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A Comparative Analysis of the Nature of Stock Return Volatility in BRICS and G7 Markets

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Abstract: Through globalization and financial market liberalization, the opening up of markets has increased cross-border investments as investors search for higher risk-adjusted returns. This ability to invest internationally has raised the attention given to emerging markets that offer higher risk-adjusted returns relative to developed markets. However, despite the growing importance of emerging markets, the literature on the nature of volatility in global markets is typified by generalizations of findings from developed markets. To fill this gap, this study comparatively examined the nature of stock return volatility in developed G7 and emerging BRICS markets. Broad market index data and GARCH models over the period 2003:01–2020:08 were employed. The study found evidence of volatility persistence, asymmetry, mean reversion and weak evidence of a risk premium in both emerging and developed markets. There was also evidence of significant differences in the nature of volatility within the two sets of markets. These volatility patterns in both groups cast doubt on the assertion that developed markets are more informationally efficient than emerging markets. Thus, markets in the same group may not always have the same nature of volatility, especially in the wake of structural events such as the COVID-19 global pandemic.

Keywords: volatility; persistence; asymmetry; mean reversion; risk–return; BRICS; G7; COVID-19

JEL Classification: G11; G12; G14; G15; G40

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1. Introduction

Among all of the stock market phenomena, stock return volatility—the fluctuation in returns over a certain period—enjoys significant attention and consideration in investing activities due to its implications on investors' portfolio risks and the returns they expect to earn from their investments (Adrian and Rosenberg 2008). High volatility increases the risk of loss for investors. It may also reduce the returns through its impact on liquidity in financial markets. This return reduction results from investors shunning the markets that exhibit high volatility and favouring more stable markets, a flight-for-safety action (Talwar et al. 2021). Any subsequent liquidation of specific portfolio holdings to reallocate capital to more stable investment comes with a significant price impact. Such influence of volatility on risk and returns highlights why it is essential to understand the nature of stock market volatility.

In the most recent global financial crisis in 2007–2008, the influence of volatility on risk and returns was exhibited (Ma et al. 2018). Before the crisis, markets were very stable in a long bullish and very liquid stretch. Investors earned significantly high and increasing returns due to the optimistic pricing of financial assets on the markets. However, pricing bubbles started developing. Inadvertently, the housing pricing bubble burst, and markets became extremely volatile (Jin and An 2016). Due to the higher risk of loss on their investments caused by the increased volatility, investors started moving away from the markets, which led to a decline in liquidity (Jin and An 2016). Returns from the subsequent liquidation of investments fell significantly because of the poor and declining market liquidity.

It is, thus, not surprising that stock market volatility has been the subject of many studies. The focus of most of these studies has been on certain features of volatility—persistence, asymmetry, reversion and premium—all examined to understand its nature. 'Persistence' refers to the long memory in volatility (Mashamba and Magweva 2019); 'asymmetry' refers to the asymmetric volatility responses to positive and negative shocks (Wu 2017); 'mean reversion' refers to how volatility tends to move towards its long-term average level over time (Goudarzi 2013), and the 'risk premium' refers to the compensation for risk exposure (Guo and Neely 2008). While the definitions, descriptions and explanations of these volatility features are generally standard, how they occur may differ significantly according to market structure.

More specifically, similar volatility patterns in prices cannot be expected across two different markets, even if those markets are exposed to identical shocks. This is because the reaction of prices which manifests as volatility is dependent on factors such as the level of financial market development, the economic classification of that market, the level of technological advancement, the investor composition in the market and the level of liquidity, among others (Eizaguirre et al. 2004; Drechsler et al. 2020). However, there have been sweeping generalizations, mostly based on developed market studies, regarding the nature of stock return volatility. Consequently, there is a notable shortage, not only of studies from other markets such as frontier and emerging markets but also of studies comparing volatility patterns in markets of different economic classifications.

Yet, emerging markets have recently become popular destinations for investors seeking higher risk-adjusted returns as increased integration and slow growth in developed markets has made them less attractive in terms of improving their returns or diversifying their portfolio risks (International Monetary Fund 2018). More businesses continue to move to emerging markets due to their superior economic growth relative to the more mature developed markets. As a result, knowing how their capital markets function and react to various shocks has become more critical (International Monetary Fund 2016). These developments have increased the demand for examinations of stock market phenomena such as volatility patterns instead of relying on generalizations from developed markets. However, the demand remains unmet, as literature has not yet caught up with the flow of funds to these markets, which creates an opportunity for gross generalizations.

The importance of volatility examinations is further heightened by its implications for financial market efficiency. In traditional finance, Fama's (1970) efficient market hypothesis is arguably the most popular theory. It is based on the concept of investor rationality and informational efficiency, where prices of financial assets in an efficient market immediately adjust to reflect any information as it enters the market. Thus, the market prices of assets are equal to the intrinsic values of those assets, because they fully reflect all of the available information—past and present, public and private. The adjustments to the latest news instantaneously eliminate any pricing errors and returns earned are proportional to the amount of risk borne. As the information flow is random, the changes in security prices are unpredictable. So, investors in an efficient market cannot consistently earn abnormal returns.

Based on this theory, volatility should be impersistent rather than persistent. This is because volatility persistence suggests a sluggish response of prices to information flowing into the market. Secondly, positive and negative shocks of the same magnitude should induce the same sized changes in price volatilities. Asymmetric responses of volatility to positive and negative news suggest poor information processing in that market (Elyasiani and Mansur 2017). Thirdly, there should not be any mean reversion as a new equilibrium is always reached immediately after a shock due to a quick and accurate response of prices to the shock (Mobarek 2009). Fourthly, the risk premium should always be positive and significant, indicating that the market rewards investors with higher returns for taking on additional risk in their portfolios (Mandimika and Chinzara 2012).

Thus, any evidence of volatility features such as persistence, asymmetry, mean reversion and insignificant or negative risk premiums is evidence against the theory of efficient markets (Hussain et al. 2019; Mukhodobwane et al. 2020). These volatility features also go against all the other levels of efficiency identified by Fama (1970), namely, weak form, semi-strong form and strong-form efficiency. In the weak form market, which is based on the random walk theory, prices reflect all the information in past prices and exhibit no serial correlation. In a semi-strong form market, security prices fully incorporate all public information—historical prices, financial statements and the economic environment. The strong form is the most stringent efficiency level as all the information, including private information, is fully incorporated into share prices.

This is surprising because the various features of volatility have been reported on markets that have been designated as, at least, weak-form efficient, and in some cases, strong-form efficient. This realization, among other factors, could explain the burgeoning of behavioural finance theory, a new strand of thought in finance wherein investor irrationality in investment decisions is recognized (Wong 2014). Most of these empirical features align better with behavioural finance theory and dispute the existence of efficient markets, even at the lowest weak-form efficient level. There is extensive evidence that stock market participants are affected by behavioural biases such as overconfidence, conservatism, sentiment and herding (Baker and Wurgler 2006; Daniel and Hirshleifer 2015), most of which are grounded on the representative heuristics.

Most examinations of asset pricing use the theory of efficient markets as the point of departure because it represents the founding mainstay of traditional finance theory. Most theories and models propounded after Fama's (1970) theory either support or provide evidence against the theory. This study was no exception; the examination of the nature of stock return volatility was essentially based on a comparison of what patterns would be expected in an efficient market versus an inefficient market on the twelve markets that are the subject of the analysis. As alluded to above, there are expectations regarding what volatility features—persistence, asymmetry, mean-reversion, risk premium and spillovers—should look like in an efficient market versus an inefficient market. The same is in line with the designation of markets as either emerging or developed. The former is usually considered less efficient than the latter.

Accordingly, this study comparatively analyzed the nature of volatility in the emerging country markets—Brazil, Russia, India, China and South Africa (BRICS)—and developed country markets—Canada, France, Germany, Italy, Japan, the United States and the United Kingdom (G7). Specifically, the study sought to comparatively determine the nature of volatility in terms of persistence, asymmetry, mean reversion and the risk premium within these two groups of markets given the sweeping generalizations in literature. The study found evidence of volatility persistence, volatility asymmetry and volatility mean reversion and weak evidence of a risk premium in both emerging and developed markets.

2. Literature Review

Various explanations have been forwarded to explain the different features of volatility. For instance, volatility persistence has been attributed to slow information flow into the market and the resultant sluggish absorption of that information into market prices, leading to long-term adjustments (Beg and Anwar 2012). It has also been linked to the overall state of the market, specifically in bearish conditions. Significant volatility persistence was noted when the markets were under stress during the bearish 2007–2009 financial crisis period but less so in the bullish period before the crisis (Wang and Yang 2018). Volatility persistence is also strongly influenced by large negative returns more than positive returns (Wang and Yang 2018) and increases with volatility levels (Su and Wang 2019). This suggests that returns and volatility levels are systematic factors affecting volatility persistence.

The mixture of distributions hypothesis of Clark (1973), Tauchen and Pitts (1983), and Andersen (1996) has been offered as another explanation. Its proponents argue that because trading volumes and returns are driven by the same information flow process, so trading volume and volatility should also share long-range dependence. That is, because the trading volume and return volatility have a similar degree of fractional integration, they should both display long memory. The aggregation of microeconomic linear dynamic models has also been proposed as an alternative explanation for the long memory observed in volatility. According to a study by Zaffaroni (2004), a series corresponding to the aggregation of autoregressive-moving average processes driven by a common and idiosyncratic shock may exhibit long memory even if those processes are short memory processes.

Various explanations have also been offered for volatility asymmetry. Campbell and Hentschel (1992) suggested that the asymmetric nature of the volatility could simply reflect the existence of time-varying risk premiums if volatility is priced. Bekaert and Wu (2000) suggested the presence of volatility feedback as another explanation. This phenomenon relies on volatility persistence, where a large realization of news, positive or negative, increases both current and future volatility. It also depends on the existence of a positive intertemporal relationship between expected return and conditional variance. An increase in volatility increases expected returns and lowers current stock prices, which dampens volatility in the case of good news and increases it in the case of bad news. This is consistent with earlier discussions by Backus and Gregory (1993); Campbell (1993) and Glosten et al. (1993).

Duffee (2002) argued that firm value changes are likely to be accompanied by changes in the values of a firm's riskier assets relative to its less risky assets, which might lead to changes in stock return volatility. A drop in the value of the stock increases financial leverage, which makes the stock riskier and increases its volatility. the opposite is true for an increase in the stock value. This economic balance sheet effect—termed so because its composition changes when the value of the firm changes, even though the accounting balance sheet may be unaltered—implies that cross-sectional betas and book-to-market ratios should predict the strength of the return-volatility relationship. Dzieliński et al. (2018) and Chen et al. (2020) forwarded aspects such as investor attention, differences of opinion among market participants, institutional ownership, and idiosyncratic volatility as possible explanations of asymmetric volatility.

Regarding mean reversion, Gimpel (2007) asserted that it could be explained by the obtainability prejudice of the market and investors' tendency to take their decisions based on available information. In an early study by Schwarz et al. (1991), it was shown that the ease of information retrieval might be considered as the information itself, and investors may put significant weight on the information they have. Investors may also consider any other information they may not have as non-existent or inconsequential to their investment decisions. The overreliance on current events and easy-to-retrieve information means that investors overreact, especially those prone to behavioural biases and more speculative on a stock's valuation, causing volatility to increase sharply (Gimpel 2007). When the market corrects, and as the incidence of speculative investors lowers, volatility mean-reverts to its long-run level.

Another explanation of volatility mean reversion is related to risk aversion. When negative news triggers massive loss in returns, investors move their funds into other assets (Guiso et al. 2018). In addition to creating significant volatility in the market, the effect on prices may persist for an extended period because the shunning of the market by the risk-averse investors results in low liquidity (Kondor and Vayanos 2019). For prices to correct to their fundamental level, ample liquidity is required. However, after a certain period when the bad news has passed, equity prices return into profit, and the risk-averse investors re-enter the markets. As a result, volatility mean-reverts. This is consistent with the finding that investors are attracted to low prices of equities because they can earn significant profits (Trypsteen 2017).

Regarding the risk premium, a positive premium reflects compensation for risk borne in portfolios. However, negative risk premiums have also been observed and Lettau and Ludvigson (2001) attributed them to the misspecification of the time-varying nature of the risk–return relationship. There is a possibility that the relationship between risk and returns is not constant but depends on market regimes and business cycles. This is in line with Whitelaw (1994), who asserted that the negative premium, which represents a significant departure from the risk–return relationship in most traditional theories, casts doubt on the value and validity of focusing on the contemporaneous relationship between expected returns and volatility at the market level. Thus, any analysis that imposes a constant linear relationship between the first two return moments may suffer from erroneous inferences.

Secondly, per Balios (2008), the negative risk premium can be attributed to the non-synchronization of trading in an illiquidity market. Investors are forced to forgo premiums in pursuit of a successful transaction, especially in highly volatile periods. Lastly, Koutmos (1993) argued that the negative risk premium could demonstrate that local investors are not faced with foreign exchange risk. Thus, they will not demand an exchange rate risk premium (returns are measured in local currency). It is possible that once returns are converted to a foreign currency, such as the US dollar, the positive risk premium will become evident (Koutmos 1993). This departure from the positive relationship could be attributed to flight-to-safety by investors well in advance of volatile periods through portfolio adjustments (Ghysels et al. 2016).

Several studies have examined various aspects of stock market volatility in different developed markets. Except for a few studies, the stylized features of volatility were reported to be present and significant in the markets examined which, as alluded above, casts doubt on the theory of efficient markets. Many of these studies employed GARCH-type models, with a few applying some modifications to these models. While not all the studies examined all these features at once, a majority evaluated at least two aspects, the popular ones being volatility persistence and volatility asymmetry. Further, most of the studies employed extensively long sample periods to examine these aspects of volatility, which helps in generalizing the findings across long periods. Thus, instead of grouping the studies by the subject or analysis method, the literature review is presented chronologically based on the year of publication.

For models that employed GARCH models, Glosten et al. (1993) examined the relationship between the monthly conditional mean and conditional volatility of stocks listed on the New York Stock Exchange (NYSE) between 1951 and 1989 and found evidence of volatility persistence, asymmetry and a negative risk–return relationship. Goyal (2000) also found a statistically significant negative relationship between volatility and asset returns on the US market over the period 1962 to 1998, possibly due to the non-synchronous trading, significant illiquidity and thin trading that characterized the markets in the early decades. The study also found that volatility was highly persistent and mean reverted with a half-life of 5 months, meaning that it took five months for the volatility to return to the average level after experiencing shocks. This implies predictability and protracted mispricing on markets, suggesting the presence of irrational traders that extrapolate information into the future.

Engle and Patton (2007) on the US market found evidence of persistent volatility and volatility asymmetry over the period 1988 to 2000. The study, like Goyal (2000), also found evidence of volatility mean reversion. However, the volatility half-life was about 73 days, contrary to the 5 months reported by Goyal (2000). The difference may be explained by the two studies' different study periods. Markets may have increasingly developed to process information and adjust faster. In the same year, Lundblad examined volatilities in both the UK and the US between 1836 and 2003. The study found evidence of volatility persistence, asymmetry and a significant and positive risk–return relationship in those two markets.

Alberg et al. (2008) analyzed the Tel Aviv Stock Exchange returns between 1997 and 2005. They found evidence of volatility persistence and asymmetry, in line with US and UK studies. Also, on a different market, Frijns et al. (2010) developed an implied volatility index for the Australian stock market (ASX) and tested its information content over the period 2002 to 2006. Their results showed considerable evidence of volatility asymmetry and persistence. The implied volatility measure was superior to historical volatility and improved GARCH models' performance, but it failed to capture volatility asymmetry fully.

Kumar and Dhankar (2010) on the US market found evidence of time-varying, persistent and asymmetric volatility over the period. They also found a negative risk premium, which suggested that investors adjusted their portfolios in advance with respect to expected volatility. In the same market, Xue and Gençay (2012) used market index data between 1971 and 2011 and found evidence of volatility clustering which was induced by signal extraction by rational traders. Bohl et al. (2016) on the German stock found that an increase in volatility persistence accompanied the financial crisis, especially for stocks subject to short-selling constraints for the period 2008–2010. Aslanidis et al. (2016) employing factor models found that the risk–return trade-off was generally negative on 13 European over the period 1986 to 2012. This risk–return trade-off varied over time based on the state of the economy.

Dedi and Yavas (2016) analyzed the stock returns and volatilities of Germany, the UK, China, Russia, and Turkey from 2011 to 2016. They found evidence of persistent and asymmetric volatility in all five markets. However, they only found a significant and positive risk–return relationship in the UK market. In a follow-up paper, Yavas and Dedi (2017), using daily exchange-traded funds data, investigated the stock returns and volatilities of Germany, France, Italy, the UK and the US before, during and after the 2007–2008 financial crisis period. They found that volatility was persistent in all five countries, and it increased during the crisis. However, after the financial crisis, high volatility persistence was only recorded for the US while it declined in the other four countries.

Schmitt and Westerhoff (2017), using US index data from 1871 to 2014 and a financial market model, found that volatility clustering arises due to speculators' herding behaviour. In the case of heightened uncertainty, speculators follow other speculators' actions. Market makers then face unbalanced excess demand. Consequently, they adjust prices more vigorously, causing volatility to cluster. In the same market, Chatzikonstanti (2017) reported significant outliers associated with significant stock market events using a wavelet algorithm and a CUSUM-type test over the period 1983 to 2013. There was also evidence of volatility clustering. This implies that outliers may bias the volatility persistence parameter estimates and ignoring possible breaks leads to spuriously high volatility persistence estimates.

Asai et al. (2017), on the US market, found that asset returns exhibited significant asymmetry and long memory, between 1998 and 2012, which their newly developed model could capture. Wang et al. (2017) examined the cross-sectional risk–return trade-off on the US stock market from 1962 to 2014 using several intuitive risk measures. Contrary to the positive relationship between risk and expected returns, the study found a negative risk–return relation that was much more pronounced among firms in which investors faced prior losses. However, they found a positive risk–return trade-off among firms in which investors faced prior gains. They concluded that reference-dependent preference was the most promising explanation of their results.

Eraker and Wu (2017) found evidence of a negative risk–return relationship, asymmetry and volatility persistence on the US market from 2006–2013. On the same market, Goldman and Shen (2018), over the period 2002–2017, reported volatility persistence, asymmetry and a positive risk premium. Tsuji (2018) found that standard GARCH and EGARCH models' volatility persistence parameter values decreased when structural breaks were considered. Thus, failure to consider structural breaks may result in an overestimation of volatility persistence of international stock returns.

Wang and Yang (2018) examined volatility persistence on the US market from 2000 to 2014 using a modified heterogeneous autoregressive model. They found that volatility persistence changes with the size and sign of daily returns, and the effect is economically large. Daily volatility persistence increased with returns and decreased with current volatility. Baur and Dimpfl (2018) employed a leveraged quantile heterogeneous autoregressive model to examine volatility persistence and the asymmetric leverage effect in major stock markets from 2000 to 2016. They found that low volatility was not persistent. However, high volatility was found to be persistent and had properties of explosive processes. The study also found that asymmetry of volatility is only a high volatility phenomenon as there was no asymmetry in low volatility regimes.

Mallikarjuna and Rao (2019) examined the volatilities in Australia, Canada, France, Germany, Japan, South Korea, Switzerland, the UK and the US from 2000 to 2018. They reported significant volatility persistence in all these developed markets together with informational asymmetries and leverage effects. In Japan and between 1998 and 2014, Narwal et al. (2018) found that Japan's implied volatility index responds asymmetrically to the positive and negative NIKKEI 225 index returns contemporaneously rather than at lagged returns, thereby rejecting the leverage and volatility feedback hypothesis. This finding fitted behavioural explanations better. They also found that implied volatility could predict future realized variance. On the US market, Dicle (2019), from 2000 to 2017, found that the risk–return relationship was positive in calm, bullish and low-risk markets, but negative in volatile, bearish and high-risk markets. This suggests that investors are less rational in the presence of fear but act more rationally in calmer markets.

Adrian et al. (2019) documented a highly significant, strongly nonlinear dependence of US stock returns on past equity market volatility as measured by the VIX from 1990 to 2014. This was based on the estimator they proposed that exploits the variation in the cross-section of returns. This revealed the flight-to-safety phenomenon where expected returns increased for stocks when volatility rose from moderate to high levels. Their findings support dynamic asset pricing theories in which the price of risk is a nonlinear function of market volatility. Borup and Jakobsen (2019) examined volatility persistence on the US market and found that in a volatility-timing trading strategy based on volatility persistence, substantial utility gains for a mean-variance investor could be earned at longer investment horizons. On the same market, Aliyev et al. (2020) found evidence of volatility persistence and leverage effects from 2000 to 2019.

Similarly, studies have been conducted on emerging markets to examine the same aspects of volatility. Most of these studies also used GARCH models and examined more than a single aspect of volatility. In one of the early studies, Bekaert and Harvey (1997) employed semi-parametric ARCH models to examine the stock return volatility of 20 emerging markets over the period 1976–1992. They found evidence of persistent and asymmetric volatility in most emerging markets. However, they found no evidence of leverage effects in 11 out of the 19 countries; negative return innovations seemed to decrease volatility in most countries, a finding that is contrary to the leverage effects hypothesis. This could be a result of the exit from the market of noise traders. Further, they noticed that capital market liberalizations significantly decreased volatility in emerging markets, possibly due to increased liquidity on these markets. Bose (2007) on the Indian market found significant evidence of volatility mean reversion, persistence and asymmetry from 2000 to 2007.

Kasman (2009) on the BRIC markets reported that persistence reduced significantly when structural breaks were accounted for, from 1990 to 2007. This suggests that ignoring structural breaks may lead to the overestimation of volatility persistence. In any hedging strategies that rely on the nature of volatility, the author concluded that less weight should be given to past volatility values and more weight to the current shocks. Chinzara and Aziakpono (2009) analyzed the stock market return volatility of South Africa, Australia, China, Germany, Japan, the UK and the US from 1995 to 2007. They found significant evidence of volatility asymmetry and persistence on all seven stock markets. However, they found no evidence of a risk premium. Adu et al. (2015), on the BRICS markets, over 1995–2014 found that volatility was persistent in all the markets. However, volatility mean-reverted quickly in all the markets except for Brazil. There was also evidence of a positive risk premium on all markets except for Russia and significant leverage effects on all markets except for South Africa.

Hemavathy and Gurusamy (2015) on the BRIC markets from 1996 to 2014, found evidence of volatility persistence in all markets and China was found to be the most volatile market. Wu (2017) examined the reverse return-volatility asymmetry, also known as the anti-leverage effect, and the impact of short-sale constraints on the Chinese stock markets over 2002–2015. The results from the study provided robust evidence of significant reverse return–volatility asymmetry. The authors also found that removing short sale constraints lowered the return–volatility correlation, while margin trading increased the correlation.

Kuhe (2018) on the Nigerian stock market over 1999–2017 found evidence of high volatility persistence and that this persistence was significantly reduced when structural breaks were incorporated in the estimated models. Kuhe (2018) also found evidence of volatility asymmetry. However, there were no leverage effects. This meant that positive news increased volatility more than negative news of the same magnitude. The study concluded that the omission of structural breaks in volatility modelling might significantly overestimate volatility persistence and lower investor confidence in stock markets. Contrary, Naik et al. (2018) found evidence of volatility asymmetry and leverage effects on the South African stock market over 2006–2016. A positive and contemporaneous relationship between volume and volatility was also evidenced, but not between volatility persistence and trading volume. This was also confirmed by Lin (2018) modelled. Volatility was found to be time varying, persistent and asymmetric with leverage effects in the Chinese Composite Index volatility over the period 2013–2017. The clustering was attributed to poor information disclosure because of speculation that inhibited optimum stock price discovery and resource allocation.

De Gaetano (2018) on the BRICS markets over 1999–2015 found a significant effect of structural breaks from global and specific-country events. Hussain et al. (2019) reviewed the empirical literature of over 40 studies on stock return volatility. Their results revealed that GARCH models had broader applicability in modelling volatility persistence. Further, Hussain et al. (2019) showed evidence of a weak leverage effect but the evidence on the risk–return relationship was largely mixed at best. Mallikarjuna and Rao (2019) examined the stock market volatility in Brazil, China, Egypt, India, Indonesia, Mexico, Russia, South Africa, Thailand and Turkey from 2000 to 2018. All the emerging markets exhibited volatility persistence and leverage effects, but the frontier markets had no leverage effects.

Mukhodobwane et al. (2020) modelled the BRICS stock market volatility over 2010–2018 and found evidence of volatility persistence, with China recording the highest, followed by South Africa, Russia, India and Brazil. However, the study only employed the symmetric GARCH (1.1) specification for all the markets.

Caporale et al. (2020) on the Russian market from 2010 to 2018, found evidence of volatility persistence and mean reversion. Wei et al. (2020), on the Chinese market from 2012 to 2018, found evidence of volatility asymmetry; however, this was significantly higher for small companies than for large companies. This was attributed to the status of information reception in China. It was easier for large companies to receive information than small companies; therefore, information asymmetry was minimal for large companies, whereas small companies were more likely to experience higher negative responses to information.

On the same market, Chen et al. (2020) proposed a proxy to measure retail investors' asymmetric attention from 2008 to 2018. They found that the asymmetric attention proxy was significant and positively related to volatility asymmetry. Contrary to Wu's (2017) findings, negative information arrivals induced higher volatility asymmetry, and asymmetric attention, which acted as a mediator, incorporated more negative information flows into the market, triggering high asymmetric volatility. This asymmetric response proxy was an independent variable from the idiosyncratic financial leverage, but its influence on asymmetric volatility increased with the market's systematic risk. This suggests that retail investors' asymmetric response to the Chinese market is an alternative determinant for the leverage effect.

It is notable from the above-reviewed literature that volatility is mostly persistent and asymmetric in developed markets, but the evidence from the emerging markets is mostly mixed. Most of the studies from the emerging markets used varying datasets. This could have been of consequence because these markets have been experiencing significant changes over the years. Thus, the presented findings may not reflect the true nature of these markets' volatility, a gap this study attempted to fill. One common result from both the developed and emerging markets is the mixed evidence on the risk–return relationship. Interestingly, only a few studies commented on the mean reversion of volatility in both developed and emerging markets. Overall, the summary of Hussain et al. (2019) on stock return volatility corroborates the reviewed empirical findings in this section.

3. Data and Methodology

For the analysis, broad market indices were employed. Table 1 below identifies the indices for each market and the data source thereof. The BRICS were considered to be representative of emerging markets because of the characteristics they possess—significant GDP growth, increasing contribution to global production, and a potential for rapid growth and investment (Christy 2021). Similarly, the G7 markets were considered to be representative of developed market countries because they possess high stability, a relatively high level of economic growth, well-developed capital markets, a high level of regulation and oversight, and good liquidity in debt and equity markets (Morgan Stanley Capital International 2021). The G7 countries account for about 40% of global production.

Table 1. BRICS and G7 broad market indices.

Country	Name of Index	Abbreviation	Data Source
Brazil	Ibovespa São Paulo Stock Exchange	IBOVESPA	S&P Capital IQ
Russia	Moscow Exchange	MOEX	S&P Capital IQ
India	National Stock Exchange Fifty	NIFTY	EquityRT
China	Shanghai Stock Exchange Composite Index	SSE	EquityRT
South Africa	FTSE Johannesburg Stock Exchange All Share Index	FTSE/JSE ALSI	S&P Capital IQ
Canada	S&P Toronto Stock Exchange Composite Index	S&P/TSX	S&P Capital IQ
France	Continuous Assisted Trading 40	CAC 40	S&P Capital IQ
Germany	German Stock Index	DAX 30	S&P Capital IQ
Italy	FTSE Milan Stock Exchange Index	FTSE/MIB	S&P Capital IQ
Japan	Japan's Nikkei 225 Stock Average	NIKKEI 225	S&P Capital IQ
UK	Financial Times Stock Exchange 100	FTSE 100	S&P Capital IQ
US	Standard and Poor's 500	S&P 500	S&P Capital IQ

The sample period spanned from 2003 to 2020, and thus, included recent major economic events such as the 2007–2008 global financial crisis and the coronavirus pandemic in 2019, which allowed for irregular economic shocks and drastic regime changes to be effectively studied and understood. To examine stock return volatility, the daily stock returns were calculated as:

$$r_t = \ln(P_t/P_{t-1}), \tag{1}$$

where r_t is the daily return, calculated as the first difference of the natural logarithm of P_t, the share price index at period t, and P_{t-1}, the share price index in period $t-1$.

The first step in the analysis was to run diagnostic tests—stationarity, normality, autocorrelation, and heteroscedasticity—to understand the return series' characteristics. The presence of ARCH effects warranted the subsequent usage of GARCH models—GARCH (Bollerslev 1986), GJR-GARCH (Glosten et al. 1993) and E-GARCH (Nelson 1991). The GARCH models counter the shortcomings of Engle's (1982) ARCH model, such as its requirement of long lag lengths and large numbers of parameters and how the model is a function of past squared residuals and assumes that past volatility does not affect current volatility (Toggins 2008). In a parsimonious GARCH framework, the conditional variance depends on the previous periods' squared residuals and the conditional variance (Bollerslev et al. 1994).

The GARCH models estimated have two equations—the mean and variance equations. The former allows for the examination of the risk–return relationship. A significant and positive risk premium coefficient would correspond with finance theory on compensation for risk-bearing. Accordingly, to examine the risk premium, θ, in the broad market index returns, y_t, the mean equation was modelled with a GARCH-in-mean specification (GARCH-M). By combining the autoregressive (p) and moving average (q) models, an ARMA (p, q) specification was obtained wherein the return series, y, depended on its own previous values plus a combination of current and prior white noise error terms (Brooks 2019). The mean equation was specified as:

$$y_t = \mu + \alpha y_{t-1} + \nu\varepsilon_{t-1} + \theta\sigma^2_{t-1} + \varepsilon_t, \tag{2}$$

where α is the effect of past returns and ν is the effect of past shocks. This mean equation specification was assumed for all of the three GARCH variants employed in this study. On the other hand, to examine the other aspects that speak to the nature of volatility—persistence, mean reversion and leverage effects—three different variance equations were estimated as:

$$\sigma^2_t = \omega + \beta\varepsilon^2_{t-1} + \lambda\sigma^2_{t-1}, \tag{3}$$

$$\sigma^2_t = \omega + \beta\varepsilon^2_{t-1} + \lambda\sigma^2_{t-1} + \delta S_{t-1}\varepsilon^2_{t-1}, \tag{4}$$

$$\ln\left(\sigma^2_t\right) = \omega + \beta\ln\left(\sigma^2_{t-1}\right) + \lambda\frac{\varepsilon_{t-1}}{\sqrt{\sigma^2_{t-1}}} + \delta\left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma^2_{t-1}}} - \sqrt{\frac{2}{\pi}}\right], \tag{5}$$

where Equations (3)–(5) are the of the GARCH (1.1), GJR-GARCH (1.1) and E-GARCH (1.1) variance equations, respectively. σ^2_t is the conditional variance, ω is a constant, β captured the effect of past shocks, ε^2_{t-n} is the lagged squared residual from Equation (2) and λ captured the effect of past volatility on current volatility. Model adequacy tests were employed to confirm the choice of the number of lags in light of Bollerslev et al.'s (1994) assertion regarding the parsimonious GARCH specification. Volatility persistence—the degree of dependence in volatility over time (Brooks 2019)—was measured by $\beta + \lambda$. The persistence in volatility should be less than one if volatility is mean-reverting. The non-negativity conditions in the variance equation ($\omega > 0$, $\beta > 0$, $\lambda \geq 0$ and $\beta + \delta \geq 0$) and stationarity condition ($\beta + \lambda < 1$) should hold for the model to be admissible (Brooks 2019).

Although Equation (3) can capture volatility aspects such as persistence, it cannot account for the leverage effects. Positive and negative shocks of the same magnitude may have a varying or asymmetric impact on current volatility. Failure to capture these leverage effects means that the true nature of volatility may not be thoroughly examined using the standard GARCH model. Accordingly, from Equation (4), S_{t-1} is a dummy variable that was added and took the value of 1 if the shock at time $t-1$ was negative and zero otherwise. δ captured the asymmetric volatility response to positive versus negative shocks. A significant and positive δ indicated that negative shocks increase volatility more than positive shocks, which implied the presence of the leverage effect. The contribution of a positive innovation is equal to β, while the contribution of negative innovations is captured $\beta + \delta$ (Brooks 2019).

However, in Equation (4), both the non-negativity conditions in the variance equation ($\omega > 0$, $\beta > 0$, $\lambda \geq 0$ and $\beta + \delta \geq 0$) and stationarity condition ($\beta + \lambda < 1$) had to hold. Accordingly, artificial constraints on the coefficients needed to be placed so that the non-negativity constraints would not be violated (Brooks 2019). Equation (5) was estimated to counter this potential drawback. Therein, there is no requirement of the artificial imposition of non-negativity constraints as the equation models conditional variance in logs. The log of the conditional variance makes the leverage effect exponential instead of quadratic; therefore, the estimates of the conditional variance are guaranteed to be non-negative. However, the conditions $\omega > 0$, $\beta + \lambda < 1$ still needed to be met. The leverage effect under the E-GARCH is shown when $\delta < 0$, that is, δ had to be negative and statistically significant (Brooks 2019).

The last component, mean reversion, was examined using the half-life measure of Engle and Patton (2007). This measures the time it takes for volatility to revert halfway back towards its unconditional mean value after a shock. This measure is not only helpful in comparing the persistence of shocks on volatility for different series, but is also an objective and easy measure to interpret. According to Charteris et al. (2014), the volatility half-life values can be calculated using the β and λ parameters from the GARCH models as:

$$HL = \ln(0.5) / \ln(\beta + \lambda), \tag{6}$$

The GARCH models were estimated and compared under three error distribution assumptions—normal, Student's t and generalised. This was because the residuals from GARCH models are generally leptokurtic and, therefore, yield asymptotically inefficient parameter estimates (Belhoula and Naoui 2011). While the Student's t and the generalized distributions can capture the leptokurtic pattern, the same cannot be said in normal distribution specifications. Further, the parameter estimates based on these two distributions are not overly influenced by extreme observations with a low probability, such as market crashes. Of note, although Shi et al. (2010) show that the choice between the Student's t and generalized distributions is inconsequential, all three distribution assumptions were considered, and the best model was chosen based on Schwarz's Bayesian information criteria.

There is a tendency to assume that GARCH processes are stationary even in cases where their sample periods span periods of economic turmoil, such as the 2007–2008 global financial crisis and the COVID-19 global pandemic, where structural breaks are present. Structural breaks due to global and country-specific financial, economic, social and political events may have a significant impact on volatility (De Gaetano 2018), thus, structural breaks were considered in the estimations as the sample period covers the aforementioned two most recent crises. The multiple structural change test by Bai and Perron (2003) was used to identify the break dates in volatility and incorporate them into GARCH models. Allowing for up to five breaks points, a regression model consisting of a constant regressor was first estimated, specified as:

$$y_t = c + \mu_t \tag{7}$$

where y_t is the return series, c is the constant and μ_t is the error term. To allow for serial correlation in the errors, a quadratic spectral kernel-based HAC covariance estimation was specified using pre-whitened residuals. Subsequently, the Bai and Perron (2003) test of globally optimized breaks against the null of no structural breaks was conducted. The error distributions were allowed to differ across breaks, and the number of breakpoints and the breakpoint dates were then identified based on the significant F-statistic.

4. Results

tables 2 and 3 display the descriptive statistics and stationarity test results for the BRICS and G7 broad market indices, respectively. Except for Italy, all the mean daily returns for the BRICS and G7 markets were positive, suggesting a bullish market over the sample period. However, the mean returns were close to zero. The 2007–2008 global financial crisis and the COVID-19 global pandemic might have dampened the returns. India and China recorded the highest and lowest mean daily returns amongst the BRICS markets, respectively. China's low returns may be explained by the stock market crash it experienced in 2015 and the COVID-19 pandemic that originated therein.

Table 2. Descriptive statistics for the daily returns on the BRICS markets.

Statistic	Brazil	Russia	India	China	South Africa
Mean (%)	0.0499	0.0507	0.0540	0.0218	0.0406
Median (%)	0.0766	0.0816	0.0932	0.0553	0.0744
Std. Dev. (%)	1.7664	1.9407	1.4450	1.5720	1.2133
Skewness	−0.4586	−0.2744	−0.4321	−0.5071	−0.3719
Kurtosis	11.72914	23.4805	14.3632	7.6610	8.5065
JB	14,136.69 ***	76,989.62 ***	23,468.65 ***	4086.157 ***	5672.001 ***
ADF	−69.2628 ***	−65.8411 ***	−63.3004 ***	−64.3699 ***	−65.9703 ***
KPSS	0.2395	0.1623	0.1966	0.0931	0.2406

*** denotes significance at the 1%, level. The critical values for ADF and KPSS tests were obtained from MacKinnon (1996) and Kwiatkowski et al. (1992).

Table 3. Descriptive statistics for the daily returns on the G7 markets.

Statistic	Canada	France	Germany	Italy	Japan	UK	US
Mean (%)	0.0204	0.0104	0.0331	−0.0048	0.0224	0.0128	0.0296
Median (%)	0.0743	0.0437	0.0836	0.0744	0.0606	0.0565	0.0703
Std. Dev. (%)	1.1047	1.3763	1.3843	1.5279	1.4711	1.1108	1.2163
Skewness	−1.0828	−0.2767	−0.1882	−0.7024	−0.4694	−0.4410	−0.5422
Kurtosis	24.0833	11.14625	10.6196	13.6895	10.5702	12.9245	17.2888
JB	82,933.39 ***	12,550.17 ***	10,915.04 ***	21,683.21 ***	10,471.64 ***	18,473.17 ***	37,989.14 ***
ADF	−25.2969 ***	−69.0754 ***	−67.5716 ***	−69.2556 ***	−67.7292 ***	−68.3185 ***	−76.8031 ***
KPSS	0.1015	0.0643	0.0730	0.0634	0.0788	0.1119	0.0841

*** denotes significance at the 1% level. The critical values for ADF and KPSS tests were obtained from MacKinnon (1996) and Kwiatkowski et al. (1992).

Amongst the G7 markets, Germany and Italy had the highest and lowest mean daily returns, respectively. The low return in Italy is attributable to the Eurozone debt crisis that led to poor economic performance in Europe, especially in Italy. Also, Italy was one of the hardest-hit countries by the COVID-19 global pandemic. This affected productivity in its economy (Allain-Dupré et al. 2020). On the other hand, Germany quickly recovered from the Eurozone debt crisis based on its superior export performance and capital flows in the Eurozone relative to other countries (Young and Semmler 2011). Its economy is considered to be more robust relative to its Eurozone counterparts.

Further, Italy is the top wine-producing country globally. However, the wine industry has been struggling significantly with floods, heatwaves and storms (Ellyatt 2020). This could further explain the Italian broad market index's poor performance, which derives a significant amount of weight from wine-producing companies listed on the Italian market. Overall, the BRICS markets recorded higher mean daily returns than the G7 markets. The higher returns in the emerging markets relative to the developed markets can be explained by the fact that emerging markets are still growing. They grow from a lower base and have more significant upside potential than the developed markets (Lawlor 2020).

Notably, the risk patterns in the G7 markets do not correspond with return patterns. For instance, Italy had the highest standard deviation but the lowest return. This suggests that risk is not a commonly priced factor in these markets as measured by the standard deviation. This is inconsistent with the view that high risk should be associated with high returns and may indicate high noise trading. Schmeling (2007) identified Italy as one of the countries with high irrational behaviour levels among the developed markets. Overall, the BRICS markets had higher standard deviations than the G7 markets. This is consistent with the high risk and volatility noted in these markets (Lawlor 2020).

All returns were negatively skewed for both groups, indicating that more of the market daily returns were below the mean (Mandimika and Chinzara 2012). This is not surprising given that the sample period covered the 2007–2008 financial crisis, the 2015 Chinese stock market crash, the 2018 US stock market slide and the 2020 stock market crash caused by the COVID-19 global pandemic. The kurtosis for all the markets was over three, meaning that there was a higher incidence of substantial deviations from the mean. Consistently, the null hypothesis of a normal distribution was rejected for all series based on the JB tests. This suggests that the series were leptokurtic and that investors were exposed to extremely low or high returns.

The stationarity and unit root test results for the broad market indices are also shown in tables 2 and 3. The ADF test statistics for all the markets were significant at 1% while the KPSS test statistics were insignificant. Accordingly, the returns' series were employed in levels in the GARCH models. Figures 1 and 2 show the daily return plots for the BRICS and G7 markets, respectively. These plots show that some periods appear riskier than others, as depicted by the higher volatility of returns in those periods. Notable events that coincide with these riskier periods, which appear in all markets, are the 2007–2008 global financial crisis and the COVID-19 global health and economic crisis that started in 2019. However, the plots confirm all the series' stationarity as they all exhibit constant means over the sample period.

Among the BRICS markets, China's stock return plot appears to exhibit higher risk than all the BRICS markets based on its high volatility. China also experienced a stock market crash in 2015, which saw the stock market bubble bursting and a loss of about a third of A-shares' value on the Shanghai Stock Exchange over a month. This is in addition to the crises mentioned above. This might explain the higher volatility in its returns over the sample period more than its BRICS counterparts. The G7 markets, on the other hand, appear to have similar return patterns, as shown by the return plots. Then, across the G7 and BRICS markets, the BRICS returns appear more volatile than the G7 returns. Hence, they were presumed to be risky.

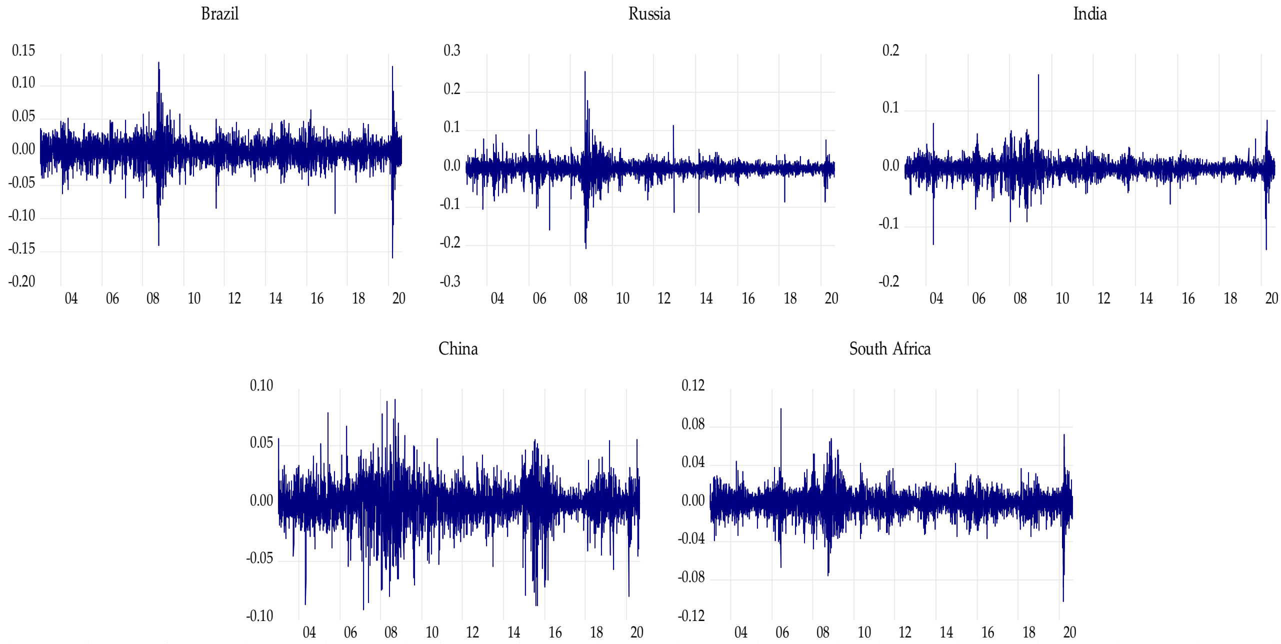

Figure 1. Daily returns series of the BRICS markets.

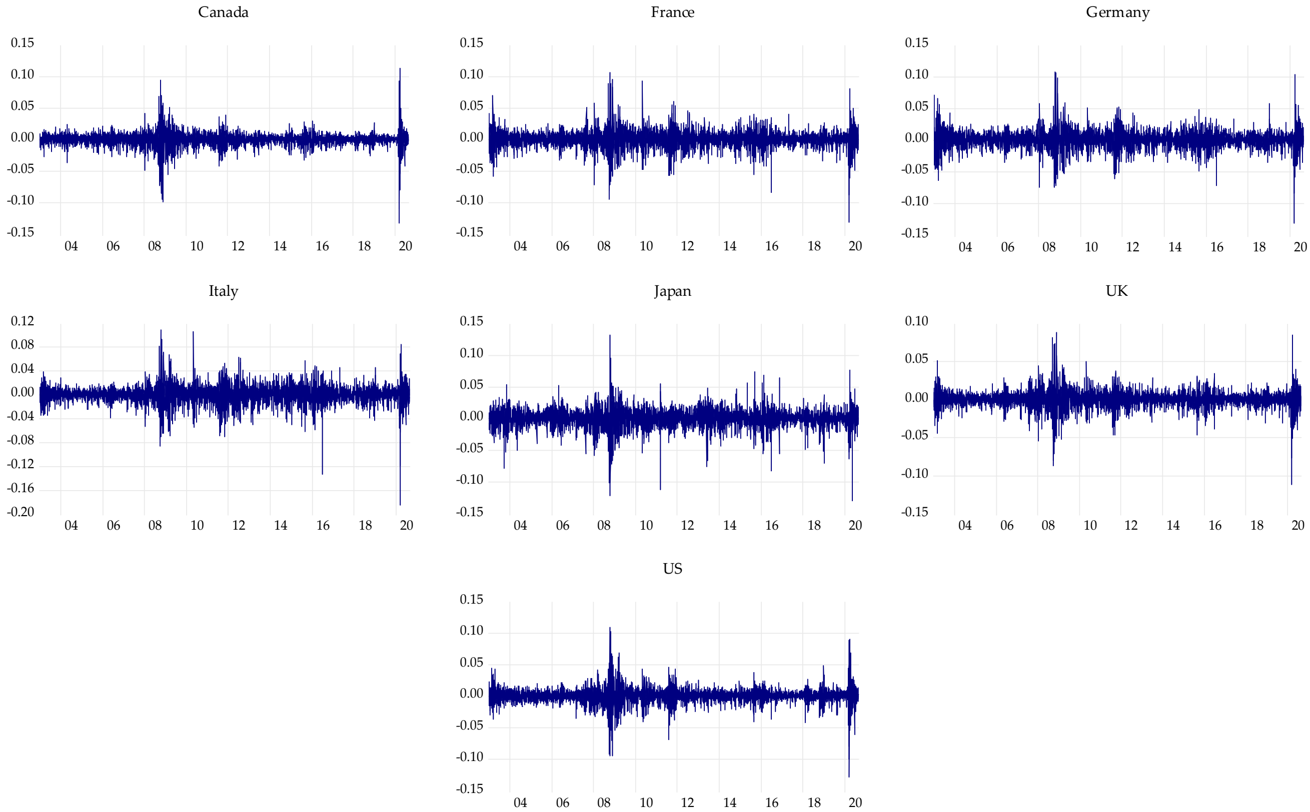

Figure 2. Daily returns series of the G7 markets.

In addition to the descriptive statistics, ARCH effects and autocorrelation tests were conducted on the broad market indices and there was evidence of serial correlation in returns and squared returns. Evidence of serial correlation in these return series contrasts the assertion of informational efficiency in the EMH (Fama 1970). The serial correlation evidenced in the squared returns reveals that the series' second moments are time varying, meaning that there is heteroscedasticity. Given the results of these two tests, GARCH models were deemed appropriate in modelling the conditional volatility of these market return series as they capture time-varying conditional volatility.

Table 4 reports the results from the Bai and Perron (2003) multiple structural change tests. Apart from China, only a single breakpoint was identified in the other index returns in Table 4. Most structural breakpoints identified fall between 2007 and 2009, a period that includes the global financial crisis that affected virtually every market. For China, five breakpoint dates were identified. This suggests that either the Chinese market does not suffer much from noise or the events coinciding with these dates had a significant effect on the returns and caused significant structural changes. These could include the 2005 tripling of Chinese trade surplus, the 2007–2009 global financial crisis and the 2015 Chinese stock market crash. Therefore, the breakpoint dates in Table 4 were used in the construction of a structural breaks dummy for each market in analysing the nature of volatility in those markets. The dummy variable was added to both the mean and variance equations for each market.

Table 4. Number and breakpoint dates in the BRICS and G7 raw series data.

Market	Number	Break Point Dates
Brazil	1	05/21/2008
Russia	1	01/05/2007
India	1	01/09/2008
China	5	08/31/2005, 05/06/2008, 09/05/2012, 04/28/2015, 12/18/2017
South Africa	1	05/20/2008
Canada	1	07/20/2007
France	1	10/10/2007
Germany	1	12/31/2007
Italy	1	05/21/2007
Japan	1	05/09/2006
UK	1	06/18/2007
US	1	03/10/2009

The study employed both symmetric and asymmetric GARCH model specifications under the normal, Student's t and generalised error-distribution assumptions. The appropriate model for each market was chosen based on the SBIC. The symmetric GARCH-M (1.1) specification was chosen in five markets—three with the Student's t error distribution (Russia, France and the UK) and two with GED (China and Germany). The asymmetric GJR-GARCH-M (1.1) model specification with the Student's t error distribution assumption was chosen for Brazil, India, South Africa, Canada and Italy, whereas the GJR-GARCH-M (1.1) specification with the GED was selected for Japan and the US.

The most-selected model in the BRICS markets was the GJR-GARCH-M (1.1) whereas the most-selected model in the G7 markets was the GARCH-M (1.1). These findings suggest that leverage effects are more highly prevalent in emerging markets than in developed markets. However, even though symmetric models were finally selected and interpreted for France, Germany and the UK, asymmetric models were initially chosen based on the information criteria. However, these models were explosive, so the next best models were chosen. The same applies to the US, except that the model initially chosen violated the non-negativity constraints.

Notably, consistent with the Jaque-Bera test, none of the GARCH specifications chosen was based on the normal error distribution assumption. More so, the Student's t distribution and the GED have thick tails to capture the leptokurtic pattern evidenced in the descriptive statistics section better. As such, the standard error estimates from one of these two distributions should be more dependable than based on a normal distribution. Also, parameter estimates are not overly influenced by extreme observations that occur with a low probability, such as market crashes if these distributions are used, considering that the sample spans over the 2007–2008 financial crisis, 2015 Chinese market crash and the 2020 US Stock market crash and the COVID-19 pandemic.

5. Discussion

5.1. Mean Equation Results

The risk premium parameter, θ, in tables 5 and 6, was positive and statistically significant for India and South Africa within the BRICS markets and in UK and US within the G7 markets. This shows that risk, as measured by conditional variance, increased with the mean daily return, implying a positive compensation for bearing risk. These findings suggest that a positive risk premium is a characteristic of both emerging and developed markets. The evidence of a significant risk premium in India and South Africa was also documented by Adu et al. (2015), who examined the stock returns distribution of the BRICS markets. However, unlike Adu et al. (2015), volatility was not priced in China and Brazil. This could be explained by the different sample periods and the models used to analyse the data. Adu et al. (2015) employed the E-GARCH for all the markets, whereas this study used GARCH models selected by information criteria for each market.

Table 5. Selected model outputs for the BRICS markets without structural breaks.

Market	Brazil	Russia	India	China	South Africa
Selected Model	GJR-GARCH-M t-Dist.	GARCH-M t-Dist.	GJR-GARCH-M t-Dist.	GARCH-M GED	GJR-GARCH-M t-Dist.
			Conditional Mean Equation		
μ	−0.0003 *	0.0004	0.0000	0.0005	−0.0004
θ	0.0739	0.0484	0.0773 *	0.0450	0.0948 *
α	0.6326 *	0.9091 ***	−0.1816	0.9875 ***	−0.3984
υ	−0.6469 *	−0.9165 ***	0.2595	−0.9765 ***	0.4224
			Conditional Variance Equation		
ω	0.0000 ***	0.0000 ***	0.0000 ***	0.0000 ***	0.0000 ***
β	0.0210 **	0.1090 ***	0.0280 ***	0.0624 ***	0.0022
λ	0.8966 ***	0.8838 ***	0.8812 ***	0.9347 ***	0.9109 ***
δ	0.0947 ***	-	0.1378 ***	-	0.1299 ***
γ	10.0031 ***	5.6774 ***	7.6683 ***	1.1284 ***	15.1714 ***
(β + δ)	0.1157	-	0.1658	-	-
(β + δ)/β	5.5095	-	5.9214	-	-
β + λ	0.9176	0.9928	0.9092	0.9971	0.9109
HL	8.0604	95.9234	7.2817	238.6695	7.4274
SBIC	−5.5250	−5.6567	−6.1168	−5.8431	−6.3314

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. All mean equations were modelled as ARMA (1.1) processes except for China which was an ARMA (2.2) process.

Table 6. Selected model outputs for the G7 markets without structural breaks.

Market	Canada	France	Germany	Italy	Japan	UK	US
Selected Model	GJR-GARCH-M t-Dist.	GARCH-M t-Dist.	GARCH-M GED	GJR-GARCH-M t-Dist.	GJR-GARCH-M GED	GARCH-M t-Dist.	GARCH-M GED
			Conditional Mean Equation				
μ	0.0001	0.0004	0.0002	0.0005	0.0000	−0.0000	−0.0000
θ	0.0595	0.0278	0.0732 *	−0.0041	0.0532	0.0652	0.1121 ***
α	−0.3367	0.8408 ***	−0.6142 **	−0.1312	−0.4503	0.9377 ***	0.6141 ***
υ	0.3614	−0.8772 ***	0.5960 **	0.0936	0.4263	−0.9559 ***	−0.6802 ***
			Conditional Variance Equation				
ω	0.0000 ***	0.0000 ***	0.0000 ***	0.0000 ***	0.0000 ***	0.0000 ***	0.0000 ***
β	0.0262 **	0.1041 ***	0.0899 ***	0.0026	0.0311 ***	0.1120 ***	0.1261 ***
λ	0.8889 ***	0.8881 ***	0.8993 ***	0.9213 ***	0.8652 ***	0.8758 ***	0.8608 ***
δ	0.1246 ***	-	-	0.1306 ***	0.1425 ***	-	-
γ	8.3647 ***	6.4811 ***	1.3080 ***	7.2071 ***	1.4080 ***	7.5090 ***	1.2424 ***
(β + δ)	0.1508	-	-	-	-	-	-
(β + δ)/β	5.7557	-	-	-	5.5820	-	-
β + λ	0.9151	0.9922	0.9892	0.9213	0.8963	0.9878	0.9869
HL	7.88125	88.5179	63.833	8.4561	6.3312	56.468	52.5646
SBIC	−6.8852	−6.1549	−6.1143	−5.9645	−5.9399	−6.6470	−6.6486

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. All mean equations were modelled as ARMA (1.1) processes.

On the other hand, the developed markets findings support the evidence found in previous studies, particularly the US market—Lundblad (2007); Goldman and Shen (2018) and Dicle (2019)—but are contrary to the negative risk premium that has also been observed in the same markets by authors such as Glosten et al. (1993); Goyal (2000); Kumar and Dhankar (2010); Aslanidis et al. (2016); Wang et al. (2017) and Eraker and Wu (2017). The difference may be explained by the different sample period lengths, starting and ending periods and market events covered, methods used and different broad market indices. Either way, this mixture of findings highlights the dangers of assuming relationships between variables.

The risk premium parameter was insignificant for Brazil, Russia, China, Canada, France, Germany, Italy and Japan. This is in line with the results of the descriptive statistics that suggested that volatility was not a priced factor for some of the G7 markets. Yet, this contradicts the CAPM and EMH predictions that risk should be commensurate with returns. This means that there was no feedback from the conditional variance to the conditional mean equation (Brooks 2019). Therefore, investors may deem other risk measures, such as skewness, as superior to the conditional variance of returns (Alagidede and Panagiotidis 2009).

Within the BRICS, the serial correlation parameter, α, was positive and statistically significant for Brazil, Russia, and China and within the G7 markets, France, the UK and the US, implying that past positive returns could be used to explain future returns on these markets. However, Germany exhibited a negative serial correlation. The positive and negative serial correlation is evidence against the weak form of efficiency, as abnormal returns can be earned by using technical trading strategies (Fama 1970; Bodie et al. 2019). Evidence of predictability of returns suggests the presence of market frictions such as non-synchronous trading on these markets.

Of note, return predictability in developed markets is surprising. It contradicts the assumption that developed markets are more efficient than emerging markets. The growth in technology may have eradicated some differences between developed and emerging markets (Sutthisit et al. 2012). Further, due to lower trading costs, more unsophisticated traders are now active on the markets, which can explain this predictability (Madaan and Singh 2019). On the other hand, the markets with an insignificant serial correlation parameter suggest that they are at least weak-form efficient.

The effect of past shocks on returns, ν, was negative and statistically significant for the same markets that exhibited serial correlation, suggesting that past negative shocks could be used to explain future returns on these markets. However, the parameter was positive and statistically significant for Germany, implying that past positive shocks could explain future returns. The results show that past shocks can significantly affect the returns of both emerging and developed markets. For the rest of the markets, the parameter was insignificant.

5.2. Variance Equation Results

The leverage effect parameter, δ, was significant and positive for Brazil, India and South Africa in the BRICS and Canada, Italy and Japan in the G7, which confirms the presence of the leverage effect as negative shocks increased volatility more than positive shocks of the same magnitude. Two economic explanations are commonly used to explain the leverage effects: the financial leverage hypotheses of Black (1976) and Christie (1982) and the volatility feedback effect. The financial leverage hypothesis states that negative returns increase financial leverage, leading to an increase in stock return volatility. As such, the financial leverage effects have been commonly associated with asymmetric volatility. Yet, it is possible that the evidence of asymmetric volatility could simply reflect the existence of time-varying risk premiums (Mandimika and Chinzara 2012).

On the other hand, the volatility feedback effect focuses on the relationship between volatility and expected returns. That is, an anticipated increase in volatility results in an increase in expected returns, which leads to a decline in the stock price (Talwar et al. 2021). This occurs because investors view volatility as a measure of risk. Therefore, if investors are assumed to be risk-averse, then an increase in stock volatility will result in a decline in demand for that stock leading to a fall in price (Guiso et al. 2018). Thus, for investors to hold or buy the risky asset, they would require a higher return; therefore, there is a positive relationship between volatility and stock returns. As a result, if volatility is priced, an increase in volatility increases the required return on equity, leading to an instant decline in the share price, which is the volatility feedback effect (Karmakar 2007).

However, it is possible that both the financial leverage and volatility feedback effects can be at play concurrently. For example, if the market expects an increase in volatility, market participants would place more sell orders than buy orders in anticipation of a volatile market. This results in a price drop to balance the buying and selling volume. As such, an anticipated increase in volatility leads to an instant price decline, as predicted by the volatility feedback hypothesis (Mandimika and Chinzara 2012). This decline in share prices raises the leverage ratio on the economic balance sheet as the compositions of equity and debt change, despite no change on the accounting balance sheet. According to the leverage effect hypothesis, this can bring about a further decline in price (Karmakar 2007; Wu 2017). This is because the stocks will appear riskier based on the perceived financial risk from the "new capital structure".

Regardless of the cause of the asymmetry, the implication affects the pricing of securities and portfolio selection. The conditional variance equation results show vastly different volatilities following a negative shock amongst the different markets. If returns are linked to volatility, then Brazil, India, South Africa, Canada, Italy and Japan would have greater risk premiums since volatility increases following negative news. However, Russia, China, France, Germany, the UK and the US would offer lower risk premiums as the effect of both negative and positive shocks of the same magnitude was assumed to be the same in these markets. More so, the dynamic hedging strategies associated with the two sets of volatilities would differ significantly based on the volatility persistence (Karmakar 2007). These results show that the leverage effects are characteristic of both emerging and developed markets.

The effect of past shocks, β, was significant for Brazil, Russia, India, China, Canada, France, Germany, UK, US and Japan and insignificant for South Africa and Italy. This indicates that past innovations could explain current volatility on ten markets, which suggests that these markets are inefficient. Of note, however, the β parameter for all the indices was less than δ, implying that the effect of negative shocks was much larger than positive shocks of the same magnitude. The contribution of a positive innovation is equal to β, while the contribution of negative innovations is $\beta + \delta$. For example, for a one-unit positive shock on the Brazilian market, volatility would increase by 0.0210, whereas for the same size negative shock, volatility would increase by 0.0947. An intuitive measure of asymmetry, as per Bohl and Siklos (2003), is the ratio ($\beta + \delta/\beta$). Based on this measure, the results show that India exhibited the highest volatility asymmetry levels in the BRICS, whereas the lowest levels were recorded in Brazil. For the G7 markets, Canada had the highest volatility asymmetry levels, whereas Japan had the lowest.

The degree of volatility persistence, as measured by β+λ, was high for all the markets suggesting the presence of volatility clustering, a common phenomenon in financial time series data. This implies that current volatility shocks influence the expectation of volatility for many periods in the future (Engle and Patton 2007). It is important in determining the relationship between volatility and returns since only persistent volatility justifies changes in the risk premium (Mandimika and Chinzara 2012). Although volatility is persistent, β + λ is less than one for all markets; thus, the stationarity condition was met for all models in all markets. Notably, the return generating process in Russia, China and France was characterized by an exceedingly high degree of persistence as $\beta + \lambda$ was remarkably close to one. This implies long memory in the conditional variance, and as such, a shock in time t will persist for many future periods.

The highest volatility persistence was recorded in China with 0.9971, whereas the lowest was in Japan with 0.8963. These results show that volatility persistence is a common feature in both emerging and developed markets. According to Poterba and Summers (1988), a high degree of volatility persistence reveals that stock return volatility has a large effect on stock prices and that mean reversion to the average volatility occurs slowly. The idea of mean reversion in volatility implies a normal volatility level to which volatility will eventually return after a volatility shock. As a result, even the very long-run forecasts of volatility should converge to this same normal volatility level (Engle and Patton 2007). This persistence in volatility could be mimicking the persistence in the information flow in these markets as per the mixture of distributions hypothesis of Clark (1973), Tauchen and Pitts (1983), and Andersen (1996).

For the G7 markets, the evidence is consistent with the findings of most studies, such as those by Mallikarjuna and Rao (2019) and Borup and Jakobsen (2019). The volatility persistence findings in the BRICS markets corroborate numerous studies, such as those by Ijumba (2013) and Hemavathy and Gurusamy (2015). They found evidence of persistent volatility in all the BRIC markets, with China and Russia having the highest coefficients, respectively. This is attributable to the structure of these markets; they are the most closed markets, despite the increasing financial liberalisation of markets globally. As a result, they suffer from slow information flow and sluggish absorption of news into the market prices leading to long-term adjustments. Notably, the extremely high volatility persistence levels of close to 1 in China and Russia may suggest significant evidence of structural breaks (Kasman 2009; Tsuji 2018).

For the BRICS markets, China had the highest half-life measure among the emerging markets, as it took 239 days for a shock to the conditional volatility to decline by half. This meant that volatility took longer to revert to the average. Russia, Brazil, South Africa and India followed. These results are consistent with the results derived from the volatility persistence measure. However, the evidence is contrary to Adu et al.'s (2015) findings that volatility decayed quickly in all BRICS markets except for Brazil.

In this study, India's volatility decayed faster than all the BRICS markets, followed by South Africa, Brazil, Russia, and China, which had a long memory in returns. The G7 markets also exhibited evidence of slow mean reversion. France had the highest volatility half-life measure among the developed markets and was followed by Germany, the UK, the US, Italy, Canada and Japan. Of note, volatility shocks decayed faster in developed markets than in emerging markets on average. This suggests that in as much as both the developed and emerging markets have irrational traders who propagate inefficiency on these markets, these traders' effects are lesser on developed markets than on the emerging markets. This is expected based on literature, as developed markets tend to be more efficient than emerging markets (Sutthisit et al. 2012; Madaan and Singh 2019).

The intercept, ω, is the time-invariant mean value to which volatility should revert. It was statistically significant and close to zero for all the markets. The non-negativity conditions in the volatility equation ($\omega > 0$, $\beta > 0$, $\lambda \geq 0$ and $\beta + \delta \geq 0$) were all satisfied. The estimated degrees of freedom parameter, γ, for all the four models with a GED assumption were significant and less than two, the required value for normality. This shows that the GED was fat-tailed as suggested by the kurtosis and JB statistics (Brooks 2019). The degrees of freedom parameter for the models with a Student's t distribution was low (below 30), suggesting that the returns distribution was heavy-tailed and not normally distributed.

Two model adequacy tests—the ARCH LM and the Ljung-Box tests—were conducted to assess the validity of the chosen models. The standardised residuals should be without significant autocorrelation and heteroscedasticity. From the LB test, the test statistics were insignificant for all the markets. This meant that the mean equation was correctly specified for the models of all markets. The results of Engle's (1982) ARCH test showed that there were no ARCH effects in the standardised residuals of any of the indices as the test statistics were insignificant. Thus, the mean and variance equations for the indices in the respective selected GARCH models were correctly specified.

5.3. Structural Breaks

tables 7 and 8 show the results from the GARCH models that were adjusted for structural breaks in both the BRICS and G7 markets. It can be noted that the structural breaks dummy variable was only statistically significant and negative in the variance equation for Brazil, China and South Africa for the BRICS markets and France, Germany and the US, for the G7 markets. This suggests that negative structural events affect volatility in these markets. The consideration of structural breaks in the GARCH models also came with some changes to the coefficients in the mean and variance equation. In the mean equation, the risk premiums for China, Canada, France, Italy and the UK became statistically significant whereas that of Germany and the US became insignificant. In the variance equation, volatility persistence decreased for all the BRICS markets except for

South Africa where it was explosive. In the G7 markets, volatility persistence increased for all the markets except for Germany, Italy, Japan and the US where it decreased.

Table 7. Selected model outputs for the BRICS markets without structural breaks.

Market	Brazil	Russia	India	China	South Africa
Selected Model	**GJR-GARCH-M t-Dist.**	**GARCH-M t-Dist.**	**GJR-GARCH-M t-Dist.**	**GARCH-M GED**	**GJR-GARCH-M t-Dist.**
			Conditional Mean Equation		
μ	0.0007	0.0004	−0.0004	−0.0026 *	−0.0002
θ	−0.0086	0.0412	0.1413 ***	0.1448 *	0.0650 ***
α	0.0001	−0.9711 ***	0.9567 ***	−0.0034	0.0055
υ	0.0048	0.9739 ***	−0.9308 ***	−0.0024	0.0056
BREAKS	−0.0173	−0.1612	−0.0036	−0.0003	−0.0069
			Conditional Variance Equation		
ω	0.0001 ***	0.0000 ***	0.0000 ***	0.0001 ***	0.0000 ***
β	0.0516 ***	0.1211 ***	0.0133 *	0.1098 ***	0.3106 **
λ	0.5716 ***	0.8714 ***	0.8928 ***	0.5773 ***	0.8055 ***
δ	−0.0084	-	0.1488 ***	-	0.3378 **
γ	17.4810 ***	5.1965 ***	6.3703 ***	-	2.3644 ***
BREAKS	−0.0004 **	0.0008	0.0005	−0.0003 ***	−0.0002 ***
(β + δ)	0.0516	-	0.1658	-	-
(β + δ)/β	-	-	5.9214	-	-
β + λ	0.6232	0.9925	0.9061	0.6871	1.1161
SBIC	−5.2921	−5.6699	−6.1458	−5.6963	−6.2575

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. All mean equations were modelled as ARMA (1.1) processes except for China which was an ARMA (2.2) process.

Table 8. Selected model outputs for the G7 markets without structural breaks.

Market	Canada	France	Germany	Italy	Japan	UK	US
Selected Model	**GJR-GARCH-M t-Dist.**	**GARCH-M t-Dist.**	**GARCH-M GED**	**GJR-GARCH-M t-Dist.**	**GJR-GARCH-M GED**	**GARCH-M t-Dist.**	**GARCH-M GED**
				Conditional Mean Equation			
μ	0.0001	0.0000	−0.0002	−0.0015 ***	0.0000	−0.0003	6.41×10^{-5}
θ	0.0692 *	0.0500 **	0.0481	0.1264 ***	0.0172	0.1293 ***	0.0209
α	−0.1185	−0.0127	0.0041	−0.0187	0.0050	−0.0294	0.0034
υ	0.1447	−0.0184	0.0042	−0.0028	0.0050	0.0267	0.0030
BREAKS	−0.0039	0.0001	−0.0163	−0.0180	−0.0062	−0.0044	0.0614
				Conditional Variance Equation			
ω	0.0000 ***	0.0000 ***	0.0000 ***	0.0000 ***	0.0002 ***	0.0000 ***	0.0001 ***
β	0.0312 ***	0.3296 ***	0.0913 **	0.2066 *	0.1500 **	0.1124 ***	0.1276 ***
λ	0.8918 ***	0.8341 ***	0.5817 ***	0.6362 ***	0.6000 ***	0.8766 ***	0.5846 ***
δ	0.1137 ***	-	-	0.7757 ***	0.0500	-	-
γ	7.2759 ***	2.4830 ***	1.4340 ***	2.5532 ***	2.0000 ***	7.0082 ***	1.8192 ***
BREAKS	0.0001	−0.0002 ***	−0.0002 **	−0.0001	0.0000	-3.33×10^{-5}	−0.0004 ***
(β + δ)	0.1449	-	-	-	-	-	-
(β + δ)/β	3.6754	-	-	-	5.5820	-	-
β + λ	0.9228	1.1637	0.6730	0.8428	0.7500	0.9890	0.7122
SBIC	−6.8852	−6.1549	−6.1143	−5.9645	−5.9399	−6.6470	−6.6486

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. All mean equations were modelled as ARMA (1.1) processes.

However, it should be noted that based on the SBIC, the GARCH models adjusted for structural breaks were only selected for Russia and India for the BRICS and Canada and US for the G7. This suggests that when modelling volatility in those markets, models should be adjusted for structural breaks for accurate volatility capturing.

The findings from this study have important implications for academics concerned about modelling volatility, investors who may use this information in their investment activities, firms who use capital markets to get financing for their operation, and policy-makers. First, the finding that volatility is generally not priced in Brazil, Russia, China, Canada, France, Italy, Japan and UK, as indicated by an insignificant risk premium parameter, warrants the consideration of other factors such as skewness as risk measures. Other factors such as book-to-market ratios, momentum effect, or the firms' relative size can also be considered in place of the standard deviation in constructing portfolios and other investment activities, in developing policy and strengthening the financial market regulatory framework and in issuing stock as firms seek capital to finance their operations.

Secondly, an examination of stock market efficiency indicated that most markets are inefficient—Brazil, Russia, China, France, the UK, the US and Germany—while a few are weak-form efficient at best—India, South Africa, Canada, Italy and Japan. This finding is astounding as most developed markets are generally considered to be efficient. For investors, this finding determines the appropriateness of their investment and trading strategies. For example, investors in efficient markets will know that technical analysis-based strategies may be futile in earning abnormal returns in weak-form efficient markets but useful in inefficient markets. In their search for capital, firms will also be concerned about the pricing of their stock on financial markets and the cost of capital in an inefficient environment. Finally, policymakers will need to design policies that improve the efficiency and functioning of the markets as this is in the economy's best interest.

Thirdly, among all the volatility patterns, stock return volatility persistence was the most significant in both emerging and developed markets. Most of the models were explosive because of high volatility persistence that could not be modelled accurately. This finding implies that volatility shocks persist longer, most likely due to the significant incidence of irrational traders in these markets. Therefore, policymakers need to develop control tools that restrict irrational trading behaviour, especially in negative shock periods, as indicated by the evidence of volatility asymmetry with leverage effects in both sets of markets. The same policy tools may also cause volatility shocks to decay faster and improve the efficiency of the markets. This finding is also valuable for investors aiming to design appropriate portfolio strategies, especially when considering their investment horizons. Firms can also benefit from market timing based on identifying periods of low volatility when issuing shares. However, volatility persistence was sensitive to structural events such that it increased in G7 markets and decreased in the BRICS when models were adjusted for structural breaks.

For scholars, the results show that model generalisation across markets may lead to inaccurate results. Of note, even in the same group of countries—emerging or developed—different GARCH models were chosen as appropriate. Secondly, unlike most researchers who ignore the error distribution assumption and assume a normal distribution, this study shows that financial time series data is not normally distributed in emerging and developed markets. None of the models selected based on information criteria had a normal distribution. This suggests that these markets' returns have a fat-tailed distribution as the Student's t and GED distributions were selected. Thirdly, the results on efficiency indicate that traditional asset pricing models such as the CAPM and APT will be inadequate to model returns in these markets. Therefore, these and volatility models such as GARCH need to add behavioural factors such as sentiment to capture these irrational investors' effects.

Future studies should consider examining the volatility features on denoised returns. This could help to avoid the overestimation of these features and allow for proper modelling of volatility. Behavioural factors should be considered when examining the different features of volatility. The patterns in these features point to market inefficiency for most markets. Other distribution assumptions, such as those that account for skewness to better model the data, should also be considered. This is in addition to the three error distribution assumptions that were employed herein. Further enquiry may also focus on determining whether the level of efficiency identified in each market remains the same in different market regimes by examining the different volatility patterns in different market regimes. This is because Lo and MacKinlay (1988) hypothesised that markets are adaptive in their levels of efficiency. Regime-switching GARCH models or any other models that recognise the existence of more than one state on financial markets would be useful in this regard. Lastly, extending this study to developing and frontier markets could be worthwhile.

6. Conclusions

The empirical literature on the nature of volatility is inundated with mixed evidence, generalizations of findings from developed markets and assumptions regarding the nature of volatility. Accordingly, this study examined the nature of stock market volatility in terms of persistence, mean reversion, risk–return relationship, and asymmetry in BRICS and G7 markets to fill some of these gaps. Firstly, regarding volatility persistence, the respective coefficients were high in all markets, with some differences in size, meaning that shocks in volatility persist for prolonged periods in both groups of markets. On average, and contrary to expectation, developed markets exhibited slightly higher volatility persistence relative to emerging markets. Irrational traders have the potential to amplify volatility persistence. Therefore, the presence of volatility persistence in both groups casts doubt on the assertion that developed markets are more informationally efficient than emerging markets as well as the applicability of the Fama' (1970) theory of efficient markets.

Secondly, both the emerging and developed markets exhibited volatility mean reversion, some more than others, based on the half-life measure. However, volatility shocks decayed faster in developed markets than in emerging markets. This is in line with the assertion that developed markets tend to be more efficient than emerging markets (Sutthisit et al. 2012; Madaan and Singh 2019). However, the half-life measure in the emerging markets was high due to a single outlier value from the Chinese market. Excluding China from the average calculation saw a lower emerging market average than in the developed markets, in line with the volatility persistence findings. This further cast doubt on developed markets' efficiency.

Regarding the risk premium, there was weak evidence in both the developed and emerging sets of markets. Only two markets from each group exhibited significant risk premium parameters, with three of those significant at only a 10% level. The finding of no evidence of a significant risk premium in most of the markets suggests poor information processing and price discovery processes. On the other hand, the US market's highly significant risk premium is consistent with the identification of this market as the most efficient market in some studies. However, the other aspects of volatility examined herein suggest that the US is not efficient. Overall, there seem to be no significant differences between emerging and developed markets.

Evidence of volatility asymmetry with leverage effects was found in some of the BRICS and all the G7 markets, although some of the asymmetric models were explosive for the latter group. Yet this is surprising, considering that volatility asymmetries should occur in inefficient markets, considered to be the developing and emerging country markets. This is because high volatility asymmetries are associated with poor information processing and high information asymmetries. However, this finding corresponds with the other observations regarding the distinct aspects of volatility. Accordingly, the generalization of developed markets as efficient markets is contrary to the results herein.

Overall, there is evidence of significant differences in the nature of volatility within the BRICS and the G7 markets. This suggests that markets in the same group may not always have the same nature of volatility. There are also similarities and differences in volatility patterns across the two sets of markets. This shows that markets in different groupings can have a similar nature of volatility, which means the level of development in a market may not explain the differences in the nature of volatility across markets. Looking at all these findings, there may be a significant prevalence of irrational investors in both sets of markets that work in concert to produce the different characteristics identified in the BRICS and G7 markets data. Understanding the differences in the nature of volatility within and across these two market groups is essential in modelling volatility, asset pricing and investment strategies development. The results are also relevant in developing and implementing tools necessary to the proper functioning of markets, especially during market downturns.

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