19905)	-0.376776 (0.14760)	-0.020058 (0.020058)	0.142008 (0.09950)
0.000000	0.000000	1.000000	-0.098739 (0.31145)	0.645677 (0.44068)	0.345421 (0.32677)	-0.125089 (0.06249)	0.334819 (0.22027)

Source Calculated Data

As per Table 6.7a, there is no cointegration evidence by trace test as well as the max-eigenvalue test at a 5% significance level; that is, those variables do not move together in the long run. However, according to the normalized coefficients, a 1% upsurge in PRR_LIR can lower SRV by 2.44%; a 1% rise in IPI improves SRV by 1.68%; and a 1% escalation in CPI_IR reduces SRV by 1.48%. Despite the lack of empirical proof of cointegration, the model suggests that increasing PRR_LIR can reduce the SRV. The null hypothesis Hb0, was accepted before COVID-19.

Table 6 (b) Johansen Co-Integration Test On SRV, CPI_IR, PRR_LIR And IPI After

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical value	Prob.	Max-Eigen Statistic	0.05 Critical value	Prob.
None*	**0.522012**	**67.29835**	**47.885613**	**0.0003***	**33.95576**	**27.58434**	**0.0066***
At most 1*	**0.330916**	**33.34259**	**29.79707**	**0.0187***	18.48490	21.13162	0.1128
At most 2	0.218388	14.85769	15.49471	0.0622	11.33426	14.26460	0.1382
At most 3	0.073736	3.523433	3.841465	0.0605	3.523433	3.841465	0.0605
		1 Cointegrating Equation(s):		**Log-likelihood**	**410.1224**		
Normalized co-integrating coefficients (standard error in parentheses)				**Adjustment Coefficients (standard error in parentheses)**			
SRV	**IPI**	**CPI_IR**	**PRR_LIR**	**D(SRV)**	**D(IPI)**	**D(CPI_IR)**	**D(PRR_LIR)**
1.000000	-0.002567 (0.03782)	**-2.565383 (0.43578)**	**0.792387 (0.14182)**	**-0.337634** (0.14770)	**-0.270947** (0.50783)	0.191070 (0.04808)	-0.336091 (0.31476)
		2 Cointegrating Equation(s):		**Log Likelihood**	**419.3648**		
Normalized co-integrating coefficients (standard error in parentheses)				**Adjustment Coefficients (standard error in parentheses)**			
SRV	**IPI**	**CPI_IR**	**PRR_LIR**	**D(SRV)**	**D(IPI)**	**D(CPI_IR)**	**D(PRR_LIR)**
1.000000	0.000000	**-2.527122 (0.40467)**	0.782705 (0.11665)	-0.502276 (0.21589)	-1.986899 (0.65605)	0.137997 (0.07029)	-0.152034 (0.46450)
0.000000	1.000000	**14.90264 (2.97511)**	**-3.771132 (0.85763)**	-0.036935 (0.03657)	-0.393293 (0.11112)	-0.012676 (0.01191)	0.043123 (0.07867)
		3 Cointegrating Equation(s):		**Log Likelihood**	**425.0319**		
Normalized co-integrating coefficients (standard error in parentheses)				**Adjustment Coefficients (standard error in parentheses)**			
SRV	**IPI**	**CPI_IR**	**PRR_LIR**	**D(SRV)**	**D(IPI)**	**D(CPI_IR)**	**D(PRR_LIR)**
1.000000	0.000000	0.000000	4.198020 (1.09716)	-0.528393 (0.20977)	-1.937024 (0.64996)	0.146964 (0.06804)	-0.051002 (0.41700)
0.000000	1.000000	0.000000	-23.91151 (6.48002)	0.036773 (0.03542)	-0.393603 (0.10976)	-0.012732 (0.01149)	0.042495 (0.07042)
0.000000	0.000000	1.000000	1.351464 (0.42918)	0.908746 (0.40502)	-1.202549 (1.25493)	-0.602834 (0.13138)	0.292372 (0.80515)

According to Table 6.7b, in short-run adjustment behaviour, 33.76% of any instability between actual and long-run SRV is rectified, while 27% of disequilibrium in IPI is addressed monthly. In the longer term, at a 5% significance level, the trace statistic suggests the existence of two co-integrating equations, but the maximum eigenvalue statistic implies the existence of one. The results show that there is certainly one stable, long-run relationship. According to the main normalized cointegrating values, in the first equation, a 1% increase in CPI_IR is related to a statistically significant decrease of 2.565% in SRV, while a 1% increase in PRR_LIR supports a 0.792% gain in SRV over time. For the model with two cointegrating equations, a 1% increase in the CPI_IR leads to a 2.53% decrease in SRV, while a 1% increase in IPI causes a 14.9% increase in CPI_IR and a 3.77% decrease in PRR_LIR in the long term. The null hypothesis (Hb0) is rejected because there is active co-integration between selected macroeconomic data and share price volatility. From the VECM model, it is understood that there exists a long and short-term co-integrating relationship between SRV, IPI, CPI_IR and PRR_LIR in both pre-COVID and post-COVID periods. Equilibrium and causality linkages are restored statistically through vector error correction and lag dynamics empirically.

5. CONCLUSION

According to empirical research, the relationship between financial markets and macroeconomy in India's pharmaceutical industry is far from as stable as commonly assumed based on before-and-after COVID-19 statistics. Time series behaviour of stock return differential, industrial production index changes, price level hikes, as well as money lending interest rates has been changing across trends, volatility patterns, stationarity tests, causality mechanisms, and long-run co-movements in general. The COVID-19-induced crisis in economics has fundamentally impacted the operating dynamics of the real sector and financial markets. To accommodate these transitions, regulatory and policy changes may be required. Specifically, whereas a lack of cointegration was previously identified, the pandemic has restored strong connections among the variables, suggesting deeper interdependence across the domains following the crisis. Furthermore, reversal is found in the factors that affect the stock market's behaviour over time. Before COVID, industrial output characterized stock variations; but, with COVID, market turmoil now anticipates macroeconomic trends. Finally, the analysis shows convincing evidence that COVID-19 has had a significant impact on the performance of India's pharmaceutical industry and the overall economy, necessitating comprehensive fiscal-monetary policies to regulate this trend. This result of the study supports the findings of Naka (1998), Chavarkar & Nayak (2022), Feng-Yun (2004), Albulescu (2016), Valcarcel (2012) and Naik (2012). It highlights further investigation into the specific factors driving the changing macro-financial transmission mechanisms, to understand the evident interdependence of macroeconomic variables and capital market, in the decision-making of policymakers, financial managers and investors for economic growth strategy building, financial planning and investment decisions.

CONFLICT OF INTERESTS

None.

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