The Interplay between Stock Market Movements and Monetary Policy in India: A Spillover Analysis

Abstract

In the face of ongoing global economic shifts, particularly in the wake of the pandemic, geopolitical conflicts, and inflationary pressures, central banks in emerging markets like India are confronted with new challenges in the transmission of monetary policy. This study examines the dynamic relationship between monetary policy and stock prices in India, focusing on the spillover effects between financial markets and policy interventions. Using a time-varying parameter vector autoregressive (TVP-VAR) model, this study analyzes data from 2003 to 2023 to assess how stock prices, represented by the NIFTY50 index, respond to monetary policy shocks. Contrary to conventional expectations, the findings reveal that the NIFTY50 acts as a spillover transmitter to monetary policy, reflecting market-driven expectations, rather than a receiver. In contrast, the Call Money Rate (CMR)—a proxy for monetary policy—primarily absorbs spillovers, adjusting to market shifts rather than directly influencing stock prices. These results highlight the evolving complexity of monetary policy in India, offering new insights for policymakers, economists, and investors navigating the intricate relationship between policy, financial markets, and the broader economic landscape.

1. Introduction

In recent years, there has been a growing recognition that certain networks operate within financial markets. For example, banks form financial networks through interbank lending transactions, while another type of network is based on market returns (Anghel & Caraiani, 2024). Additionally, Brunetti et al. (2019) found that the interconnected financial networks have expanded over time. Interest rates, a key factor in financial market dynamics, play a crucial role in influencing economies and financial markets (Anghel & Caraiani, 2024). Monetary policy (MP) decisions impact market prices, interest rates, and volatility, which, in turn, affects stock market returns. Theoretically, interest rate policies are believed to have a significant influence on stock price fluctuations. An increase in interest rates lowers the present value of future dividend payments, thereby reducing stock prices. Conversely, a decrease in interest rates makes borrowing less expensive, which encourages investment and raises stock values (Moizz & Akhtar, 2024). Monetary aggregates are also found to have a crucial relationship with market returns. It has been observed that stock returns adjust more slowly than changes in monetary policy (MP) (Hamburger & Kochin, 1972; Homa & Jaffee, 1971). However, in contrast, Cooper (1974) and Rozeff (1974) argued that the ability to predict past changes in the value of money is not significant.

Another channel observed is through banks, as certain firms respond strongly to MP due to their reliance on bank loans (Sharif et al., 2025). Jensen et al. (1996) indicated that the discount rate, identified as a key MP tool, influences market participation, which in turn affects stock performance. Furthermore, Bernanke & Kuttner (2005) found that shocks in MP had a significant impact on equity prices through shifts in the equity premium. Meanwhile, Castelnuovo & Nisticò (2010) emphasized that economic setbacks led to exchange rate fluctuations, exacerbating inflationary pressures and ultimately affecting stock market performance. The effectiveness of MP in stabilizing the economy remains a highly debated issue, as policy modifications influence the equity market, which plays a critical role in driving trade and industrial growth (Cobbinah et al., 2024a).

Another major financial indicator influenced by MP is market liquidity. Financial market liquidity refers to how quickly and efficiently one can buy or sell assets such as stocks, bonds, or commodities (Amihud, 2002a). It represents the ability to sell an asset rapidly without significantly lowering its price (Chu, 2015a). The notion of stock market liquidity has received considerable attention, particularly in the post-economic crisis phase. For example, Goyenko and Ukhov (2009) stated that restrictive monetary policy (MP) lowers U.S. stock market liquidity. Liquidity in the stock market is a fundamental necessity for the efficient functioning of financial markets, while MP plays a crucial role in determining stock market liquidity (Lyu & Hu, 2024). Fernández-Amador et al. (2013a) found that expansionary or contractionary MP by the European Central Bank significantly affects stock market liquidity. Therefore, stock market liquidity is a key precondition for minimizing market risk.

To maintain economic stability, both monetary and fiscal policies are implemented (Cobbinah et al., 2024b). According to Abille et al. (2020), central banks use MP as a primary instrument to regulate economic expansion and stability. By adjusting the money supply and interest rates, central banks influence employment, inflation, and the overall state of the economy. The global central banks' extensive MP efforts to increase financial system liquidity during economic downturns have proven effective (Debata et al., 2021a). During financial crises or market shocks, Fernández-Amador et al. (2013a) claim that central banks worldwide intervened through MP to stabilize stock markets. However, the manipulation of asset yields through MP forces investors to reassess their holdings, often leading to a shift from low-yield bonds to riskier investments like stocks during expansionary policies (Cobbinah et al., 2024b). This creates a complex relationship between investor decision-making and MP. Whether MP effectively preserves stock market stability remains a contentious issue among investors, who adjust their investment strategies based on market conditions (Fauzi & Wahyudi, 2016). Therefore, understanding the relationship between stock market dynamics and MP is crucial for forecasting risk management and formulating appropriate monetary strategies (Raza et al., 2023).

Stocks are among the most liquid assets for investors, as the ability to finance holdings at low costs can reduce investment risks. Fernández-Amador et al. (2013a) assert that since MP significantly affects financing and holding costs, it also influences liquidity. Additionally, changes in business cycles are closely related to both MP and liquidity. Consequently, MP is

expected to have a notable impact on stock market liquidity (Brunnermeier & Pedersen, 2009a). Stricter MP has been shown to decrease stock market liquidity, as evidenced by positive interest rate shocks and negative borrowed reserve shocks (Goyenko & Ukhov, 2009a). Even an expansionary MP reportedly has only modest predictive power over stock market liquidity since its implementation coincides with a general increase in market liquidity (Chordia et al., 2005a).

The explanation of this relationship remains somewhat ambiguous. Chordia et al. (2005a) documented that MP exhibits liquidity forecasting strength, particularly during financial crises. Similarly, Watanabe (2004) found that from 1965 to 1982, monetary liquidity had a significant impact on stock market liquidity, but this relationship was not observed between 1983 and 2001. Fernández-Amador et al. (2013) further suggested that while market capitalization increases traded stocks, the impact of MP diminishes. However, the observed similarities suggest that MP is a common factor influencing stock liquidity across the market.

In this study, we examine how central bank monetary policies influence the stock market. Specifically, we analyse the relationship between the Indian stock market and MP actions undertaken by the Reserve Bank of India (RBI).

2. Literature Review

One significant factor influencing stock market performance is monetary policy (MP). While substantial contributions have been made to the body of knowledge on how MP affects the stock market, certain aspects remain underexplored. Bernanke and Kuttner (2005) emphasize that unexpected changes in MP, such as alterations in the federal funds rate, have a significant impact on equity value by influencing the equity return premium. Another strand of literature (Rigobon & Sack, 2003) suggests a bidirectional causal relationship between interest rates and stock prices. Ehrmann and Fratzscher (2009) argue that MP affects domestic stock markets by altering volatility and influencing average stock returns.

Recently, there has been growing interest in analyzing the impact of monetary policy uncertainty (MPU) on stock returns. Si et al. (2021), using a time-frequency method, examined the volatility dynamic connectivity between China's sectoral stock markets and varying levels of policy uncertainty, finding a strong correlation. Similarly, Ugurlu-Yildirim et al. (2021) highlight a temporary yet disadvantageous bidirectional relationship between stock markets and MPU.

The concept of stock market liquidity has also gained increasing attention among researchers (Amihud, 2002; Apergis et al., 2015; Bekaert et al., 2007; Jun et al., 2003). Evaluating return variance, ensuring financial market stability, and fostering capital market development have become crucial issues. However, the theoretical link between MP and stock liquidity remains complex. Garcia et al. (1989) propose that MP influences stock liquidity by affecting financing costs and stock market risk. Changes in borrowing regulations and capital flows into stocks, driven by central bank policies, directly impact liquidity. Capital constraints can prevent

market participants from meeting margin requirements, leading to liquidity shortages (Brunnermeier & Pedersen, 2009). Conversely, a decline in market liquidity raises the cost of capital, reducing traders' financial flexibility. Based on these arguments, it is anticipated that expansionary or contractionary MP will either decrease or increase the cost of margin borrowing, thereby facilitating or discouraging financial liquidity.

Existing research primarily focuses on developed hybrid markets (Chordia et al., 2005; Fernández-Amador et al., 2013; Goyenko & Ukhov, 2009). However, order-driven markets function differently (Brockman & Chung, 2002), as they provide supply and demand schedules that align with perfect competition. Studies have documented varying relationships between MP and stock liquidity across different economic structures (Ma et al., 2016). While some findings indicate that MP can predict U.S. stock liquidity from 1962 to 2003 (Goyenko & Ukhov, 2009), others suggest that MP significantly influences liquidity only during crises, as observed in the NYSE (Chordia et al., 2005). Fernández-Amador et al. (2013) claim that no common determinants predict stock liquidity in the Eurozone. However, pro-growth MP policies by the European Central Bank have collectively enhanced stock market liquidity in France, Italy, and Germany. Chu (2015) examined the asymmetric effects of economic shocks on stock liquidity but failed to establish a firm-level relationship between MP and liquidity. These mixed findings suggest the need for further investigation, particularly in emerging markets like India.

India’s growing capital market has made significant strides in terms of volume and liquidity. Debata et al. (2021) report that the market volume increased from 17.83% in 1991 to 72.4% in 2015, making it the second-largest globally. The literature suggests that MP transmission depends on financial system development, capital inflows, government spending, market integration, financial structure, central bank autonomy, and exchange rate policies (Jain-Chandra & Unsal, 2014; Kandil, 2014). As a result, MP transmission may have diverse effects on stock liquidity (Mishra & Montiel, 2013).

Since India's economic reforms began in 1991, MP has undergone significant transformation. Initially focused on monetary targeting, it has gradually shifted toward inflation targeting (Mishra & Mishra, 2012). However, while MP transmission is quick and efficient in the bond market, its impact on the stock market is relatively limited (Ray, n.d.). In India, the effectiveness of MP remains constrained by country-specific factors, particularly in the interest rate channel (Debata et al., 2021). Given that emerging economies have more fragmented and immature financial systems than developed nations, it is worthwhile to examine the relationship between MP and stock liquidity in India.

3. Methodology

3.1 Data and variable Descriptions

This study explores the dynamic relationship between monetary policy (MP) and stock markets. To ensure robust estimation and understanding of this relationship, the study integrates a dataset spanning from January 1, 2003, to January 1, 2023. The NIFTY 50 index

is used to represent the stock market variable, as it serves as NSE's flagship benchmark, comprising the top 50 equity stocks out of the 1,600 listed on the exchange.

Monetary policy is measured using Monetary Aggregates (MA01) and the Call Money Rate (CMR). The control variables include the Industrial Production Growth Rate (IP), Consumer Price Index (CPI) as a measure of inflation, and returns from the CNX NIFTY 50 Index (Return). Additionally, Global Economic Policy Uncertainty (GEPU) and India Economic Policy Uncertainty (EPU) are included as stock market shock variables to ensure that the dataset accurately captures market dynamics under extreme conditions.

For the time series analysis, a total of 241 observations were used. The data was gathered from credible sources: stock market variables were obtained from Investing.com, GEPU and EPU statistics were sourced from the Economic Policy Uncertainty Index database, and macroeconomic fundamentals were collected from the FRED database.

3.2 Methods

The Time-Varying Parameter Vector Autoregression (TVP-VAR) approach, proposed by Antonakakis et al. (2020), is employed to investigate the time-varying dynamic connectedness between monetary policy and the Indian stock market.

This method is an advanced extension of the standard rolling-window VAR connectedness approach introduced by Diebold & Yılmaz (2014). For modeling complex financial variables that are subject to variations due to various uncertainties, this extension enhances the original approaches in four key ways:

(i) It captures potential changes in parameters more accurately than the rolling-window approach.
(ii) It is less sensitive to outliers compared to traditional rolling-window methods.
(iii)It eliminates the need to arbitrarily select a rolling-window size.
(iv) It prevents data loss in the calculation of dynamic measures.

By allowing the coefficients of the VAR model to fluctuate over time, this model more accurately represents varying relationships.

This approach integrates bootstrapped generalized impulse response functions (Koop et al., 1996; Pesaran & Shin, 1998) with joint confidence bands for impulse response functions, as suggested by Lütkepohl et al. (2015), to generate confidence intervals for dynamic connectedness. Additionally, by allowing forgetting factors and Minnesota priors to vary randomly, this method provides an uncertainty estimation for the TVP-VAR-based connectedness measure.

3.2.1 Dynamic connectedness: TVP-VAR approach

To examine time-varying error and parameter variance this study adopts dynamic connectedness approach by (Antonakakis et al., 2020a) with TVP-VAR. The model used in this study is defined using following equations:

$$z_t = \propto_t z_{t-1} + \theta_t , \quad \theta_t | \ Q_{t-1} \sim N(0, \omega_t) \tag{1}$$

$$vec(\propto_t) = vec(\propto_{t-1}) + \psi_t , \quad \psi_t | \ Q_{t-1} \sim N(0, \eta_t) \tag{2}$$

In equation 1, z_t and θ_t represents dependent variable and error term vectors respectively. Both vectors have dimension of $n \times 1$. $\propto_t$ represents time varying coefficient matrix. ω_t represents time varying variance-covariance matrices of the error terms θ_t. Both $\propto_t$ and ω_t are matrices of $n \times n$ dimensions. z_{t-1} is the lagged value of the dependent variable. In equation 2, $vec(\propto_t)$ represents vectorised form of $\propto_t$. ψ_t represents error term vector. Both $vec(\propto_t)$ and ψ_t are $n^2 \times 1$ dimensional vectors and η_t is an $n^2 \times n^2$ dimensional matrix in period t. In both equation 1 and 2, Q_{t-1} represents the set of information available at $t-1$.

To estimate generalized connectedness based on Generalized Forecast Error Variance Decomposition (GFEVD) and Generalized Impulse Response Functions (GIRF), time-varying coefficients and time-varying variance-covariance matrices are utilized.

To implement GFEVD and GIRF, as proposed by (Koop et al., 1996)and (Pesaran & Shin, 1998), and as suggested by several studies (Antonakakis et al., 2020b); (Balcilar et al., 2021); (Guo & Tanaka, 2022) the TVP-VAR model is transformed into a Vector Moving Average (TVP-VMA) model using the Wold representation theorem. The following equations represent the TVP-VMA model:

$$q_t = \sum_{i=1}^{s} \propto_{it} q_{t-i} + \theta_t = \sum_{j=1}^{\infty} P_{jt} \, \theta_{t-j} + \theta_t, \quad j = 0,1, \ldots \tag{3}$$

In equation 3, q_t and q_{t-i} are vectors with dimension of $n \times 1$ in the time t and $t-i$ respectively. $\propto_{it}$ represents time-varying VAR coefficients and variance-covariance matrix with dimensions of $n \times n$. P_{jt} indicate coefficients of TVP-VMA model with dimensions of $n \times n$ and θ_t is the error term.

A shock in variable i and its response on all variables j is represented by GIRFs. K is the forecast horizon which is independent of errors. Compared to impulse response functions it is more suitable for interpretation of VAR based approach. The difference between *K* step ahead forecast, at one instance where variable i is shocked and at another instance where variable i is not shocked, is attributed to the shocks in variable i. The GIRF is calculated using the following equations:

$$\mathrm{GIRF}_t\left(\mathrm{K}, \sqrt{\omega_{jj,t}}, Q_{t-1}\right) = E\left(z_{t+K} \middle| \varepsilon_{j,t} = \sqrt{\omega_{jj,t}}, Q_{t-1}\right) - E(z_{t+J} | Q_{t-1}) \tag{4}$$

$$\Psi_{j,t}(K) = {\omega_{jj,t}}^{-\frac{1}{2}} P_{K,t} \omega_t \varepsilon_j \tag{5}$$

In equation 4 and 5, ε_j is an of $n \times 1$ selection vector with unity in the jth position and zero otherwise.

The pairwise directional connectedness from j to i and the influence variable j has on variable i in terms of the forecast error variance is explained by GFEVD. This is explained in following equations:

$$\chi_{i,j,t}(K) = \frac{\sum_{t=1}^{K-1} \Psi_{ij,t}^2}{\sum_{j=1}^{n} \sum_{t=1}^{K-1} \Psi_{ij,t}^2}, \sum_{j=1}^{n} \chi_{i,j,t}(K) = 1 \quad (6)$$

with $\sum_{j=1}^{n} \chi_{i,j,t}(K) = 1$ and $\sum_{i,j=1}^{n} \chi_{i,j,t}(K) = n$

The cumulative effect of all the shocks represented by the denominator, while the cumulative effect of a shock in variable i is illustrated by the numerator. The total connectedness index is constructed using GFEV which is presented in the following equation:

$$TCI(K) = \frac{\sum_{i,j=1, i \neq j}^{n} \chi_{ij,t}(K)}{\sum_{i,j=1}^{n} \chi_{ij,t}(K)} \times 100 = \frac{\sum_{i,j=1, i \neq j}^{n} \chi_{ij,t}(K)}{n} \times 100 \quad (7)$$

Total directional connectedness from others is defined as the total directional connectedness variable i receives from variables j. It is the ratio of sum of squares of error variance of variables i in time period t to sum of squares of error variances of all other variables j.

The following equation describes the total directional connectedness from other variables to i:

$$FROM_{i \leftarrow j,t}(K) = \frac{\sum_{j=1, i \neq j}^{n} \chi_{ij,t}(K)}{\sum_{i=1}^{n} \chi_{ij,t}(K)} \times 100 \quad (8)$$

The total directional connectedness to others is defined as the transmission of shocks of variable i to all other variables j in the system. It is the ratio of sum of squares of the error variance of variable i to sum of squares of forecast error variances of other variables j in period t. The following equation describes this approach:

$$TO_{i \rightarrow j,t}(K) = \frac{\sum_{j=1, i \neq j}^{n} \chi_{ji,t}(K)}{\sum_{j=1}^{n} \chi_{ji,t}(K)} \times 100 \quad (9)$$

The net total directional connectedness measures the influence of variable *i* on the analyzed network. It is obtained by subtracting the total directional connectedness *to* others from the total directional connectedness *from* others. This metric indicates whether the influence of variable *i* on other variables is greater than the impact of other variables on *i*.

At a given period *t*, a net positive value indicates that variable *i* is a net transmitter**,** meaning it affects other variables more than it is affected by them. Conversely, a net negative value at period *t* suggests that variable *i* is a net receiver, meaning it is influenced by other variables more than it influences them.

The following equation explains the net total directional connectedness:

$$NET_{i,t}(K) = TO_{i \rightarrow j,t}(K) - FROM_{i \leftarrow j,t}(K) \quad (10)$$

Net pairwise directional connectedness examines the bidirectional relationship to see strong or weak pattern of connectedness in pair of assets. Net pairwise directional connectedness is calculated using the following equation:

$$NPDC_{ij}(K) = \frac{\Psi_{jit}(K) - \Psi_{ijt}(K)}{k} \times 100 \quad (11)$$

Pairwise connectedness index (PCI) of variables i and j in period t is defined as,

$$PCI_{ij,t}(K) = 2\left(\frac{\Psi_{ij,t}(K) + \Psi_{ji,t}(K)}{\Psi_{ii,t}(K) + \Psi_{ij,t}(K) + \Psi_{ji,t}(K) + \Psi_{jj,t}(K)}\right), 0 \leq PCI_{ij,t}(K) \leq 1 \quad (12)$$

4. Results

4.1 Descriptive Statistics

Table 1: Descriptive statistics

	Mean	Std.Dev.	Max.	Min.	Skewness	Kurtosis	Jarque-Bera
Nifty50	1.399	6.436	28.070	-26.410	-0.366	5.926	90.972***
MA01	1.065	1.821	10.854	-15.628	-4.190	47.324	20348.68***
CMR	6.444	1.339	10.250	4.250	0.693	3.111	19.342***
CPI	6.622	2.812	16.216	1.083	0.782	3.455	26.532***
FPI	5204.8	19065.9	71046.0	-118203.	-1.038	10.907	668.269***
IIP	90.467	21.786	125.813	47.779	-0.394	2.083	14.649***
IEPU	90.536	48.538	283.689	23.353	1.431	5.260	132.939***
GEPU	151.157	77.509	431.786	49.228	0.979	3.379	39.841***

Note: 10%, 5% and 1% are represented by *, ** and *** respectively

Before proceeding further, a detailed statistical analysis of the dataset is conducted. The dataset consists of monthly observations of the variables spanning from January 2003 to January 2023. Table 1 presents the descriptive statistics of the study. The mean values represent the average returns of each variable over the study period. The standard deviation (Std. Dev.) reflects the level of dispersion or volatility in the data, with FPI exhibiting the highest volatility and CMR the lowest. Examining skewness, we find that Nifty50, MA01, IIP, and FPI are negatively skewed, indicating that their distributions have longer left tails. Conversely, CPI, CMR, IEPU, and GEPU are positively skewed, suggesting longer right tails.The kurtosis values indicate that all variables are leptokurtic (i.e., having high peaks or long tails), as their kurtosis values exceed 3. This suggests a distribution with extreme values, deviating from a normal distribution.The Jarque-Bera (JB) test assesses the normality of the variables. The JB test values are statistically significant at the 1% level (***), indicating that all variables deviate from normality. Since the p-value is less than 0.05, we reject the null hypothesis of normality for all variables. Overall,

these statistics suggest that the data exhibit high volatility, non-normal distribution, and asymmetric behavior, which should be accounted for in further econometric modeling.

4.2 Stationarity test:

Prior to estimation, all variables' stationarity is examined using the ADF unit root tests. The variables Nifty50, MA, FPI, GEPU, IEPU, and IIP were discovered to reject the initial assumption that the series had a unit root at level at the 1% significance level, however, CMR and CPI reject the initial assumption of a unit root for both series.

Table 1: Stationarity test results

Variables	MA	CMR	FPI	NIFTY50	IIP	CPI	GEPU	IEPU
Unit root	-8.005*	-11.247*	-10.124*	-14.919*	-13.806*	-6.312*	-12.376*	-3.194*

Note: 10%, 5% and 1% are represented by ***, ** and * respectively

4.3 Connectedness results

4.3.1 Static connectedness analysis

Table 2 presents the results of the static connectedness analysis, showing the extent to which each variable influences and is influenced by others in the system. The "FROM" column represents the proportion of shocks received by each variable from others, while the "TO" row indicates the proportion of shocks transmitted by each variable. The NET connectedness measures whether a variable is a net transmitter or receiver of shocks.

Table 2: Average Static Connectedness Results

	MA	CMR	FPI	NIFTY50	IIP	CPI	GEPU	IEPU	FROM
MA	83.87	1.53	6.48	3.68	0.18	2.26	0.89	1.11	16.13
CMR	1.40	55.43	4.91	2.75	8.24	8.72	8.71	9.84	44.57
FPI	2.76	0.74	69.06	17.29	0.67	0.91	4.16	4.41	30.94
NIFTY50	1.56	0.85	14.96	71.54	0.11	1.67	2.45	6.85	28.46
IIP	0.35	0.80	8.18	8.01	75.77	0.48	4.44	1.97	24.23
CPI	1.22	1.05	0.65	1.20	0.31	87.98	0.59	7.00	12.02
GEPU	1.08	2.21	11.00	4.43	5.49	0.81	71.13	3.84	28.87
IEPU	0.59	1.32	3.41	9.18	0.57	9.50	6.12	69.29	30.71
TO	8.97	8.51	49.59	46.54	15.57	24.36	27.36	35.03	215.93
TOTAL	92.83	63.94	118.65	118.08	91.34	112.34	98.49	104.32	cTCI/TCI
NET	-7.17	-36.06	18.65	18.08	-8.66	12.34	-1.51	4.32	30.85/26.99

In Table 2, the static connectedness analysis reveals the dynamic interactions among the variables. MA (Monetary Aggregates) has a notable impact on several variables, transmitting spillovers to FPI (Foreign Portfolio Investment) and NIFTY50 with the highest influence, at 2.76% and 1.56%, respectively. MA also affects CMR (Call Money Rate) (1.40%), IIP (Index of Industrial Production) (0.35%), CPI (Consumer Price Index) (1.22%), GEPU (Global

Economic Policy Uncertainty) (1.08%), and IEPU (Indian Economic Policy Uncertainty) (0.59%). The spillover from MA to FPI and NIFTY50 is significant, especially during periods of economic downturn, highlighting how negative returns in monetary aggregates influence these financial market variables. The FPI and NIFTY50 show a strong bidirectional relationship, with FPI having the highest impact on NIFTY50 (14.96%), and NIFTY50 exerting the greatest influence on FPI (17.29%). This mutual impact suggests that fluctuations in foreign portfolio investments and stock market performance are closely linked, particularly during market or economic crises.

Looking at the NET connectedness**,** FPI and NIFTY50 emerge as the strongest net transmitters of shocks, meaning they influence other variables more than they are impacted by them. Conversely, CMR is the largest net receiver of shocks, followed by FPI and IEPU, indicating that these variables are more susceptible to external shocks than they contribute to the system. Notably, CMR has a strong impact on IIP**,** GEPU**,** and IEPU**,** particularly during economic downturns. CPI is primarily influenced by IEPU**,** underscoring the connection between inflation and economic policy uncertainties.

The total connectedness of 30.85% signifies a moderate but significant level of dynamic interdependence among the variables, indicating that shocks in one variable are likely to spill over to others. This highlights the interconnectedness of financial markets and economic variables, suggesting that fluctuations in one part of the economy can have widespread effects. In conclusion, the static connectedness analysis underscores the importance of understanding the transmission of shocks within the economic system, with FPI and NIFTY50 playing key roles as transmitters and CMR emerging as a significant receiver of shocks.

4.3.2 Dynamic connectedness analysis

The dynamic analysis of total connectedness provides a clear understanding of the factors influencing connectedness across different sectors of the Indian financial market from 2011 to 2024. With this context in mind, we can now focus on the dynamics of directional connectedness over time. The static full-sample connectedness analysis offers a good characterization of the "average" or "unconditional" aspects of each connectedness measure. However, it does not capture the dynamic nature of the relationships. This sub-section delves into the dynamic analysis. Unlike the static empirical analysis, which progresses from “micro to macro”—from pairwise connectedness to total connectedness—here, it is more effective to proceed in reverse order, from macro to micro. We begin our dynamic analysis with total connectedness and then move to various levels of disaggregation (total directional and pairwise directional connectedness).

Figure 1 illustrates the dynamic Total Connectedness Index (TCI) of the network from 2011 to 2024. The results are derived using a TVP-VAR model with a lag length of order one (mention the selection criteria) and a 10-step ahead forecast. In the figure, the x-axis represents time, capturing the evolution of connectedness over the observed period, while the y-axis denotes the TCI, indicating the percentage of total connectedness in the system. The black-shaded area represents the dynamic connectedness measure, which remains relatively stable over time with

occasional fluctuations. Notably, there is a visible spike around 2020, suggesting a significant disruption in the network's connectedness.

Such spikes in connectedness often coincide with major economic, financial, or global events that increase uncertainty and interdependence among economic agents. For instance, the sharp rise around 2020 could be attributed to the COVID-19 pandemic, which led to extreme market volatility, supply chain disruptions, and heightened global economic uncertainty.

Figure 1: Dynamic total connectedness (TCI)

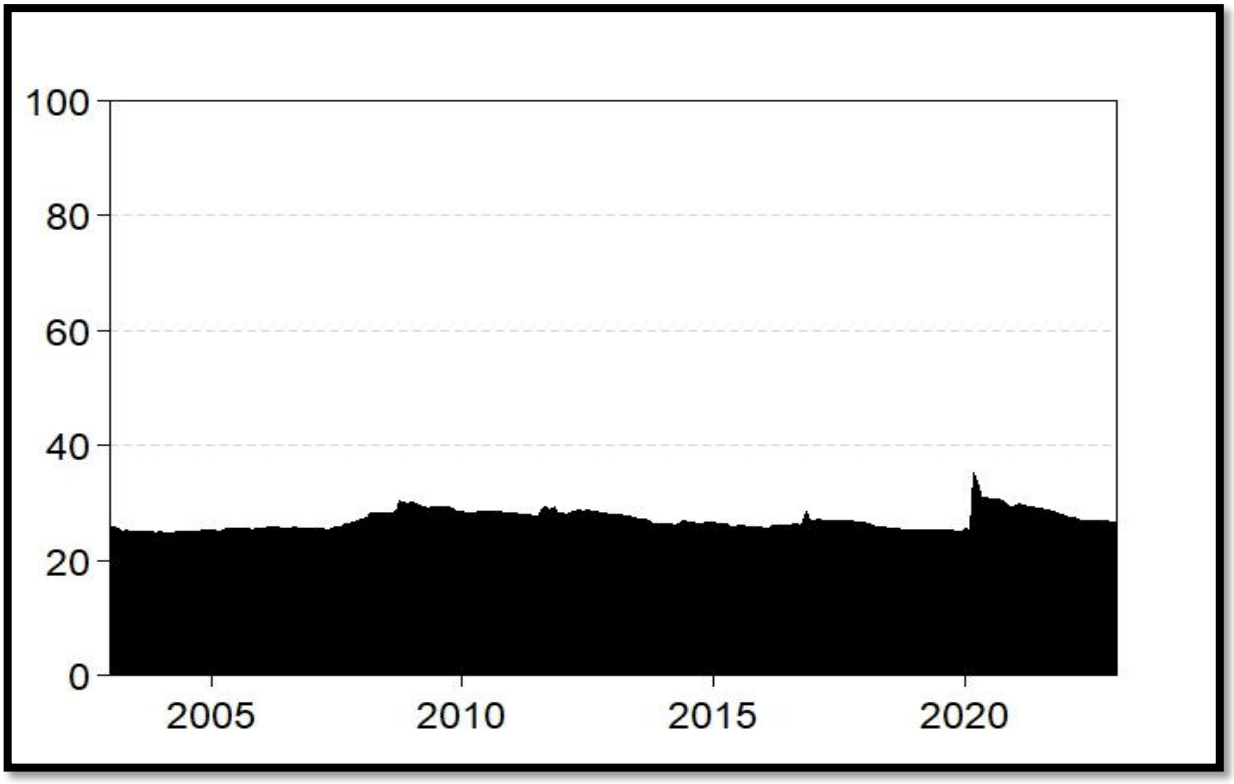


Figure 2: Dynamic “TO” Total Directional Connectedness

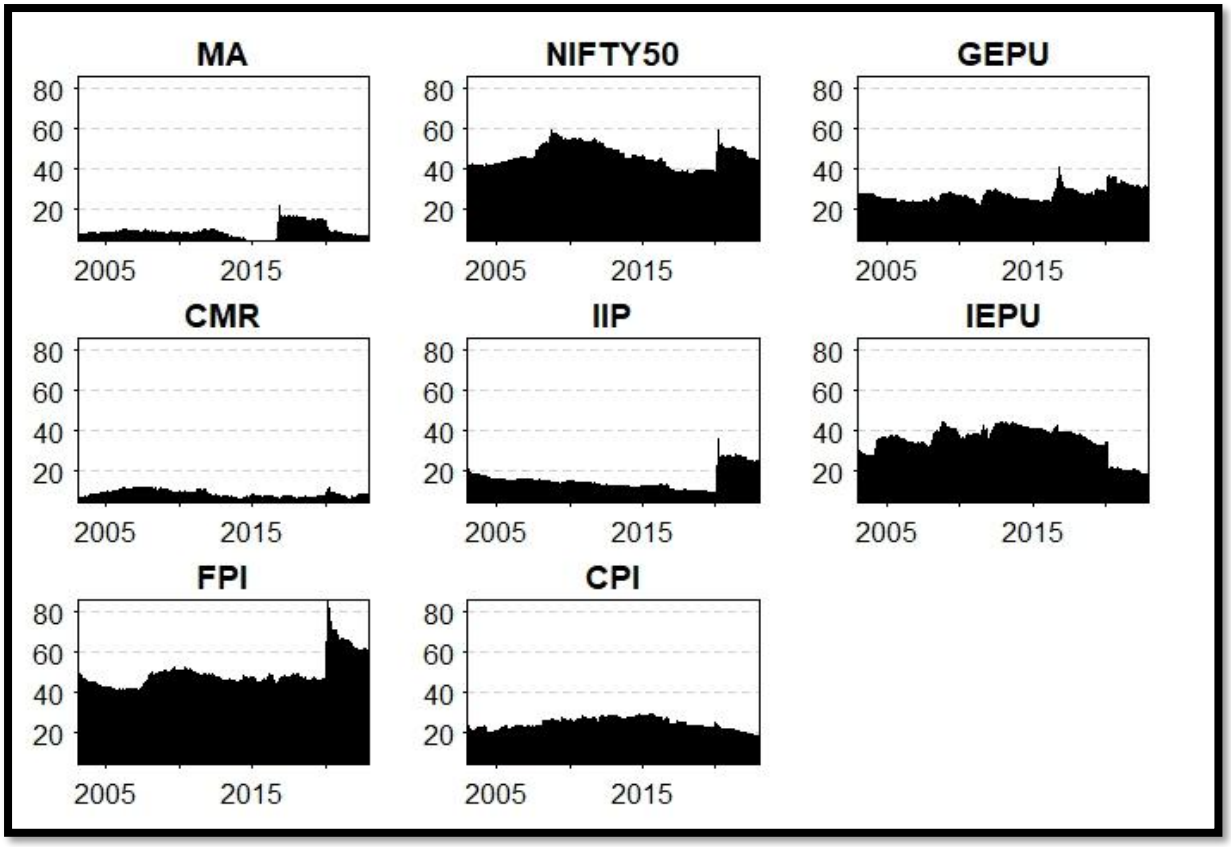


Figure 2 presents the time series of total directional connectedness ("to" degrees) for each variable separately. The x-axis represents time, while the y-axis indicates the extent of the total directional connectedness at a given time. The plots illustrate the total directional connectedness flowing "to" other variables over the observed period. The black-shaded areas represent the variations in connectedness, with most variables exhibiting relatively stable patterns except for occasional spikes. Notably, certain variables, such as *FPI (Foreign Portfolio Investment)* and *NIFTY50 (Stock Market Index)*, display significant spikes, particularly around 2020, indicating increased influence on other variables during that period. This surge in connectedness could be attributed to economic shocks such as the COVID-19 pandemic, financial market turbulence, or policy-driven changes.

Figure 3 presents the dynamic *from* total directional connectedness, illustrating the extent to which each variable receives connectedness from others over time. The x-axis represents time, while the y-axis indicates the magnitude of the *from* directional connectedness at a given point. Compared to Figure 2, which depicts *to* connectedness, there is a substantial difference in the patterns observed in Figure 3. Some variables, such as *CMR (Call Money Rate)* and *IIP (Index of Industrial Production)*, exhibit sharp spikes, suggesting periods when they were significantly influenced by external shocks. Meanwhile, other variables like *FPI (Foreign Portfolio Investment)* and *CPI (Consumer Price Index)* show relatively stable trends, indicating a consistent level of connectedness received from others. The fluctuations in connectedness levels across different periods highlight the dynamic nature of interdependencies within the

system, where certain economic and financial variables become more reactive to external influences during times of economic uncertainty or market volatility.

Figure 3: Dynamic "FROM" Total Directional Connectedness

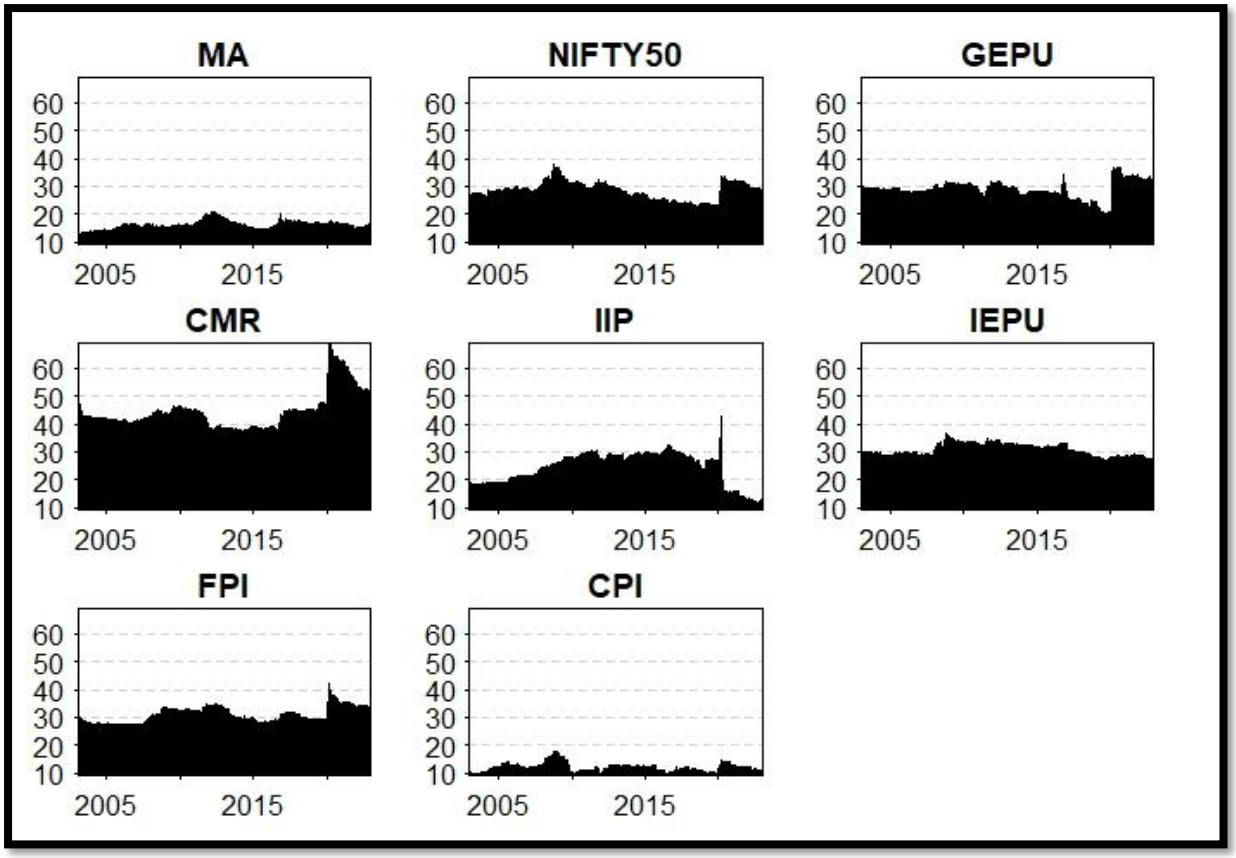


Figure 4 presents the dynamic *net* total directional connectedness, illustrating the difference between the total connectedness transmitted *to* others and the total connectedness received *from* others for each variable over time. The x-axis represents time, while the y-axis indicates the magnitude of *net* directional connectedness at a given point. This figure provides insights into whether a variable is a net transmitter or a net receiver of shocks within the system. The results, derived using a TVP-VAR model, cover the period from 2011 to 2024.

Compared to Figures 2 and 3, which separately depict *to* and *from* connectedness, Figure 4 captures the overall influence of each variable in the network. A positive net connectedness value suggests that a variable acts as a dominant transmitter of shocks, exerting influence on others, while a negative value indicates that it is more reactive, receiving external shocks from the system.

Figure 4: Dynamic “NET” Total Directional Connectedness.

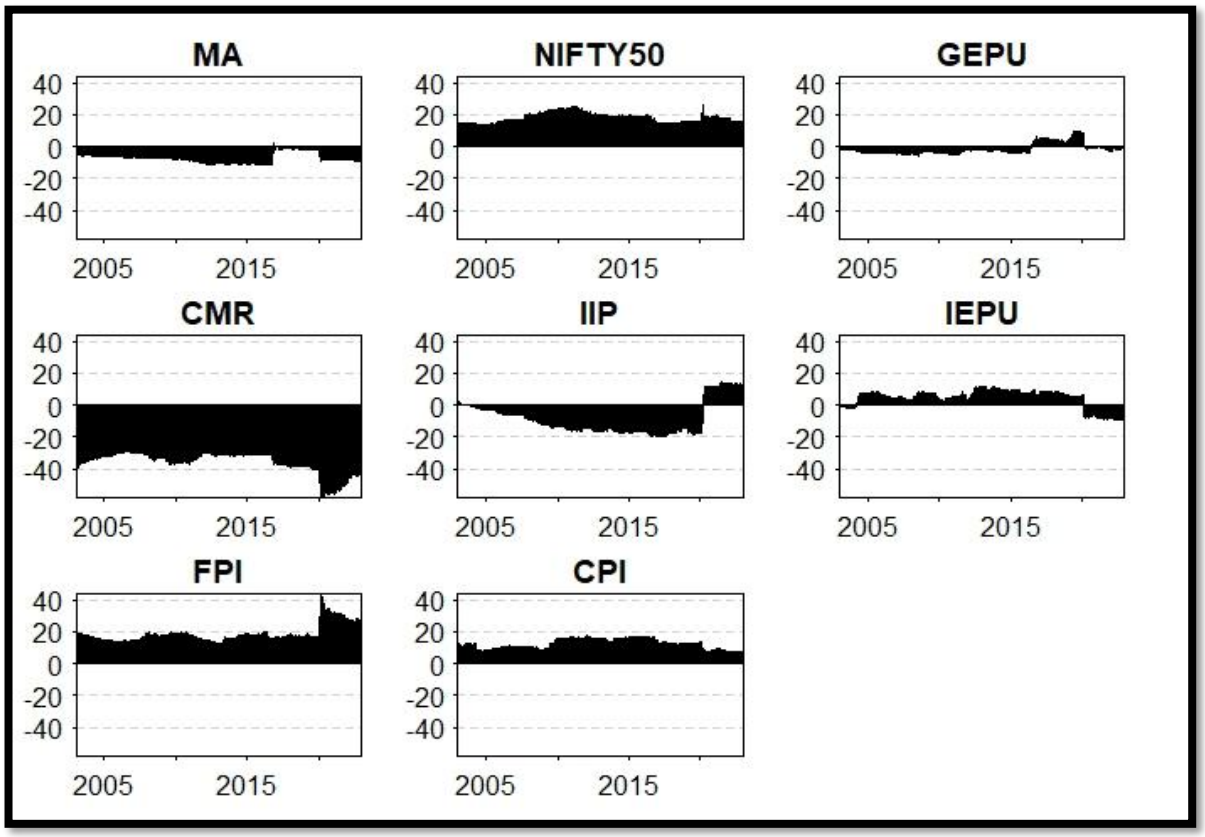


Figure 5: Connectedness Network

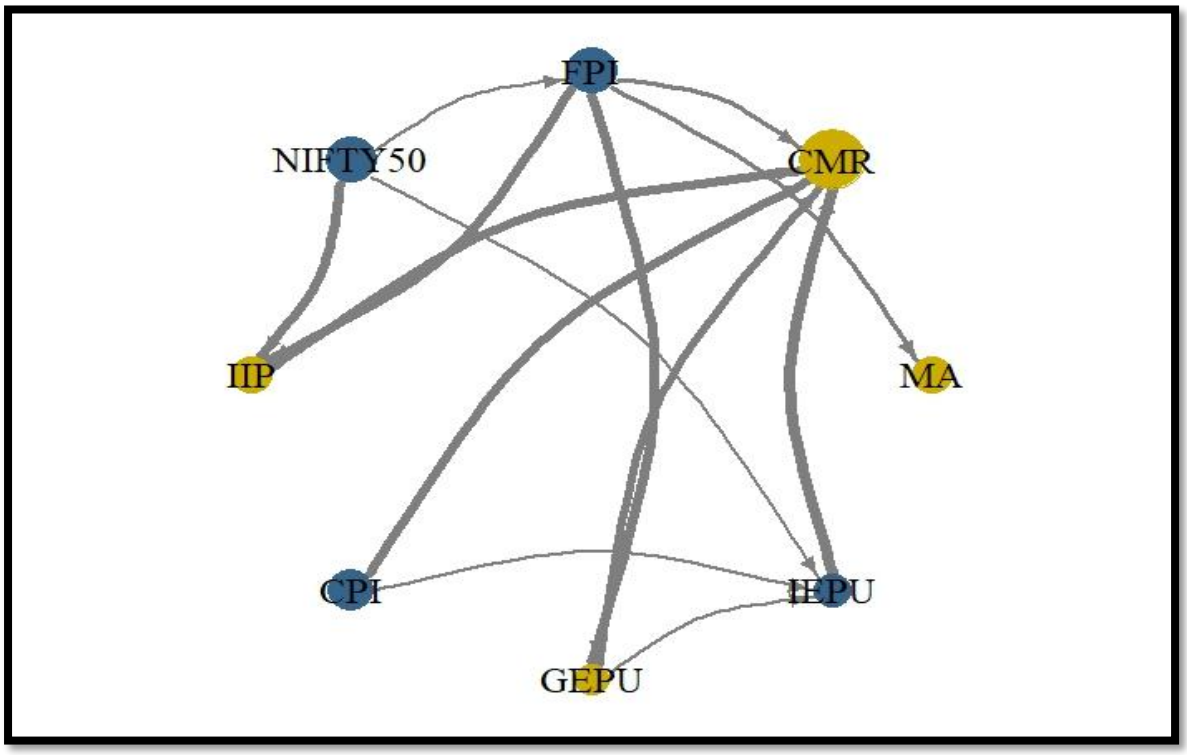


Figure 5 illustrates the network channel of the variables, highlighting the directional spillover dynamics among them. FPI (Foreign Portfolio Investment) and NIFTY50 (Stock Market Index) emerge as key transmitters of net directional spillover, consistently influencing other variables, especially during periods of significant crises. In contrast, CMR (Call Money Rate), which serves as a proxy for monetary policy, receives the highest amount of net directional spillover. This indicates that monetary policy is highly responsive to changes in the broader financial and economic environment, reflecting its role in absorbing systemic shocks. The strong spillover received by CMR suggests that fluctuations in liquidity conditions, interest rates, and overall financial stability are significantly influenced by external factors such as stock market movements, inflationary trends, and global economic uncertainty.

Furthermore, MA (Monetary Aggregate) and CMR primarily function as receivers, meaning they absorb spillovers from other variables but do not significantly act as transmitters. However, IIP (Index of Industrial Production), CPI (Consumer Price Index), GEPU (Global Economic Policy Uncertainty), and IEPU (Indian Economic Policy Uncertainty) act as strong transmitters to CMR, reinforcing its sensitivity to both domestic and global economic shocks. The results also indicate that IEPU receives spillovers from CPI, GEPU, and NIFTY50, suggesting that economic downturns in the stock market (NIFTY50) and inflationary pressures (CPI) are closely tied to uncertainty in the economy. Additionally, IIP functions as a net receiver of spillovers from NIFTY50 and FPI, implying that fluctuations in the stock market and foreign investment directly impact industrial production.

5. Conclusion

This study aims to examine how central bank monetary policies influence the stock market, specifically focusing on the relationship between the Indian stock market and the monetary policy actions undertaken by the Reserve Bank of India (RBI). Using the Vector Autoregressive Time-Varying Parameter Model (TVP-VAR), we analyze the interconnectedness between key variables over the period from 2003 to 2023. The study incorporates monthly time series data for the Nifty 50 as a proxy for the stock market, monetary aggregates (MA) and the Call Money Rate (CMR) as proxies for monetary policy, and control variables such as the Index of Industrial Production (IIP), Consumer Price Index (CPI), and Foreign Portfolio Investment (FPI). Additionally, the Global Economic Policy Uncertainty (GEPU) and Indian Economic Policy Uncertainty (IEPU) are included as shocks to examine their impact on the relationship.

The findings reveal that the Nifty50, FPI, and CPI serve as net spillover transmitters to other variables, while MA and CMR, representing monetary policy, function as net spillover receivers. Notably, CMR absorbs the highest spillovers from the other variables, positioning it as the most sensitive shock receiver. Contrary to conventional economic theory, our results indicate a reverse dynamic in which the Nifty 50 impacts monetary policy, rather than the anticipated effect of monetary policy on the Nifty50. Furthermore, the analysis shows that IEPU receives spillovers from CPI, GEPU, and Nifty50, suggesting that economic downturns in the stock market (Nifty50) and inflationary pressures (CPI) are closely linked to economic uncertainty.

These findings offer valuable insights for investors and policymakers by providing a comprehensive view of the interactions between various economic and financial variables over time. The strong spillover effect observed for CMR underscores the central role of monetary policy in responding to economic fluctuations. Given that CMR is a key determinant of short-term liquidity and borrowing costs, its high degree of connectedness indicates that policy interventions aimed at stabilizing liquidity conditions must consider broader macroeconomic linkages. According to Shang & Hamori (2024), long-term connectivity is typically associated with significant structural changes or systemic risks, reflecting fundamental shifts in investor expectations. This suggests that markets and the broader macroeconomic system adjust gradually to evolving conditions. In contrast, short-term connectedness reflects the rapid processing of information and quick reactions to unexpected shocks, highlighting the more market-sensitive and reactive nature of financial and economic systems. Understanding these dynamics can assist stakeholders in navigating economic uncertainties and formulating informed monetary and financial policies.

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Declaration of Interest Statement

The author declares that there are no conflicts of interest related to the content of this manuscript. No financial or personal relationships with other people or organizations have influenced the research, findings, or interpretations presented in this study. This submission is the result of independent academic work, free from any commercial or financial ties that could be perceived as a conflict.

Thank you very much for considering this submission.

Sincerely,

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