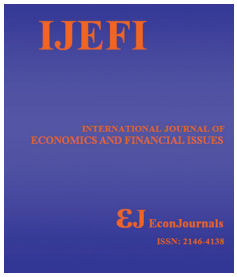

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Stock Returns and Volatility Spillover Dynamics between National Stock Exchange's Overall Index and Small and Medium Enterprises' Index

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ABSTRACT

This study conducts an in-depth analysis of the dynamic interrelationship between the National Stock Exchange's (NSE) primary index, NIFTY 50, and the stock index for small and medium enterprises (SMEs), EMERGE, in India. Utilizing the Granger causality test, the research aims to determine the directional causality between the two time series. Furthermore, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is employed to scrutinize the volatility spillover effects between the two indices using daily stock data from December 2019 to November 2023. The empirical results reveal statistically significant autoregressive volatility spillovers within both NIFTY 50 and EMERGE indices. Additionally, the study uncovers substantial cross-volatility spillover effects between the indices, indicating a bidirectional volatility transmission. Specifically, there is a statistically significant volatility spillover from NIFTY 50 to EMERGE, and conversely, from EMERGE to NIFTY 50. These findings bear critical implications for the diversification strategies within investment portfolios. They offer essential insights for investors, portfolio managers, and policymakers, especially in light of the Indian government's recent initiatives and the surge in foreign investments targeting the SME sector. The bidirectional volatility spillovers suggest that shocks in one market can significantly affect the other, thereby informing risk management and hedging strategies. Consequently, understanding these dynamic relationships is crucial for optimizing asset allocation and enhancing portfolio resilience against market fluctuations.

Keywords: EMERGE, SME, NSE, Volatility Spillover, NIFTY 50, Stock Index
JEL Classifications: G1

1. INTRODUCTION

Small and Medium Enterprises (SMEs) serve as critical drivers of economic growth in both developed and developing economies, acting as catalysts for economic expansion, particularly in emerging markets. SMEs constitute 90% of businesses and contribute over 50% to global employment, positioning them as key contributors to job creation and economic development worldwide. When accounting for informal SMEs, these figures increase substantially. Projections indicate that 600 million jobs will need to be created by 2030 to accommodate the expanding global workforce, thereby making the development of SMEs a high priority for governments globally. In emerging markets, SMEs are the primary source of formal employment, generating 7 out of every 10 jobs (World Bank, 2019).

In the context of emerging markets such as India, SMEs have consistently bolstered the economy's resilience, even during crises that severely impacted developed economies. As a result, exchanges and regulatory bodies have demonstrated a strong commitment to supporting the growth of SMEs through continuous policy innovations aimed at facilitating their development and

operational efficiency. Recognizing the significance of SMEs, the Government of India has implemented various measures, including an equity infusion of Rs. 50,000 crores, to help the sector navigate multiple challenges. Under the Atma Nirbhar Bharat Package, several initiatives were introduced to mitigate the impact of COVID-19 on SMEs, such as the Distressed Assets Fund - Subordinate Debt for MSMEs, and the Fund of Funds Scheme for MSMEs, which aims to leverage an equity infusion of Rs. 50,000 crore. Additionally, collateral-free automatic loans worth Rs. 3,000 crores have been announced for businesses, including MSMEs.

A 2019 report by McKinsey and Company highlights that, among 17 major emerging economies, India has been rapidly digitizing, second only to Indonesia since 2014. A study by the Associated Chambers of Commerce and Industry of India and PwC projects an 84% increase in the number of smartphone users in India, rising from 468 million in 2017 to 859 million by 2022. This digital expansion offers SMEs the opportunity to reach potential customers directly, bypassing intermediaries. This reduction in intermediary costs enables SMEs to lower product prices, enhancing their competitiveness against foreign counterparts and increasing operational efficiency.

Similar to many countries with developed capital markets and dedicated exchanges for emerging companies (such as AIM in the UK, TSX-Venture in Canada, GEM in Hong Kong, MOTHERS in Japan, Catalyst in Singapore, and ChiNext in China), India has two dedicated SME exchanges – BSE SME Exchange and NSE EMERGE. In recent years, SME exchanges have been as active as, if not more active than, the mainboard stock exchanges of the country (NSE and BSE). During the financial years 2018 and 2019, out of 261 SMEs listed, 123 were listed on the Bombay Stock Exchange and National Stock Exchange. SMEs raised Rs. 6,090 crores from the market between 2012 and September 30, 2019, reflecting their growing importance in India. Despite the activity of both exchanges, market volatility remains inevitable. Recent events have shown that stock markets can experience significant volatility, leading investors to reassess their investment strategies (Vigg et al., 2008).

Volatility spillovers can be categorized into own volatility spillovers and cross volatility spillovers, Kushwah and Negi (2024). Own volatility spillovers refer to a unidirectional causal relationship between past and current volatility within the same market. In contrast, cross volatility spillovers denote a unidirectional relationship between past and current volatility across different markets. Current literature primarily explores volatility spillovers between equity and commodity markets (Kushwah et al., 2024). However, given the pivotal role of SMEs in driving growth in many emerging economies, it is crucial to examine the interconnections between SME exchanges and mainboard stock exchanges in such economies.

The objective of this study is to evaluate the volatility spillover dynamics between the well-established National Stock Exchange (NSE) mainboard index (NIFTY 50) and the newly established SME stock index (NSE EMERGE) in India. The analysis of volatility spillovers between these indices provides critical insights into the mechanisms of information transmission and dissemination across these exchanges. This understanding is pivotal for investors in strategically structuring their portfolios and offers valuable guidance for policymakers in formulating regulations and policies tailored to the needs and growth trajectories of SMEs.

Volatility spillover analysis employs advanced econometric techniques, such as the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, to measure the extent and direction of volatility transmission between these indices. This methodological approach enables the identification of both own-market volatility (intramarket effects) and cross-market volatility (intermarket effects), thereby delineating the influence of market shocks from one index on the other. By capturing these spillover effects, the study elucidates the degree of interconnectedness and the potential for systemic risk propagation between the mainboard and SME markets.

Furthermore, understanding these volatility dynamics is crucial for optimizing asset allocation and enhancing portfolio resilience against market disruptions. For policymakers, the insights derived from this analysis can inform the design of regulatory frameworks that mitigate risk, promote market stability, and support the sustainable growth of SMEs. This is particularly important in the context of India's evolving economic landscape, where SMEs play a significant role in economic development and job creation. The study's findings contribute to the broader discourse on market integration and the strategic management of emerging financial markets, ultimately fostering a more robust and inclusive economic environment.

2. REVIEW OF LITERATURE

The analysis of volatility spillovers has garnered considerable interest among researchers worldwide due to its critical implications for investment and risk management strategies. Understanding the nature of volatility linkages between financial markets is essential for optimizing portfolio management and mitigating risks. It enables portfolio managers to reallocate funds across markets to achieve risk reduction, particularly when anticipating increased market volatility. Moreover, insights into the transmission of information between markets are invaluable for formulating regulatory policies that enhance market stability.

Numerous studies have explored the correlation and volatility transmission across global stock markets, yielding mixed empirical evidence, Bhatia and Kushwah (2023), Nathani and Kushwah (2022), Vigg and Holani (2005). Earlier research primarily focused on developed markets. For instance, Hamao et al. (1990) documented significant volatility spillovers between the stock markets of New York, London, and Tokyo. Pan and Hsueh (1998) identified volatility spillovers from the U.S. to Japanese futures markets, while Koutmos and Booth (1995) observed that negative market innovations tend to increase volatility in subsequent markets more than positive innovations. Susmel and Engle (1994) found no evidence of volatility spillovers between the New York and London equity markets when non-overlapping trading periods were

considered. Kanas (1998) reported significant volatility spillovers among the largest European stock markets, namely London, Paris, and Frankfurt. Similarly, Savva et. al (2009) found bidirectional volatility spillovers between the U.S. and major European stock markets. Conversely, some studies, such as those by Ng (2000), Baele (2005), and Kaur (2004), found inconclusive or no evidence of volatility spillovers between international equity markets.

The literature on volatility spillovers from advanced markets to emerging markets is sparse but growing. Studies such as those by Wang et al. (2004), Goetzmann et al. (2005), Vigg and Arora (2018), Lin and Wu (2006), Ng (2000), Worthington and Higgs (2004), and Wang et.al. (2005) have produced mixed results. Miyakoshi (2003) asserted that volatility in Asian markets is more influenced by the Japanese market than the U.S. market. Conversely, John Wei et al. (1995) found that the New York market exerted more influence than the Tokyo market on the Taiwanese and Hong Kong markets. Liu and Pan (1997) also reported that the U.S. market had a more significant impact than the Japanese market on transmitting returns and volatility to Asian markets, including Hong Kong, Singapore, Taiwan, and Thailand. Recently, Vo and Tran (2020) documented substantial volatility spillovers from the U.S. stock market to ASEAN markets. Wang and Wang (2010) established that volatility spillovers were stronger than price spillovers between the Greater China markets and the developed markets of the U.S. and Japan. Wang et. al (2005) examined return and volatility spillovers from the U.S. and Japanese stock markets to the stock markets of emerging economies, specifically the Bombay Stock Exchange, the Karachi Stock Exchange, and the Colombo Stock Exchange. Their findings indicated volatility spillovers from the U.S. to the Indian and Sri Lankan markets and from Japan to the Pakistani market, with return spillovers observed in all three markets.

Another significant area of research on volatility transmission involves the stock market and the foreign exchange market. Kanas (2000) investigated volatility spillovers between stock returns and exchange rate returns in six countries: the U.S., the UK, Canada, Germany, France, and Japan, finding evidence of spillovers in all but Germany. Yang and Doong (2004) examined the G-7 countries and reported asymmetric volatility spillovers between stock and foreign exchange markets in France, Italy, Japan, and the U.S. Fedorova and Saleem (2010) established interdependence between Emerging Eastern European and Russian equity and currency markets. Jebran and Iqbal (2016) identified bidirectional asymmetric volatility spillovers between the stock and foreign exchange markets of Pakistan, China, Hong Kong, and Sri Lanka, while noting unidirectional spillovers from the stock market to the foreign exchange market in India.

In conclusion, the examination of volatility spillovers is crucial for understanding the intricate dynamics of financial markets. It informs investment decisions, enhances risk management strategies, and provides a foundation for effective regulatory frameworks. By investigating both advanced and emerging markets, as well as the interactions between stock and foreign exchange markets, researchers can offer comprehensive insights into the global financial system's stability and interconnectedness. Interestingly, despite the substantial body of literature on stock market volatility, there remains a significant gap in examining the interconnections between volatility in well-established mainboard stock exchanges and the relatively nascent SME stock exchanges. Understanding the volatility spillovers between these two types of exchanges is crucial. A weak linkage between the mainboard and SME exchanges could provide investors with potential diversification benefits, as uncorrelated returns would reduce overall portfolio risk. Conversely, a strong linkage in returns would diminish the advantages of diversification, as market movements in one exchange would be closely mirrored in the other.

This paper aims to elucidate the interdependence between the NIFTY 50 index and the NSE EMERGE index by rigorously analyzing volatility spillovers between these two exchanges. Specifically, it investigates whether volatility fluctuations in the younger SME stock exchanges influence volatility patterns in the more established mainboard stock exchanges. This analysis not only contributes to the existing literature on market volatility but also provides critical insights for investors seeking to optimize their portfolio strategies. To achieve this, the study employs the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, specifically the GARCH (1,1) variant, to capture the extent to which volatility affects expected returns on both exchanges. The GARCH model is well-suited for this analysis as it accommodates time-varying volatility, enabling a detailed examination of how past shocks and volatility persist over time within and across the two markets.

3. DATA AND METHODOLOGY

The present study rigorously examines the volatility spillover between the primary index of the National Stock Exchange (NSE), the NIFTY 50, and the index for Small and Medium Enterprises (SMEs), the NSE EMERGE. This research aims to quantify the bidirectional volatility impact between the NIFTY 50 and the EMERGE indices. Utilizing time-series data, the study employs the Autoregressive Conditional Heteroskedasticity (ARCH) family of models, specifically the Generalized ARCH (GARCH) (1,1) model, to predict the effects of exogenous shocks on these indices. The analysis is based on secondary data consisting of daily closing prices for the NIFTY 50 and EMERGE indices, collected from the NSE website (www.nseindia.com). The dataset spans 4 years, from December 2019 to November 2023. To address heteroscedasticity, daily logarithmic returns for each index are computed. Following the methodology of Kushwah and Vigg (2023), and Kushwah and Siddiqui (2023), the return (R_t) is defined as the natural logarithm of the ratio of consecutive daily prices:

$$R_t = Log\ (p_t/p_{t-1})$$

Where R_t is the return for time t, P_t is the price at time t, and P_{t-1} is the price at time t-1. To investigate the volatility spillover using the GARCH (1, 1) Model, it is essential to examine the presence of autoregressive conditional heteroscedasticity (ARCH) effect in the study variables. Therefore, the ARCH effect is checked using

the heteroscedasticity test and the presence of the ARCH effect is seen in the variables. Furthermore, examining the stationarity of the data is also necessary for applying the GARCH (1, 1) Model. Based on the methodology of Siddiqui and Kushwah (2022), Augmented Ducky Fuller (ADF) is used to examine whether the time series is stationary or not. Figure 1 highlights the methodology applied in the study.

Table 1 provides the descriptive statistics for both time series under investigation. Ensuring stationarity in the data is crucial, as non-stationary data can lead to spurious regression results, rendering the conclusions invalid. Consequently, this study employs stationarity tests to validate the data. Nelson and Plosser (1982) highlight the significance of identifying stationarity and stochastic trends in time series analysis, recommending the use of unit root tests (Elliot et al., 1996; Dritsaki and Dritsaki-Bargiota, 2005; Kushwah et al., 2022). To assess stationarity, the Augmented Dickey-Fuller (ADF) test is utilized, following the methodology outlined by Dickey and Fuller (1979).

The ADF test model is specified as follows:

$$\Delta Z_t = \alpha_1 + \alpha_2 t + \alpha_3 Z_{t-1} + \sum_{i=1}^{p} \beta_i \Delta Z_{t-1} + \varepsilon_t$$

Where, Z_t, the logarithmic values of all model variables at time t. From NIFTY 50 to EMERGE and from EMERGE to NIFTY 50, volatility spillover is tested using the Granger Causality test (Granger, 1969, 1988). Following are the equations related to the Causality test:

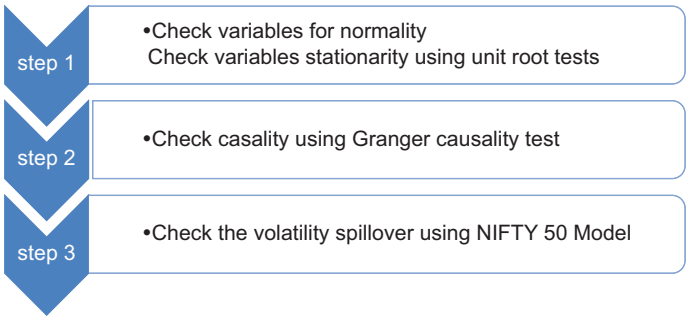
$$Y_t = \sum_{i=1}^{n} \alpha_i Y_{t-i} + \sum_{j=1}^{n} \beta_j X_{t-j} + u_{1t}$$

$$X_t = \sum_{i=1}^{n} \lambda_i Y_{t-i} + \sum_{j=1}^{n} \sigma_j X_{t-j} + u_{2t}$$

Where, Y_t and X_t are the two time series. The GARCH (1, 1) model fits best in the current study as it intends to examine the conditional volatility among the two stock indices that have heteroskedastic nature (Bollerslev, 1986; Taylor, 1986). Two equations, one for mean and the other for conditional variance, are formed. Mean equation in GARCH (1,1) Model

$$R_Y = V_1 + V_2 * W + e$$

Figure 1: Methodology



Source: Author's presentation

Where, $R_{Y.}$ = return of the dependent variable, V_1 is Constant, W is the independent variable, V_2 is the coefficient. Variance equation in GARCH (1,1) model

$$S_t = V3 + V4 * S_{t-1} + V5 * e2_{t-1}$$

Where, S_t is the variance of the dependent variable's return.

4. EMPIRICAL ANALYSIS

The study attempts to understand the volatility spillover between the Indian stock market's index, NIFTY 50 and the volatility of EMERGE, index of the small and medium enterprise. Table 1 reflects the descriptives of the study's variables. The highest mean annualized log-returns are NIFTY 50. Volatility (standard deviation) is also highest in the case of NIFTY 50. Skewness, which represents the nature of departure from normality, is observed for both the stock indices' returns. The kurtosis figures reflect that the stock indices' distribution is peaked (leptokurtic) relative to kurtosis 3 (Kushwah and Munshi, 2018; Siddiqui and Kushwah, 2021; Kushwah and Garg, 2020).

The log-transformed data for the returns of NIFTY 50 and EMERGE are tested for stationarity (Table 2) and it indicates the presence of unit root in all the time series data used in the study. The $P < 0.05$, so the hypotheses are rejected. Hence, the test results confirm that the series is stationary and authenticate the absence of autocorrelation. Since series are stationary, the next step is to determine the best mean fitting equation through the auto-regressive process. Consequently, the pre-mentioned analysis gives support and suitability to apply the ARCH and GARCH model in the gathered data.

To know the optimal lag, which came out as 2, AIC and S.C. are used. The Granger causality test results are reflected in Table 3, and it highlights that NIFTY 50 is Granger causing EMERGE at two lags but, EMERGE is not Granger causing NIFTY 50 at two lags. It witnesses a unidirectional causality between NIFTY 50 and EMERGE at two lags.

Table 1: Descriptive analysis

Statistic	EMERGE	NIFTY 50
Mean	0.00451	0.00464
Median	0.00405	0.00834
Maximum	0.78338	0.84003
Minimum	-0.041788	-0.139038
Std. Dev.	0.008231	0.011988
Skewness	4.30676	-1.947842
Kurtosis	13.39692	30.88995
Jarque-Bera	4489.559	32712.31
Probability	0.000000	0.000000
Observations	990	990

Table 2: Summary of unit root test

Variables	ADF
NIFTY 50 Level	-10.624*** (0.0000)
EMERGE Level	-17.6471*** (0.0000)

Source: Author's calculation. *Significant at 10%, **Significant at 5%, ***Significant at 1% level of significance

To explore the volatility interaction between NIFTY 50 and EMERGE, we apply the GARCH (1,1) model. Two variants of this model are employed: one scrutinizing the volatility transmission from NIFTY 50 to EMERGE, and the other assessing EMERGE's impact on NIFTY 50. We utilize Normal Gaussian Distribution, Student's Distribution, and Generalized Error Distribution under the GARCH (1,1) framework. In Model 1, focusing on NIFTY 50's influence on EMERGE, results show significant ARCH and GARCH terms using the normal distribution method. The significant P-value of NIFTY 50 implies its effect on EMERGE's returns, indicating a volatility spillover, as illustrated in Table 4. Observations reveal that EMERGE's volatility is influenced by both internal and external shocks, with evidence of volatility transmission from NIFTY 50 to EMERGE. Similar conclusions are drawn from the Student's Distribution and Generalized Error Distribution methods, as depicted in Table 4.

Model 2, examining EMERGE's impact on NIFTY 50, demonstrates significant ARCH and GARCH terms using the normal distribution approach. The significant P-value of EMERGE suggests its impact on NIFTY 50's returns, confirming a volatility spillover, as shown in Table 5. This study concludes that both self-volatility spillover and cross-volatility spillover exist within NIFTY 50. Consistent findings are obtained across all GARCH (1,1) models, regardless of distribution method.

These results contribute to understanding the volatility dynamics between NIFTY 50 and EMERGE. While no prior research specifically explores volatility relationships between SME markets and major stock markets, our findings align with previous studies by Hamao et al. (1990), Koutmos and Booth (1995), Susmel and Engle (1994), Kanas (1998), and Miyakoshi (2003). These studies identified volatility spillovers between various stock markets, indicating a broader pattern of interconnectedness. For instance, Koutmos and Booth (1995) noted that negative innovations in one market can increase volatility in subsequent markets. Similarly, Susmel and Engle (1994) observed volatility spillovers between New York and London equity markets, while Kanas (1998) documented such effects among European stock markets. Conversely, John Wei et al. (1995) found no evidence of spillover effects between markets.

To validate the efficacy of the model in elucidating the examined relationship, the study employs residual tests, namely heteroskedasticity test, serial correlation analysis, and assessment of normal distribution on the residuals. Serial correlation results across all three methods in both Model 1 and Model 2 indicate P-values exceeding 0.05, suggesting an absence of serial correlation—a favorable outcome. Heteroscedasticity tests conducted for all GARCH (1,1) methods reveal no significant heteroscedasticity effects. However, the Jarque-Bera test unveils that the residual data does not adhere to a normal distribution, which is suboptimal. Despite the non-normal distribution of residuals, the findings underscore the robustness of the models in predicting volatility spillover between the two time series, NIFTY 50 and EMERGE.

5. CONCLUSION

Despite the extensive literature on volatility spillover, this study represents the pioneering effort, to the best of the author's knowledge, in examining volatility spillover from a mature mainboard stock exchange (encompassing large-cap, mid-cap, and small-cap companies) to a nascent SME stock exchange (focused on SMEs). Given SMEs' status as catalysts for economic growth, it is crucial to attract the attention of scholars towards SME performance and comprehend the volatility connections between SME and mainboard exchanges for enhanced regulatory insights.

The study unveils the presence of unidirectional volatility transmission from the SME exchange to the mainboard stock exchange, providing empirical evidence for volatility spillover

Table 3: Results of granger causality test

Null Hypothesis	F-Statistic	Prob.
EMERGERET does not Granger Cause NIFTYRET	1.9291	0.1458**
NIFTYRET does not Granger Cause EMERGERET	7.7370	0.0005**

Source: Author's calculation. *Significant at 10%, **Significant at 5%, ***Significant at 1% level of significance

Table 4: Results of GARCH Model 1

Variable	Normal Distribution (Z-Statistic, Prob.)	t Distribution (Z-Statistic, Prob.)	Generalized Error Distribution (Z-Statistic, Prob.)
LOGRNIFTY	13.7409, 0.0000***	11.9180, 0.0000***	13.2094, 0.0000***
RESID(-1)^2	6.3956, 0.0000***	4.1937, 0.0000***	3.9851, 0.0000***
NIFTY 50(-1)	73.4929, 0.0000***	25.5098, 0.0000***	35.8970, 0.0000***

Source: Author's calculation. *Significant at 10%, **Significant at 5%, ***Significant at 1% level of significance. EMERGE is the dependent variable

Table 5: Results of GARCH Model 2

Variable	Normal Distribution (Z-Statistic, Prob.)	Student's t Distribution (Z-Statistic, Prob.)	Generalized Error Distribution (Z-Statistic, Prob.)
LOGREMERGE	12.1519, 0.0000***	9.8892, 0.0000***	10.1896, 0.0000***
RESID(-1)^2	7.7475, 0.0000***	4.4530, 0.0000***	5.0072, 0.0000***
NIFTY 50(-1)	38.7465, 0.0000***	33.5693, 0.0000***	30.6793, 0.0000***

Source: Author's calculation. *Significant at 10%, **Significant at 5%, ***Significant at 1% level of significance. NIFTY 50 is the dependent variable

within the NIFTY 50 from NSE EMERGE. The analysis of volatility interdependence yields valuable insights into information dissemination across markets, offering guidance to policymakers, investors, and portfolio managers.

The study underscores the inadequacy of current regulatory frameworks in addressing inter-market adverse effects, necessitating further measures to mitigate such impacts. Policymakers should be cautious of the potential spillover effects of mainboard exchanges on fledgling exchanges, adapting policies to mitigate adverse impacts between exchanges. Moreover, policymakers should recognize the heightened contagion risk to SMEs, particularly during financial crises, urging the implementation of policies aimed at maintaining financial stability while promoting investment in SME exchanges, especially amid governmental support and increasing foreign investments in Indian SMEs.

Furthermore, volatility spillover across markets holds significant implications for portfolio selection and risk management. The bidirectional volatility spillover suggests limited diversification potential for investors. Hence, investors should explore strategies to hedge against equity risk and diversify investments across different asset classes to mitigate losses. Consequently, prioritizing less integrated investment avenues with minimal spillover effects in portfolio construction is crucial for efficient portfolio management and safeguarding against potential financial crises.

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