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Investigating Volatility Dynamics of the Portugal Stock Market using FIGARCH Models

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A R T I C L E I N F O

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A B S T R A C T

The act of modeling and forecasting stock market volatility has become essential to risk management practice; it has become one of the most prevalent subjects in financial econometrics and has been mainly and continuously used in the valuation of financial assets and the Value at Risk, as well as the pricing of options and derivatives. The purpose of this paper is to contrast the FIGARCH model in the prospect of establishing the best algorithm to forecast PSI 20 index (PSI stands for Portuguese Stock Index). This study analyzed PSI 20 index to identify the behavior of the Portugal stock market in terms of volatility and then evaluated the forecasting ability of GARCH family models using Portugal PSI 20 index sample data for the long period from May 2010 - August 2023 (which is more than 13 years in daily data). There are 3396 daily observations. The results indicated that the PSI 20 index's volatility is asymmetric. The present empirical investigation also seeks to illustrate the potential for investment returns as well as the associated risk. Our findings may have implications for risk management in Portugal, as well as a deeper understanding of the PSI-20 Portugal stock market volatility dynamics, given the scarcity of prior such studies.

1. Introduction

Financial markets play a crucial role in modern economies, serving as hubs for capital allocation, risk management, and price discovery (Galati & Tsatsaronis, 2003)(Deng & Oren, 2006)(Qiu et al., 2023). The behavior of stock prices, in particular, has long fascinated researchers and practitioners alike due to its intricate interplay of information, investor sentiment, and economic fundamentals (Chau et al., 2016). Volatility, as a fundamental aspect of financial markets, holds the key to understanding the uncertainty and risk associated with investment decisions. Thus, comprehending the dynamics of volatility is paramount for investors, policymakers, and financial institutions (P H & Rishad, 2020)(Srivastava et al., 2023).

This research paper delves into the volatility dynamics of the Portuguese Stock Index using the Fractional integrated Generalized Autoregressive Conditional Heteroskedasticity (FIGARCH) model. The Portuguese Stock Index, represented by the PSI-20, serves as a vital indicator of the nation's economic health, comprising the twenty most liquid and capitalized companies listed on Euronext Lisbon (Afonso, 2023)(Tavares, 2023). The PSI-20 not only reflects the performance of these prominent companies but also offers insights into broader market trends, making it a pertinent subject of analysis.

The volatility of financial assets has been a subject of extensive research, with traditional models like the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) framework providing valuable insights (Fang et al., 2023)(Akin et al., 2023)(Raza et al., 2023). However, these models assume a fixed and constant volatility over time, which fails to capture the inherent time-varying nature of financial volatility. (Pourkhanali et al., 2023) the FIGARCH model, an extension of the GARCH model, incorporates the fractional integration concept to capture long memory effects, while also accounting for asymmetric shocks, which are often observed in financial markets.

The motivation behind this study arises from the need to better comprehend the underlying volatility patterns in the Portuguese stock market, particularly in the context of its sensitivity to global economic fluctuations, domestic policy changes, and industry-specific events. By employing the FIGARCH model, we aim to achieve a more accurate representation of the volatility dynamics exhibited by the PSI-20 returns. This

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understanding is pivotal not only for investors seeking to optimize portfolio management strategies but also for policymakers aiming to ensure the stability and resilience of the national financial system.

In this paper, we outline the theoretical foundations of volatility modeling, discussing the evolution from traditional GARCH models to the more sophisticated FIGARCH framework. We then proceed to detail the dataset and methodology employed, elucidating the steps taken to estimate and validate the FIGARCH model on PSI-20 return data. The empirical results of our analysis are subsequently presented and interpreted, shedding light on the distinctive volatility behaviors uncovered by the FIGARCH model.

2. Review of literature

Scholars have made numerous attempts to generalize volatility differences across markets. The returns of historical financial series can tell us a lot about the current financial climate, including whether or not the leverage effect is present. For the United States and the Netherlands, (Spulbar, et al., 2023a) have created a study of volatility patterns using the GARCH family model., while Spulbar et al. (2023b; 2023c) have conducted a study on volatility patterns using the GARCH family model to analyze sophisticated stock markets, specifically those of Austria, France, Germany, and Spain, (Meher et al., 2023) have undertaken an investigation into the examination of volatility pertaining to the OMX Tallinn Index, specifically focusing on the emerging stock market of Estonia. In this study, the PARCH model has been employed as a means to examine and understand the volatility patterns. Using the PGARCH Model, (Kumar et al., 2023)& (Kumar, et al., 2023) conducted an empirical case study of the volatility of the Toronto Stock Exchange. Using the GARCH family model, (Spulbar et al., 2023c) analyzed volatility trends in Italy and Poland.

(Dhankar, 2019)(Meher et al., 2022) examined various VaR estimation techniques and their uses. (Chang, 2020)in order to address the costs associated with diabetes hospitalization and treatment, suggest an early warning payment algorithm that uses data analytics technology. (Chamizo & Novales, 2021)try out hedging in three distinct ways: with single stocks, with sectoral portfolios, and with regional investments. Other influential work includes (Hendrych & Cipra, 2019), (Jeng et al., 2020), (Araneda, 2021).

(Guesmi et al., 2019) look into the legitimacy of Bitcoin in the market for financial services. because of the significance of geopolitical risk and its potential to predict oil price volatility.(Liu et al., 2019) intend to conduct a quantitative study of geopolitical risk (GPR), and more specifically, serious geopolitical risk (GPRS), in predicting oil volatility. (Troster et al., 2019) modeling and predicting bitcoin yields and risk requires performing a general GARCH and GAS analysis. (Bangar Raju et al., 2020)the use of EGARCH models to investigate and analyze market volatility in GOI and GOFI countries. Focusing on measuring the inherent correlation (Sun et al., 2020) to settle the heated argument over whether or not the maritime industry is exposed to extreme risk from the commodity market, a GARCH-Copula-CoVaR analysis is recommended. Other influential work includes (Gronwald, 2019), (Pal & Mitra, 2019).

3. Significance of the Study

The investigation into the volatility dynamics of the Portuguese Stock Index through the lens of the FIGARCH model holds the promise of enriching our understanding of the intricate forces that shape financial market volatility. By providing insights into both short-term fluctuations and long-term memory effects, this study contributes to the broader body of research aimed at deciphering the complexities of financial market behavior. Furthermore, the findings have practical implications for investors, risk managers, and policymakers, enhancing their ability to make informed decisions and formulate effective strategies in a dynamic and ever-changing financial landscape.

4. Data description and Econometric methodology

This study analyzed PSI 20 index (PSI stands for Portuguese Stock Index) to identify the behavior of the Portugal stock market in terms of volatility and then evaluated the forecasting ability of GARCH- models using Portugal PSI 20 index sample data for the long period May 2010 - August 2023 (which is more than 13 years daily data). There are 3396 daily observations.
Figure 1 displays the flow chart of the econometric methodology that is applied in this research.

Figure 1. Flow chart of the econometric methodology applied in this study

First, we convert sample data in to the log return value. Converting data into log returns is a common technique used in finance and statistics to analyze the relative change in a variable over time. Log returns are often preferred over simple percentage returns because they have several desirable properties, such as additive properties and a more symmetric distribution. To convert the periodic returns into log returns, we would use the natural logarithm. The formula for calculating the log return is:

Log return = 1n (1+ periodic return)

This formula assumes that the returns are expressed as decimals.

In the next, and ADF and PP test have been employed to examine whether the data is stationarity in nature. Further the volatility of the Portugal PSI 20 index has been investigated with the help of econometric (FIGARCH model).

The FIGARCH model, which stands for Fractionally Integrated Exponential Generalized Autoregressive Conditional Heteroscedasticity, is a statistical model used in time series analysis to capture both long-range dependence and volatility clustering in financial and economic data. It is an extension of the traditional GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model. The FIGARCH model incorporates the concept of fractional integration, which allows it to handle data that exhibit long memory or long-range dependence. Long memory refers to a situation where the autocorrelation decays slowly over time, leading to persistent behavior in the data. In the FIGARCH model, the conditional variance of the time series is modeled as a function of past squared observations and past conditional variances, similar to the GARCH model. However, the key difference is that the lagged terms in the FIGARCH model are fractional rather than integer lags. This allows the model to capture the long memory property of the data.
Mathematically, the FIGARCH (p, d, and q) model can be represented as follows:

$$r_t = \sigma_y \varepsilon_t$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \left(|\varepsilon_{t-1}| - \gamma|\varepsilon_{t-1}| \right) \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \sum_{k=1}^{d} \theta_k (|\epsilon_{t-k}| - \gamma|\epsilon_{t-k})$$

Where:
r_t is the return at time.
σ_y is the conditional standard deviation (volatility)
ε_t is the standardized innovation (residual)
p represents the number of lagged conditional variances in the GARCH part of the model.
q represents the number of lagged squared innovations in the GARCH part of the model.
d represents the order of fractional integration, indicating the degree of long memory in the volatility process.
α_0 is the constant term in the volatility equation.
α_i are the coefficients associated with the lagged squared innovations in the GARCH part.
β_j are the coefficients associated with the lagged conditional variances in the GARCH part.
θ_k are the coefficients associated with the lagged absolute innovations in the FIGARCH part.
γ is the fractional differencing parameter, which determines the strength of the long memory effect.

Estimating the parameters of the FIGARCH model typically involves maximum likelihood estimation or other numerical optimization techniques, and it involves specifying the order of fractional integration, the orders of autoregressive and moving average components, and the orders of the GARCH components. Once estimated, it can be used for forecasting future volatility in financial markets, which is crucial for risk management, options pricing, and portfolio optimization.

The main components of the FIGARCH model are:

Autoregressive Component: Similar to the GARCH model, the FIGARCH model includes an autoregressive component that captures the past volatility dynamics. This can be represented as an ARMA.

Fractional Integration: The fractional integration component allows the model to capture the long memory properties of the time series data. Fractional integration involves differencing the time series multiple times with fractional orders, which introduces persistence in the data.

Exponential GARCH: The FIGARCH model incorporates an exponential GARCH component, which models the conditional variance of the time series. This captures the volatility clustering effect, where periods of high volatility tend to follow each other.

Long-Memory Volatility: Fractional integration in the FIGARCH model allows for the incorporation of long memory behavior in the conditional volatility. This component is often represented as a fractionally differenced lag of the conditional variance. The long memory component helps account for the slow decay of autocorrelations in volatility observed in many financial time series. This means that past shocks can have a lasting impact on current and future volatility.

Time-Varying Conditional Volatility: The FIGARCH model allows for the conditional volatility to change over time in response to changes in the underlying data.

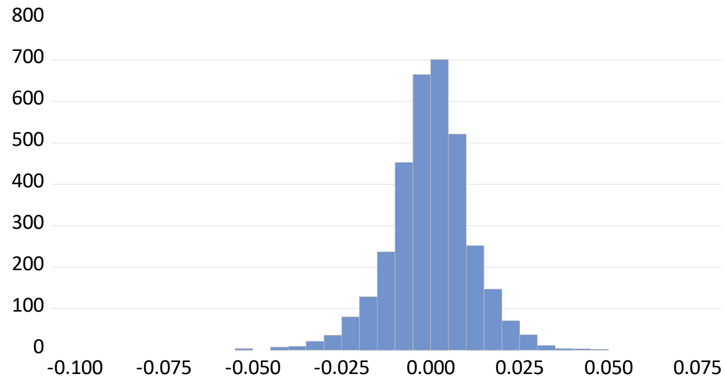
In summary, the FIGARCH model is a specialized time series model designed to capture the long memory or long-range dependence observed in financial volatility data. It combines the GARCH framework with fractional integration to provide a more accurate representation of volatility dynamics in financial markets.

Empirical Analysis

The primary stock index for the Portuguese stock market is the PSI-20 Index. The PSI-20 (Portuguese Stock Index) is the benchmark stock market index of the Euronext Lisbon stock exchange (formerly known as the Lisbon Stock Exchange) in Portugal. It represents the performance of the 20 largest and most liquid companies listed on the Euronext Lisbon. The composition of the PSI-20 index can change over time based on factors such as market capitalization, liquidity, and other criteria. It provides a snapshot of the overall performance of the Portuguese stock market by tracking the price movements of these selected companies. It serves as a benchmark for the Portuguese stock market and reflects the overall direction of the country's economy. The composition of the index can change over time based on factors such as market capitalization, trading volume, and other market dynamics. The PSI-20 index includes companies from various sectors, such as finance, energy, telecommunications, retail, and more. The composition of the index can change over time based on factors such as market capitalization, trading volume, and other criteria.

Descriptive statistics

Prior to analysing the data, it is essential to have a fundamental grasp of the statistical properties of the data series. An overview of the PSI-20 index log return's descriptive data is shown in Chart 2. The skewness, kurtosis, and standard deviation are all taken into account along with the mean, highest, and lowest values.



Name of series: PSI_20_INDEX_LOG_RETURNS
Period 5/25/2010 8/18/2023
number of sample 3396

x? -3.02e-05
x ~ 0.000285
upper value 0.075324
lower value -0.102671
?X. 0.011779
Skewness -0.599651
Kurtosis 7.803881

Chart 2. descriptive statistics of the sample data

Source- own computation using statistical software EViews 12

Since stock market return series are regressive when seen over time, the median of the PSI-20 index log return series is 0.000285 percent, or practically zero, which is consistent with stock market behavior. The PSI is extremely volatile, as evidenced by the 0.17 difference between the maximum and smallest value. Additionally, the data's skewness indicates that the PSI-20 index log returns are negatively skewed, which indicates that the data has a large tail on the left. Because of this, the value of kurtosis (7.80) is considerably greater than the value of the ordinary average distribution (3), demonstrating that the PSI-20 index data has a "sharp peak." The null hypothesis is finally disproved. As a result, the PSI-20 return series seems to follow a skewed distribution with negative skewness rather than a normal distribution.

Since GARCH models require stationary data, stationarity study is a crucial component of modelling. Having stationary data is therefore essential.

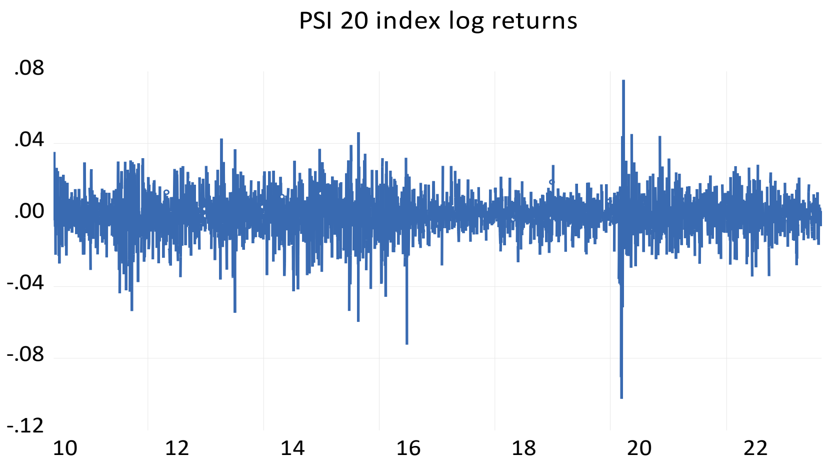


Chart 3: - Line plot of daily log return of PSI-20 indexes

Source- own computation using statistical software EViews 12

A time series analysis statistical technique known as the unit root test is used to assess if a time series variable is unit root-free or non-stationary. A unit root is a sign of non-stationarity, which is a crucial notion in time series analysis. The ADF test is intended to compare the alternative hypothesis, that the time series is stationary, against the null hypothesis, that a unit root is present in the time series. In the absence of mean reversion or long-term stability, the presence of a unit root shows that the time series follows a random walk. Phillips-Perron (PP) Test: The PP test is similar to the ADF test but allows for more flexible forms of serial correlation in the errors. It is robust to heteroscedasticity and other forms of error autocorrelation etc. The choice of which unit root test to use depends on factors such as the characteristics of the data, the potential presence of structural breaks, and the specific hypotheses being tested.

Table 1. Results of Unit root test

Null Hypothesis: PSI_20_INDEX_LOG_RETURNS has a unit root				
			t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic			-53.02184	<0.05***
Test critical values:	At <0.01level		-3.432089	
	At <0.05 level		-2.862194	
	At <0.10 level		-2.567162	
			Adj. t-Stat	**Prob.***
Phillips-Perron test statistic			-52.95322	<0.05***
Test critical values:	At <0.01 level		-3.432089	
	At <0.05 level		-2.862194	
	At <0.10 level		-2.567162	

Source- own computation using statistical software EViews 12

The heteroscedasticity of the data series must be confirmed before using the data for GARCH modelling because GARCH models are designed to capture the fluctuations of heteroscedastic data. This can be done by performing the ARCH effects test because ARCH effects are only present in heteroscedastic data. The ARCH effect follows a pattern in which a minor fluctuation is typically followed by an even smaller fluctuation. First, a large fluctuation takes place, which then triggers another one of comparable magnitude. To examine the ARCH effects in the sample series, this study uses the ARCH-LM test. The ARCH-LM test primarily uses the combination of results from the F statistic and the chi-square statistic to determine whether the ARCH effect is present. The ARCH-LM test's null hypothesis states that there are no ARCH effects in the data series, but this null hypothesis should be disregarded if the F statistic or chi-square statistic are both below the 0.05 critical value.

Table 2. Results of ARCH effects

Heteroscedasticity Test: ARCH			
F-statistic	1.996601	Prob. F(10,3374)	0.0299***
Obs*R^2	19.91326	Prob. Chi-Square(10)	0.0301***

Source- own computation using statistical software EViews 12

Estimation of FIGARCH Models for PSI-20 index (daily returns)

After the returns series have confirmed volatility clustering, stationarity using the ADF and PP tests, heteroscedasticity effects using the ARCH-LM tests, and best fitting FIGARCH models have been identified, the conditional mean and variance equations of these models are estimated using the support vector machine method and maximum likelihood estimation. In order to model the volatilities of in-sample datasets of daily returns for PSI-20 index under the various error distributions (Normal Distribution, Student-t Distribution, and generalized error distribution), FIGARCH models are utilized. First, we looked at the FIGARCH model with a normal distribution and generalized error distribution method. The values of the log likelihood for the FIGARCH model based on the student's distribution were 10644.08, whereas those for the model based on generalized error distribution methods and normal distribution method were 10608.34 and 10641.40. Based on the highest log likelihood and the minimum value of the Akaike info criterion, we determine that the FIGARCH model with student's distribution is the optimal model to investigate the volatility of the PSI-20 index price.

Table 3. Results of FIGARCH model with student distribution

Dependent Variable: PSI_20_INDEX_LOG_RETURNS				
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000328	0.000163	2.016942	0.0437
PSI_20_INDEX_LOG_RETURNS(-1)	0.074344	0.018895	3.934620	0.0001
	Variance Equation			
C(3)	4.29E-06	1.84E-06	2.336217	0.0195
RESID(-1)^2	0.254492	0.096147	2.646918	0.0081
GARCH(-1)	0.487690	0.116415	4.189245	0.0000
D	0.397771	0.062011	6.414563	0.0000
T-DIST. DOF	8.733132	1.234098	7.076529	0.0000
		Mean dependent var		-3.03E-05
Maximum Log LL	10644.08	S.D. dependent var		0.011781
DBS	1.959378	AIC		-6.266319
		SIC		-6.253680
		HQC		-6.261802

Source- own computation using statistical software EViews 12

The PSI 20 index (PSI stands for Portuguese Stock Index) market is represented in the following table as the output of the FIGARCH 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. The constant (C) in the primary equation is significant at <0.05. In the variance equation section we observed that the value of ARCH effect (RESID (-1) ^2) and GARCH effect (GARCH (-1) are considered significant at <0.05. According to the FIGARCH estimation results in above Table, indicates that bad news, i.e., the spread of COVID-19 pandemic and the war between Russia and Ukraine, had a larger and significant impact on the volatility of the company's stock price.

5. Conclusions

The primary goal of the study is to evaluate using the Normal and Student-t density function of the FIGARCH model whether there is an asymmetric influence on the conditional volatility of the PSI 20 index (PSI stands for Portuguese Stock Index). According to the analysis, the volatility stock return PSI 20 index yield exhibits asymmetries. The study discovered that the FIGARCH with Student-t distribution is better at capturing the asymmetric volatility effect of the chosen sample when comparing univariate FIGARCH models, based on several distributions. In the literature that has already been written about asymmetric volatility in time series data, researchers have mostly concentrated on measuring the asymmetric effect in the volatility of a specific financial instrument or forecasting the accuracy of GARCH family models. By extending the research on gauging the variability of financial assets using univariate GARCH models and the precision of such models' forecasts, this work adds to the body of knowledge on volatility. It increases our comprehension of a practical GARCH family model for forecasting market volatility. This offers a thorough understanding of the phenomena of asymmetric effect in the assets under examination.

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