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Quantifying Long-Term Volatility for Developed Stock Markets: An Empirical Case Study Using PGARCH Model on Toronto Stock Exchange (TSX)

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A B S T R A C T

High frequency data is a recent entrant to the world of statistics as they relate to the markets. This study measures the volatility of S& P / Toronto index by utilizing the GARCH family models (EGARCH, TGARCH, MGARCH and PGARCH models) using a daily database counted 7636 observations. The empirical results for the selected index for the whole-time frame show that it is volatile, and the PGARCH is a better-fitted model with the student's t distribution. Positive shocks have a greater impact on conditional volatility than negative shocks, according to the data. These extra analyses can be supplied to further corroborate their results and provide useful information for economic thespians interested in adding Toronto stock market index to their investment portfolios.

1. Introduction

The study of financial markets and their inherent volatility has been a subject of immense interest for economists, investors, and policy-makers alike (Chang, McAleer, & Tansuchat, 2012). Volatility analysis plays a crucial role in understanding and predicting market dynamics, enabling investors to make informed decisions, and policymakers to implement effective regulations (Pindyck, 2004) & (Cristi, et al., 2023). The Toronto Stock Exchange (TSX), one of the most significant stock exchanges in the world, provides an ideal setting for analyzing the complex dynamics of market volatility. The Power Autoregressive Conditional Heteroscedasticity (PARCH) model is used in this research article to examine the long-term volatility patterns displayed by the TSX Composite Index.

A broad market index that represents the success of the Canadian equity markets is the TSX Composite Index, sometimes referred to as the S&P/TSX Composite Index. It is made up of a wide variety of equities from different industries, such as the financial, energy, minerals, and information technology sectors (Matei, Rovira , & Agell, 2019). The TSX Composite Index, which serves as a barometer for the Canadian stock market, is an important measure of the country's economic well-being and investor confidence.

Volatility, as a measure of market risk, shows the degree of price volatility and unpredictability in financial markets. Traditional volatility models, such as the ARCH (Autoregressive Conditional Heteroscedasticity) and GARCH (Generalized Autoregressive Conditional Heteroscedasticity) models, have been widely used to analyze short-term and medium-term volatility (Liu, Manzoor, Wang, Zhang, & Manzoor, 2020) & (Onali, 2020). However, these models may not capture the long-term persistence of volatility exhibited by financial time series data accurately.

To address this limitation, the PARCH model, an extension of the GARCH model, incorporates long memory properties that capture the persistence and dependence of volatility over longer time horizons (Hawaldar, Rajesha, & Sarea, 2020), (Abounoori & Zabol, 2020) & (Manera, Nicolini, & Vignati, 2013). The PARCH model allows for a more comprehensive analysis of volatility dynamics and offers insights into the underlying processes driving long-term fluctuations in the TSX Composite Index.

This study has two primary goals. Firstly, we aim to estimate and analyze the long-term volatility of the TSX Composite Index using the PARCH model. By incorporating the long memory component, we can assess the persistence and dependence of volatility shocks, thus enhancing our understanding of the index's

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long-term behavior. Secondly, we seek to explore the potential impact of exogenous factors, such as economic indicators, market sentiment, and global events, on the long-term volatility of the TSX Composite Index. Investors can benefit greatly from this information, as it will allow them to make educated decisions and better manage their risk exposure once these factors have been identified.

In this study, we will conduct empirical analysis using a large dataset made up of daily TSX Composite Index returns from the past. The estimation process will involve fitting the PARCH model to the data, incorporating the appropriate lag structure and parameter estimation techniques. The goodness-of-fit of the model will be evaluated through statistical tests and diagnostic measures (Mukherjee & Goswami, 2017).

The outcomes of this study will add to the existing literature on long-term volatility analysis and provide insights into the specific dynamics of the TSX Composite Index. Financial professionals, investors, and policymakers will all be interested in the findings because of the useful information they provide for risk management, asset allocation, and policy development.

The purpose of this study is to illuminate trends in long-term volatility of the TSX Composite Index by employing the PARCH model. By examining the persistence and dependence of volatility, we can gain a deeper understanding of the underlying processes driving market fluctuations. The study's findings will provide significant insights into the behaviour of the Canadian stock market, assisting various stakeholders in their decision-making processes and risk management techniques.

2. Review of Literature

In recent years, a large number of research projects have been undertaken employing econometrics property to analyze stock market behavior and volatility patterns. It provides shifts and a consistent level of volatility. Many scholars have sought to abstract variations in volatility while taking into account diverse marketplaces. The autoregressive conditional heteroscedasticity model (Harvey & Sucarrat, 2014)and its generalized versionfocus on capturing efficiently volatility clustering. Many researcher (Almeida & Hotta, 2014), (Cristi, Birau, Trivedi, Simion, & Baid, 2023)&(Glosten, Jagannathan, & Runkle, 1993) used Financial econometrics i.e. GARCH model to detect the volatility based on presence of skewness and asymmetry of financial time series data. The authors (Thakolsria, Sethapramote, & Jiranyakul, 2015)(Ormos & Timotity, 2016), &(Agboluaje, Ismail, & Yip, 2016) test the test the leverage and volatility feedback effects in emerging stock markets, based on modelling two of the GJR-GARCH and PGARCH parametric asymmetric volatility models using the daily high frequency data from the Stock Exchange of Thailand.There are papers that focus on volatility using high-frequency data, so this one aims to prove that this type of data allows for a more accurate assessment of the relationship between volatility and price processes, as well as that certain stochastic volatility models can be used to analyse the pattern seen in such data(Khanthavit, 2020), (Okorie & Lin, 2020) , (Ashraf, 2020)&(Meher, Hawaldar, Mohapatra, & Sarea, 2020), (Meher, Kumar, Hawaldar, & Gupta, 2022), &(Cristi, Birau, Kumar, Simion, & Florescu, 2023)

Further, (Higgs & Worthington, 2005) used the GARCH-MIDAS model to foresee potential long-term volatility. The long-term stock market's volatility can be best modelled using the GARCH MIDAS model, which allows for variable selections to achieve this goal. Many researchers employed the model estimate not only for estimating and forecasting, but also for hedge predictions (Hawaldar, Meher, Kumari, & Kumar, 2022)&(Cristi, Birau, Hawaldar, Trivedi, & Iacob, 2023)

On how to use high-frequency data to build asymmetric price volatility models for the Canadian stock market using the high frequency data, recent research on the epidemic hasn't yet offered any insight. This research gap is a highly viable one since employing minute-level data to create asymmetric volatility models might also offer a microscopic view of the pandemics and Russia & Ukraine war impact on the price volatility of certain equities.

3. Research Methodology

Traditional heteroskedastic models either specify the conditional variance as in (Bollerslev, 1986) or describe the conditional standard deviation directly as in Taylor (1986). The Power GARCH (PGARCH) of (Ding, Granger, & Engle, 1993) represents a flexible alternative that also nests the preceding competing families due to its endogenous estimation of the optimal power transformation. The current research compares the three models in a value-at-risk context using "dynamic" estimation and out-of-sample tests. The study uses secondary data with a high frequency and is empirical in character. This paper's primary goal is to examine the method for estimating the influence of long-term volatility on the Analysis of Volatility of Toronto Stock Exchange using PARCH Model. ADF (augmented Dickey Fuller test) and PP (Phillips-Perron test statistic) have been used to determine whether the data is stationary in nature in order to apply PGARCH. Log Daily Returns have been established to convert non-stationary data into stationary. To choose the most appropriate asymmetric volatility model for stock markets, numerous criteria have been used to examine the results of the models after they had been created using different distributions. In addition, the empirical results are significant at levels of 10%, 5%, and 1%, with the 5% significant level being taken into account for the following modelling process. E-Views 10 has been applied to the creation of models for certain stock indexes. Except for legal holidays and other occasions when stock markets don't conduct transactions, the financial time series comprises of daily closing prices for the sample stock index for the years starting on January 05, 1993, and ending on May 17, 2023. The sample data series also contains 7636 daily observations in total. The log-difference of the closing prices of the stock market's chosen index, namely the S&P/Toronto Stock Exchange Composite Index, is used to calculate the continuously-compounded daily returns as follows:

Conversion of Log:

$$y_t = In\_\left(\frac{p_t}{p_{t-1}}\right) = In(p_t) - In(p_{t-1})$$

ADF Process:

$$(1-L)\,yt = \beta 0 + (\alpha - 1)\,yt - 1 + \varepsilon_i$$

PGARCH models

The variance in a PGARCH model (general) is written as:

$$\sigma_t^\delta = \omega + \sum_{i=1}^{p}(\alpha_i\,|y_{t-i}| - y_i\; y_{t-i})^\delta + \sum_{j=1}^{q}\beta_j\,\sigma_{t-j}^\delta$$

Whereσ_t^δ is the return residual, ω>0, δ>0, ≥0, -1< and ≥0 are shows constant, power parameter, ARCH term, Leverage effect as well as GARCH term respectively. With the change of δ's power the results become different at the power 1 the conditional standard deviation will be drawn, and at the power 2 leverage effects will be estimated and it's become (above equation) classic GARCH model as (Salamat, et al., 2019). This is an essential prerequisite for the positive variance. In the financial data series, higher values of the α_i coefficient show a greater volatility response to market shocks, whereas larger coefficients of the β_j coefficient show the presence of market shocks (Alsharkasi, Crane, & Ruskin, 2016).

4. Empirical Results and Findings

The property of summary of statistics provides 0.000236 mean with 0.01 degree of SD. The risk factor is increased by the excess kurtosis and positive skewness in the S&P/Toronto Stock Exchange Composite Index. The presence of leptokurtic influence on the series returns is shown by the aberrant pattern of kurtosis.

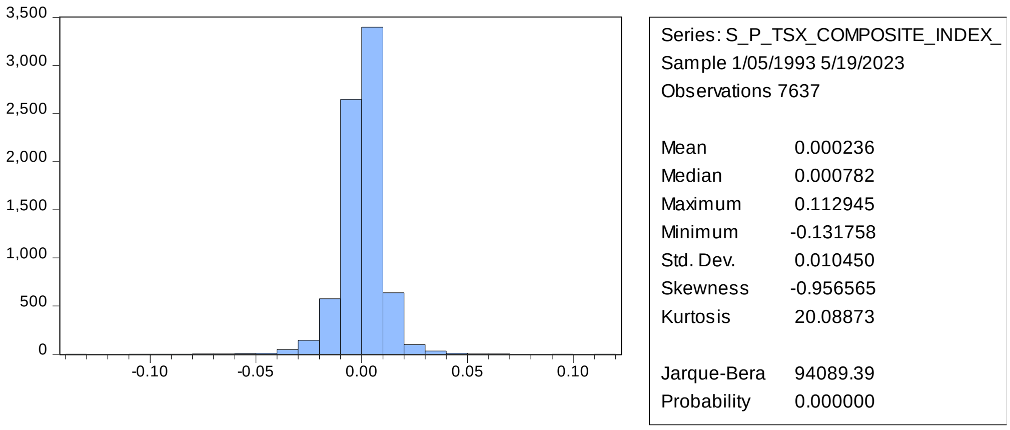


Chart 1 – Descriptive statistics and Normality of PGARCH model residues

Source: Own computations of the author using particular financial data series

The degree of standard deviation reveals a relative risk of 0.010451 in the financial series of the S&P/Toronto Stock Exchange Composite Index. It's worth noting that the skewness depicts negative returns that are almost on the cusp of the -0.956511 threshold, while the kurtosis indicates a significantly larger degree than the usual level. Nonetheless, the S&P/Toronto Stock Exchange Composite Index contains a significant number of normal volatility rates and quantifiable anomalous scales. Series returns provide a definite and obvious indicator of the market decline caused by the global financial crisis (see chart1). The post-financial crisis scale and the positive returns ratios should be the attention of investors, academics, and researchers. It unequivocally demonstrates how seriously investors take long-term investing. Unquestionably, the S&P/Toronto Stock Exchange Composite Index includes a comprehensive list of typical volatility rates and quantifiable abnormal scales.

For the three asymmetric GARCH models, EGARCH, TGARCH, MGARCH, and PGARCH, log returns for financial data series, such as the S&P/Toronto Stock Exchange Composite Index, have been determined. As a result, the sample data for the closing price of the S&P/Toronto Stock Exchange Composite Index has become static. The sample data of the Canada stock price were again tested for stationarity using the unit root test, or the Augmented Dickey Fuller Test, which includes the test equations Intercept, Trend, and Intercept and None. It was discovered that the sample data are stationary because the probability values are significant at levels of 10%, 5%, and 1%. (Table 1).

Table 1 Results of ADF and PP test

Null Hypothesis: S_P_TSX_COMPOSITE_INDEX_LOG_RETURS has a unit root			
		t-Statistic	**Prob.****
ADF test statistic		-88.82582	0.0001**
Critical values of test:	1% level	-3.431029	
	5% level	-2.861725	
	10% level	-2.566910	
		Adj. t-Stat	**Prob.****
Phillips-Perron test statistic		-88.82102	0.0001**
Critical values of test:	1% level	-3.431029	
	5% level	-2.861725	
	10% level	-2.566910	

Source: Author's own computations using Eviews10

The following sections are built on evaluating the relevant hypotheses needed to create the EGARCH, TGARCH, MGARCH and PGARCH models. Figure 2 shows graphs with the log returns of the presence of volatility clustering using the S&P/Toronto Stock Exchange Composite Index. Figure No. 2 shows the movement patterns of the S&P/Toronto Stock Exchange Composite Indexes' Stationary Series during the hypothetical period from 5 January 1995 to 17 May 2023.

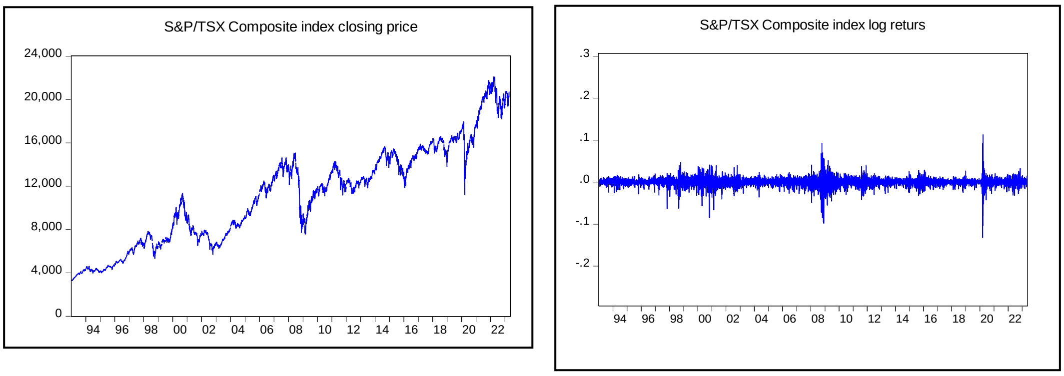


Chart 2 - Movement pattern of S&P/Toronto Stock Exchange Composite Index

Source: - Authors own computation using Eviews

The property of Fig 3 indicates there are different clusters in thisdiagram because we can see that in Line graphs figure 3, sometimes volatility is high and sometimes volatility is less.

After examining the log return graphs of a few selected financial data series in Figure 3, it is clear that the data exhibits volatility clustering, whereby large variations in log returns were followed by equally large differences in log returns, and vice versa. Moreover, it can be seen that among the most recent sample years, throughout the COVID eras. The S&P/Toronto Stock Exchange index's stock returns were very erratic. Asymmetric GARCH models would be suited for replicating the volatility of the stock prices of a given index in light of these large variations during 2020, which are an obvious indication that the pandemic is having a leveraging impact on market values.

Now, there are four asymmetric GARCH models—EGARCH, TGARCH, MGARCH and PGARCH—have been developed using different distinct error distribution constructs. The leverage effect, which is created by the negative correlation between returns and volatility, is not captured by the conventional GARCH model since it is asymmetric in nature. The PGARCH model not only takes into account the asymmetric effect, but it additionally provides another technique to describe the volatility's long memory quality. Model of Power GARCH (PGARCH) In the power GARCH model, the standard deviation replaces the variance, and an alternative parameter can be included to account for modeling asymmetry. The asymmetric PGARCH model specifies σt to be of the following form:

$$\sigma_t^{\delta} = \alpha_0 + \beta_1 \sigma_{t-1}^{\delta} + \alpha_1 (|\varepsilon_{t-1}| - y_1 \varepsilon_{t-1})^{\delta}$$

where α1 and β1 are the standard ARCH and GARCH parameters, γ1 and δ are the leverage parameter and parameter for the power term respectively.

“The log of the variance distinguishes the EGARCH model from the GARCH variance structure” (Dhamija & Bhalla, 2010). Also, "the advantage of employing EGARCH is that it works with the log of the variance, which ensures the positivity of the parameters” (Hassan, 2012).

The following formula is for EGARCH model.

$$\log\left(\sigma_t^2\right) = \omega + \sum_{j-i}^{p} \beta i \log\left(\sigma_{t-i}^2\right) + \sum_{j-1}^{q} \alpha i \left\langle \frac{\varepsilon i - t}{\sigma_{i-t}} \left| \frac{-\sqrt{2}}{n} \right| - yi \frac{\varepsilon i - t}{\sigma i - t} \right\rangle$$

For the TGARCH (1,1) model, use the following formula. The conditional standard deviation is taken into consideration in this model. TGARCH was described thusly:

$$\sigma_t = \omega + \alpha \iota \left[\varepsilon_{t=1} \geq 0\right] \varepsilon_{t=1} + \gamma \iota \left[\varepsilon_{t=1} < 0\right] \varepsilon_{t=1} \beta \alpha_{t-1}$$

If γ > 0, there is an asymmetry, showing that news with positive and negative signals has differing effects on conditional volatility. The asymmetry is evident because the impulse of the unfavorable shocks (α + γ) is higher than the impulse of the positive shocks (α).

4.1. The GARCH-M model

The GARCH model fails to account for the mechanism behind volatility feedback. It captures the “GARCH-in-mean” model, also known as the GARACH-M model, proposed by (Engle, 1986)

$$y_t = c + \xi h_t + u_{t.}$$

Or consider using the standard deviation of the series to represent risk rather than variance. That is:

$$y_t = c + \xi \sqrt{h_t} + u_{t.}$$

In order to choose the best model, it is necessary to examine the results obtained from the developed models using the various distinct distributions. "The standard method for selecting a model is for the ARCH and GARCH coefficients to be significant." Furthermore, a model with a lower AIC (Akaike Information Criterion) and SIC (Schwartz Information Criterion) and a higher Log Likelihood statistic is preferred."

4.2. Implementation of EGARCH, TGARCH, MGARCH and PGARCH Models for S&P/Toronto Stock Exchange of Canada

Almost 70% of the value of all shares traded on the Toronto Stock Exchange is represented by the S&P/TSX Composite Index, making it Canada's primary stock market barometer. Around 1,500 public firms are listed on the Toronto Stock Exchange. It substitutes the previous TSE 300 index. The possibility exists that the epidemic, the conflict between Russia and Ukraine, as well as other global concerns, may have contributed to this company's stock price volatility. In order to predict price volatility using 1-minute closing stock price data, a variety of asymmetric volatility models have been devised due to the epidemic's leverage effect.

Table 2: Choosing an appropriate model (EGARCH, TGARCH, MGARCH or PGARCH.)

Estimated model	AIC(Akaike info criterion)	SIC (Schwartz criterion)	Log Likelihood
EGARCH	-6.841576	-6.836123	26127.14
TGARCH	-6.818463	-6.813919	26037.89
MGARCH	-6.841314	-6.834952	26127.14
PGARCH	**-6.844370**	**-6.838008**	**26138.81**

Source: - Authors calculation using Eviews

The aforementioned table shows that in all fourGARCH family models with student t's distribution error construct, it was determined that PGARCH with Student t's Distribution has the lowest AIC (-6.844) and SIC (-6.838) when compared to the other four models when the AIC and SIC of all the aforementioned four models are compared. Aside from having the highest Log Likelihood (26138.81). As a result, this model is thought to be the best one. The table below lists the outcomes of the chosen PGARCH Model for theCanada index.

Table 3. Results of PGARCH (1, 1, 1) with Student's t distribution Error Construct

Dependent Variable: S_P_TSX_COMPOSITE_INDEX_LOG_RETURS				
Included observations: 7636 after adjustments				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000232	8.05E-05	2.884371	0.0039
S_P_TSX_COMPOSITE_INDEX_LOG_RETURS (-1)	0.075921	0.012069	6.290575	0.0000
	Variance Equation			
C(a)	0.000130	4.56E-05	2.860736	0.0042
C(b)	0.091835	0.004027	22.80419	0.0000
C(c)	0.599298	0.046002	13.02752	0.0000
C(d)	0.906953	0.003640	249.1943	0.0000
C(e)	1.066414	0.069083	15.43666	0.0000
R2	-0.008280	Mean dependent var		0.000236
Adjusted R2	-0.008413	S.D. dependent var		0.010451
S.E. of R	0.010495	AIC		-6.844370
Sum squared resid	0.840801	SIC		-6.838008
Log likelihood	26138.81	Hannan-Quinn criter.		-6.842187
Durbin-Watson stat	2.182904			

Source: Author's own computations using EViews 10

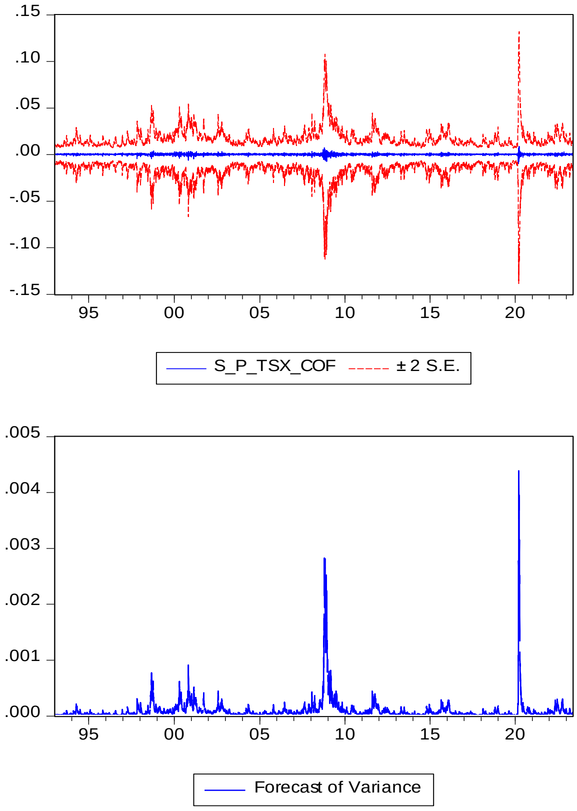
The S&P/Toronto Stock Exchange Composite indices is represented in the following table as the output of the PGARCH (1,1,1) model using Student t's Distribution Construct. The outcomes come in two sections. The variance equation is represented in the lower area, while the main equation is shown in the upper portion. Since their probability are smaller than 0.05, the constant (C) in the main equation becomes significant. Because each of their probabilities is lower than 0.05, every coefficient in the variance equation is considered significant. In addition, the model has the lowest AIC (-6.844370) and SIC (-6.838008) among comparable models. Comparing Log Likelihood to the other pertinent models, the value is greater at 26138. Focus should be placed on the fact that the co-efficient of the asymmetric term is negative, or -0.050855, and statistically significant. This would indicate that negative news has a more amplified influence on the company's stock price volatility and that there is a leverage effect at work. Table 5 displays the estimated findings of this model, which show that the leverage effect coefficient is statistically significant. This coefficient's statistical significance suggests that bad news (negative shocks) has a greater impact on conditional variance (volatility) than good news (positive shocks) of the same magnitude. Table 3 shows that the calculated coefficient from the PGARCH model is positive and statistically significant, indicating that positive shocks are linked to more volatility than negative shocks.

4.3. Forecasting Evaluation

Models are used to forecast volatility in five steps after they have been estimated (Alper, Fendoglu, & Saltoglu, 2009). The conditional variance of the returns for each time period, given its prior values, is identical to the conditional variance of the residuals for the same period, given its prior values, when employing GARCH-type models to predict volatility. By combining forecasting with GARCH model estimates, volatility may be monitored and trends can be discovered. The conditional variance equation, as previously mentioned,

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta h_{t-1}$$

Using the aforesaid method to a data set of 7636 days, we can predict the volatility of the Canadian S&P/Toronto Stock Exchange Composite indices. The following charts are meant to illustrate the expected uneven price fluctuations of the S&P/Toronto Stock Exchange Composite index across the time intervals shown in Figure 3.



Forecast: S_P_TSX_COF	
Actual: S_P_TSX_COMPOSITE_INDEX_LO...	
Forecast sample: 1/05/1993 5/19/2023	
Adjusted sample: 1/06/1993 5/19/2023	
Included observations: 7636	
Root Mean Squared Error	0.010493
Mean Absolute Error	0.006829
Mean Abs. Percent Error	NA
Theil Inequality Coefficient	0.929869
Bias Proportion	0.000002
Variance Proportion	0.846909
Covariance Proportion	0.153089
Theil U2 Coefficient	NA
Symmetric MAPE	172.7685

Chart 3 Figure of Forecast variance of Canadian S&P/Toronto Stock Exchange Composite indices

Source: - Authors own computation using Eviews

The results of the furcating table show that the return on assets is stable, and the first predicted return graph shows that the stock price returns of the sample index were consistent over the sample periods of time.

5. Conclusion

Studying the volatility is an essential process of forecasting the future returns of any financial asset. For this, it is imperative to study the features volatility. For the purpose of volatility forecasting, numerous more sophisticated econometric models have been created. Analysis of the conditional volatility of stock returns in the Canadian stock market using the PGARCH model was undertaken. According to the findings, the ARCH family of models works well for predicting stock-market swings in volatility(Indicated by the significant ARCH (αi) terms). The study discovers that PGARCH models with student t's distribution, the lowest Schwarz criterion, and the highest Log likelihood replicate the asymmetrical behavior of the Toronto Stock Exchange (TSX) volatility stock return. The volatility estimates were also found to have the leverage effect (Indicated by the significant leverage. Finally, it was inferred from the results that the stock return volatility has a clustering effect, i.e., they are found in clusters. Through this study, the most appropriate power coefficient for selected stock was also estimated. The standard deviation of logarithmic returns is a common way to measure volatility, which is the amount of variation in a trading price series over time. Volatility projections of asset returns have been examined over the years as a key concern for traders, investors, firms, and financial regulatory agencies for risk management, security valuation, portfolio diversification, and monetary policymaking objectives. One of the primary limitations of this research study is the use of only one stock market, such as the Canadian stock market. We shall take into account a comparative empirical analysis between the nations of the top five economy of the world for next research investigations. Additionally, we will diversify the study process by incorporating hybrid techniques and we will also increase the chosen time frame.

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