Quantile Regression for VaR Estimation in Egyptian Inflation Rate: A Comparative Analysis with EWMA and t-GARCH

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Quantile Regression for VaR Estimation in Egyptian Inflation Rate: A Comparative Analysis with EWMA and t-GARCH

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Abstract:

This paper investigates the efficacy of Quantile Regression, Exponentially Weighted Moving Average (EWMA), and t-GARCH models in estimating Value at Risk (VaR) for Egyptian inflation rate. Through empirical analysis and Back-testing, we demonstrate that Quantile Regression outperforms the other models in accuracy and reliability for capturing tail risks. By directly modelling the quantiles of return distributions, Quantile Regression provides a robust framework for VaR estimation, effectively addressing non-linearities and outliers in financial data. The model's ability to directly estimate quantiles allows for a nuanced understanding of extreme inflationary movements. Our findings suggest that Quantile Regression is a superior tool for risk management, offering significant advantages in precision and adaptability compared to traditional methods, which is offering valuable insights for risk managers and policymakers.

Keywords

Quantile Regression, Value at Risk (VaR), EWMA, t-GARCH, Back-testing, Kupiec's Test

1. Introduction:

Understanding and managing financial risk is crucial, particularly in economies experiencing volatile inflation rates. Value at Risk (VaR) is a key metric in this context, as it quantifies potential losses in economic value over a specified period. This paper focuses on estimating VaR for Egypt's inflation rate using advanced statistical models: Quantile Regression, Exponentially Weighted Moving Average (EWMA), and t-GARCH.

Quantile Regression offers a robust method for estimating VaR, as it directly models the distribution's tails, providing insights into extreme inflationary movements (Koenker, 2005). This feature is particularly valuable in Egyptian economic, where inflation can be unpredictable and volatile. Since the quantile is tightly linked to the volatility of time series, and since generalized autoregressive conditional heteroscedasticity (GARCH) models are proven to be effective to measure the volatility (Lee and Noh ,2010).

EWMA, part of the Risk Metrics approach, is valued for its simplicity and responsiveness to recent data, making it useful for real-time risk assessment (Mina and Xiao, 2001). However, it may not fully capture the complexities of inflation dynamics due to its assumption of constant volatility.

t-GARCH models extend traditional GARCH models by incorporating fat tails and skewness, which are common in financial data (Engle, 2001). This model can effectively capture the volatility clustering observed in inflation rates, providing a comprehensive risk assessment tool.

This research compares these three methodologies to determine which offers the most accurate VaR estimates for Egyptian inflation rate. By analyzing their performance, we aim to identify the most effective approach for risk management in volatile economic environments.

2. Literature Review

Value at Risk (VaR) is a critical tool in financial risk management, offering insights into potential losses over a given period. Various models have been employed to estimate VaR, each with distinct advantages and limitations. This review focuses on Quantile Regression, Exponentially Weighted Moving Average (EWMA), and t-GARCH, particularly in the context of inflation rate data.

Quantile Regression, introduced by Koenker and Bassett (1978), provides a robust framework for modeling different points of the conditional distribution of a response variable. Unlike traditional linear regression, which estimates the mean, quantile regression estimates the conditional median or other quantiles, making it particularly useful for capturing tail risks (Koenker, 2005). This method's ability to model the entire distribution makes it advantageous for VaR estimation, especially in volatile economic environments like Egypt, where inflation rates can exhibit significant skewness and outliers. Recent studies have expanded on the application of quantile regression in various financial contexts. For instance, Engle and Manganelli (2004) developed the Conditional Autoregressive Value at Risk (CAViaR) model, which applies quantile regression to directly estimate VaR without assuming a specific distribution of returns. This model has been shown to outperform traditional methods, particularly in volatile markets.

Also, EWMA is a widely used technique for volatility forecasting, part of the Risk Metrics approach developed by J.P. Morgan (Mina & Xiao, 2001). It applies exponentially decreasing weights to past observations, emphasizing recent data. While EWMA is computationally efficient and easy to implement, its primary limitation lies in the assumption of constant volatility, which may not capture the full dynamics of inflation rate fluctuations (Hull, 2018). Despite this, its simplicity and effectiveness in certain contexts make it a staple in risk management practices.

The t-GARCH model extends the GARCH framework by incorporating a t-distribution to account for fat tails and skewness in financial returns (Bollerslev, 1986). This enhancement allows for more accurate modeling of volatility clustering and extreme events, common in financial data (Engle, 2001). Studies have demonstrated that t-GARCH models often provide superior VaR forecasts compared to those assuming normality (Jorion, 2007). This makes it a valuable tool for assessing risk in environments with high volatility and leptokurtosis, such as inflation rate data.

The Mixed-Frequency Quantile Regression model (MF-QR) propose by Candila, Gallo, and Petrella (2023) to improve the estimation of Value-at-Risk (VaR) and Expected Shortfall (ES) when dealing with mixed-frequency data. This study provides a valuable framework for financial econometrics, particularly in contexts where data is available at different frequencies.

An advanced Conditional Autoregressive Value-at-Risk (CAViaR) model introduced by Sanchis et al. (2022) to predict exceedances of PM10 air pollution standards in Madrid. Traditional methods struggle with forecasting extreme values, so this study adapts a Value-at-Risk (VaR) approach from finance, integrating meteorological indicators to improve prediction accuracy. The extended CAViaR model surpasses standard models, such as EWMA and Gaussian GARCH, in backtesting. This approach offers crucial early-warning capabilities, aiding authorities in implementing timely air quality measures.

An approach for predicting Value-at-Risk (VaR) in currency investments explored by Blom, , and Risstad,(2023), which introduces a semiparametric VaR forecasting model that leverages quantile regression and machine learning techniques, utilizing market prices of option contracts from the foreign exchange interbank market.

The study by Saadah et al. (2024) on the dynamic quantile regression (QR) approach investigates the application of this method for VaR estimation in the Indonesian banking sector. By focusing on four major banks and analyzing daily gain/loss data from foreign exchange transactions spanning January 2016 to February 2021, the research underscores the resilience of the QR approach, particularly in scenarios with non-Gaussian distributions. It showcases the method's ability to provide dependable VaR estimates without relying on traditional distributional assumptions mandated by GARCH models.

This study is organized as follows: section 3 defines Value-at-Risk, and the models used to estimate it, section 4 presents Back-testing to evaluate VaR Models for Accuracy, section 5 includes empirical study using monthly Egyptation’s inflation rate data and section 6 presents the conclusions.

3. Methodology

This paper presents a VaR forecasting for Egyptian Inflation Rates time series based on the quantile regression, and other variance covariance model such as exponential weighted moving average EWMA and t-GARCH model

3.1 Value at Risk

Recent proposals for the disclosure of financial risk call for firm-wide measures of risk. A standard benchmark is the value at risk VaR. For a given time horizon t and confidence level p the value at risk is the loss in market value over the time horizon t that is exceeded with probability 1- p (Duffie and Pan,1997).

For clarity, we define VaR as follows, which is according to Chernozhukov and Umantsev, (2001). Let r_t denote the return of an Inflation over [t − 1, t). The 100(1 − τ) % conditional VaR is represented as:

$$VaR_{t+1}(\tau) = inf\ \{x;\ \mathrm{P}(r_{t+1} \leq x\ |\mathcal{F}_t) \geq \tau\} \tag{1}$$

Where:

- $\mathcal{F}_{\mathrm{t}}$: denotes the information up to time t
- $\mathrm{VaR}_{\mathrm{t+1}}$: an one-step-ahead 100(1 − τ) % VaR estimate at time t

3.2 Quantile Regression Model

Quantile regression is a type of regression analysis used in statistics and econometrics, it was introduced by Koenker and Bassett (1978), as a powerful statistical technique used to estimate conditional quantiles of a response variable. Unlike traditional regression methods that focus on the mean, quantile regression provides a more comprehensive view by modeling different points of the distribution, making it particularly suitable for Value at Risk (VaR) estimation (Koenker, 2005).

Whereas the method of least squares estimates the conditional mean of the response variable across values of the predictor variables, quantile regression estimates the conditional median (or other quantiles) of the response variable, (Tofallis ,2015).

Model Specification

The quantile regression model is defined by:

$$Q_y(\tau|X) = X\beta(\tau) \tag{2}$$

where:

- $Q_y(\tau|X)$:is the conditional quantile of the response variable y given the predictors X at quantile τ ,
- $\beta(\tau)$: represents the quantile-specific coefficients.

For VaR estimation, the focus is on the lower quantiles of the distribution, which capture potential losses. The quantile regression model minimizes the following objective function:

$$min_{\beta}\ \sum_{i=1}^{n} \rho_{\tau}\ (y_i - X_i\beta) \qquad (3)$$

Where:

$$\rho_{\tau}(u) = u\big(\tau - I(u < 0)\big) \qquad (4)$$

$$I(u < 0) = \begin{cases} 1 & ,if \quad u < 0 \\ 0 & ,if \quad u \geq 0 \end{cases} \qquad (5)$$

- $\rho_{\tau}(u)$: is the check function,
- I: is the indicator function.

In the context of VaR, the quantile regression model is used to estimate the VaR at a specified confidence level τ.

Quantile Regression is particularly effective in financial settings where return distributions are skewed or exhibit heavy tails, as it provides direct estimates of the tail quantiles without assuming a specific distributional form (Koenker, 2005).

3.3 The Exponentially Weighted Moving Average (EWMA) Model

The EWMA model is a popular tool for estimating volatility, which is crucial for calculating Value at Risk (VaR). Developed as part of the RiskMetrics framework (Alexander, ,2008). EWMA provides a simple yet effective method for capturing recent changes in market conditions (Mina and Xiao, 2001).

The EWMA model estimates volatility using the following recursive formula:

$$\sigma_t^2 = \lambda\sigma_{t-1}^2 + (1-\lambda)r_{t-1}^2 \qquad (6)$$

where:

- σ_t^2 is the conditional variance at time t
- r_{t-1}^2 is the return at time t-1
- λ is the smoothing parameter, typically set to 0.94 for daily data as recommended by RiskMetrics (Morgan, 1996).

The VaR at time t is calculated as:

$$VAR_t = \mu_t + z\sigma_t \tag{7}$$

Where:

- μ_t is the expected return, often assumed to be zero for simplicity, z is the z-score corresponding to the desired confidence level.

EWMA's emphasis on recent data makes it responsive to market changes, providing timely estimates of risk (Hull, 2018). Its computational simplicity and efficiency are key advantages, though it assumes that volatility is the only changing parameter, which may not capture all market dynamics.

3.4 t-GARCH Model

The t-GARCH model extends the traditional GARCH framework by incorporating a t-distribution to better capture the heavy tails often observed in financial returns (Bollerslev, 1986). This makes it a robust choice for estimating Value at Risk (VaR), particularly in volatile markets.

The t-GARCH (1,1) model is defined by the following equations:

$$r_t = \mu + \epsilon_t \tag{8}$$

where:

- r_t is the return at time t,
- μ is the mean return,
- ϵ_t is the error term, assumed to be conditionally t distributed.

And,

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{9}$$

- σ_t^2 is the conditional variance at time t,
- ω, α, and β are model parameters,
- ϵ_{t-1}^2 is the past error term

The VaR is calculated using the conditional variance and the quantile of the t-distribution:

$$VAR_t = \mu_t + t_v^{-1}(\mathcal{P}).\sigma_t \tag{10}$$

Where:

- $t_{\nu}^{-1}(\mathcal{P})$ is the inverse of the t-distribution with ν degrees of freedom at the confidence level (1- α).

The t-GARCH model captures volatility clustering and leptokurtosis, providing a comprehensive approach to risk estimation (Engle, 2001; Jorion, 2007).

4 Back-testing VaR Models for Accuracy

Back-testing methods are statistical tests designed to uncover value-at-risk (VaR) models not capable of reporting the correct unconditional coverage probability or filtering the serial dependence in the data (Escanciano and Olmo, 2011)

Back-testing is a critical process for evaluating the accuracy of Value at Risk (VaR) models. It involves comparing the VaR predictions with actual outcomes to assess model performance (Berkowitz, et al.,2007). The primary measure used in Back-testing is the number of violations, where the actual loss exceeds the VaR estimate. The results from Back-testing provide us with information on specific periods where VaR is underestimated or where the losses are greater than the original expected VaR value. These VaR values can then be recalculated if the Back-testing values are not accurate, thereby helping researchers and institutions to reduce their exposure to unexpected losses (Zhang and Nadarajah, 2017).

4.1 Violation Indicator

The violation indicator I_t is defined as (McNeil, et al ,2005).:

$$I_t = \begin{cases} 1, & if\ L_t > VAR_t \\ 0, & otherwise \end{cases} \tag{11}$$

Where:

- L_t is the actual loss at time t,
- VAR_t is the predicted VaR at time

4.2 Proportion of Failures

Suppose there are x violations in a sample of size N, which can be define as $\sum_{t=1}^{N} I_t$. Then the maximum likelihood estimator of Proportion of Failures (PF) is calculated as (Haas, 2006):

$$\hat{P} = \frac{x}{N} \tag{12}$$

With variance:

$$\sigma_{\hat{P}}^2 = \frac{\hat{P}\,(1-\hat{P})}{N} \tag{13}$$

An approximate 100(1 − α) percent confidence interval for PF is:

$$(\hat{P} - z_{\alpha/2}\frac{\hat{P}\,(1-\hat{P})}{N} \;,\;\; \hat{P} + z_{\alpha/2}\frac{\hat{P}\,(1-\hat{P})}{N}\,) \tag{14}$$

If P lies within this interval, we can consider VaR to be a good model. Otherwise, we can try to evaluate what is the true confidence level rendered by the model.

4.3 Kupiec's Test

Based on the same assumptions as the Proportion of Failures (POF) test, Kupiec's TUFF test (LR test) measures the time until the first violation.

Kupiec's POF test evaluates whether the observed failure rate is consistent with the expected rate, the test statistic can be defined as:

$$LR_{POF} = -2ln\left(\frac{(1-\mathcal{P})^{N-\mathcal{X}}\;\;\mathcal{P}^{\mathcal{X}}}{(1-\hat{\mathcal{P}})^{N-\mathcal{X}}\;\;\hat{\mathcal{P}}^{\mathcal{X}}}\right) \tag{15}$$

Where:

- $\mathcal{X}$ is the number of violations,
- $\hat{\mathcal{P}} = \frac{\mathcal{X}}{N}$ is the observed violation rate,
- $\mathcal{P}$ is the expected violation probability

The test statistic LR_{POF} follows a chi-square distribution with one degree of freedom under the null hypothesis that the model is accurate (Kupiec, 1995).

4.4 Christoffersen's Test

This test is also known as the Markov test and it examines the independence property, that is, the test examines if the probability of VaR violation on any given day depends on the outcome of the previous day. The likelihood ratio principle is used for the test. Christoffersen's test extends Kupiec's test by also assessing the independence of violations, The test statistic for independence of violations is:

$$LR_{CCI} = LR_{POF} + LR_{ind} \tag{16}$$

Where LR_{ind} tests for the independence of violations. Haas (2006) argues that this test is too weak to produce feasible results. Also, it has limited power against general forms of time dependence on violations.

5 Empirical application

5.1 Data

In this section, we explore the empirical relevance of theoretical studies, this is done by evaluating and comparing three VAR models, based on the VQR test, all computations are performed with “quantreg”, “PerformanceAnalytics” and “rugarch” packages in R-Studio software

we apply the proposed three VAR models to the monthly Egyptation’s inflation rate data which were selected from central bank of Egypt’s website (https://www.cbe.org.eg/ar), for the period January 2005 to July 2024 that consists of 235 observations of the following four type of inflation rates as: Headline, Core, Regulated Items and Fruits and Vegetables

5.2 Data description

The data used was collected for four type of inflation rates as:

1. Headline (m/m): This is the overall inflation rate, measuring the percentage change in the consumer price index (CPI) from one month to the next. It includes all items, such as food, energy, and services.
2. Core (m/m): This inflation rate excludes volatile items like food and energy. It provides a clearer view of underlying inflation trends by focusing on more stable prices.

3. Regulated Items (m/m): This measures the inflation rate for items whose prices are controlled or influenced by government regulations, such as utilities or transportation fares.
4. Fruits and Vegetables (m/m): This rate specifically tracks the inflation for fruits and vegetables, which can be subject to seasonal fluctuations and supply issues.

We split the data set into two parts: training set (80%) with 188 observations and the test set (20%) with 47 observations. The training set is used to fit the models, while test set is used to test the model and evaluate the accuracy.

The statistical descriptive, as shown in Table (1) provides key statistical measures for four variables: Headline, Core, Regulated Items, and Vegetables and Fruits. Each variable has 235 valid observations with no missing data.

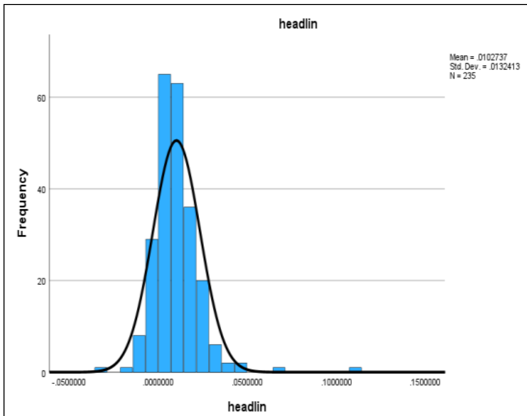
Table [1] descriptive statistics for data

Statistics					
		Headlin	**Core**	**Regulated_itm**	**Vegatable_friuts**
N	**Valid**	235	235	235	235
	Missing	0	0	0	0
Mean		.010273689	.009385472	.009783106	.019092638
Median		.009460000	.006300000	.003700000	.019790000
Mode		-.0015300[a]	.0022800[a]	.0000000	-.1948800[a]
Std. Deviation		.0132412939	.0139479361	.0162381252	.0648089516
Variance		0.000175332	0.000194545	0.000263677	0.0042002
Skewness		2.469	4.193	1.935	.238
Std. Error of Skewness		.159	.159	.159	.159
Minimum		-.0339000	-.0226000	-.0377700	-.1948800
Maximum		.1137400	.1324200	.0954700	.2760200
Percentiles	**25**	.002400000	.002280000	.000000000	-.019800000
	50	.009460000	.006300000	.003700000	.019790000
	75	.015790000	.011960000	.014500000	.053200000

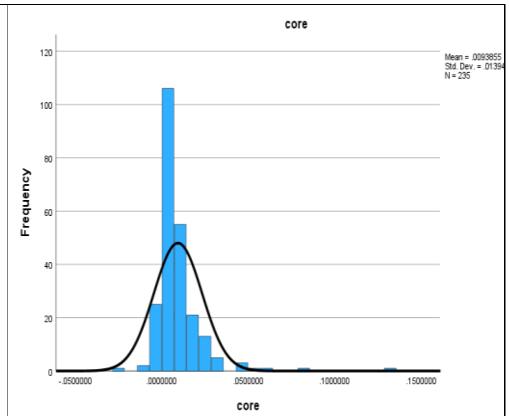
The distribution for each inflation rate is shown in Figure (1) which is slightly skewed with most values clustered around the mean, indicating stability with occasional higher values.

Distribution of inflation rates for both regular items and vegetables and fruits show more variability, reflecting changes in regulated prices, likely to show more volatility due to seasonal and market factors.

The distributions suggest headline and core inflation are relatively stable, while regulated items and food-related inflation show more variability. This highlights the impact of external factors on certain inflation components.



Headline inflation rate



Core inflation rate

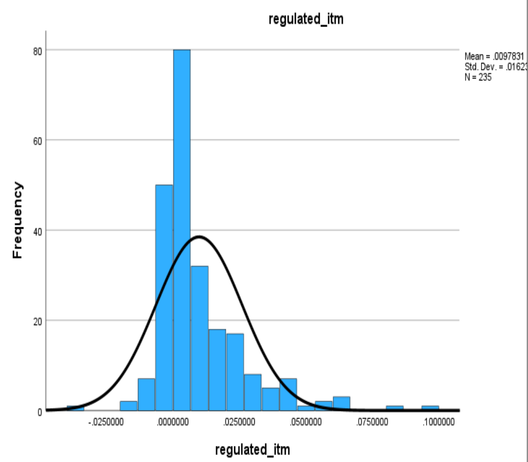
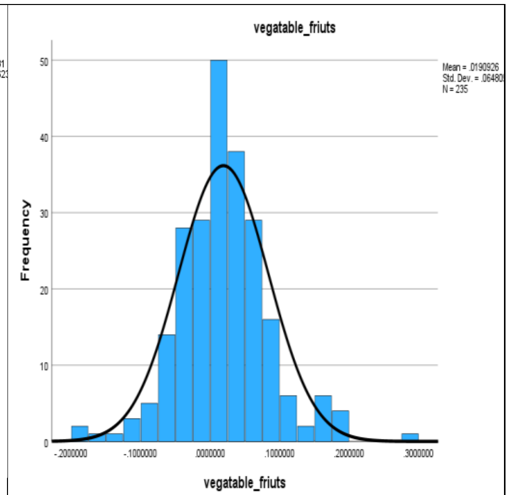
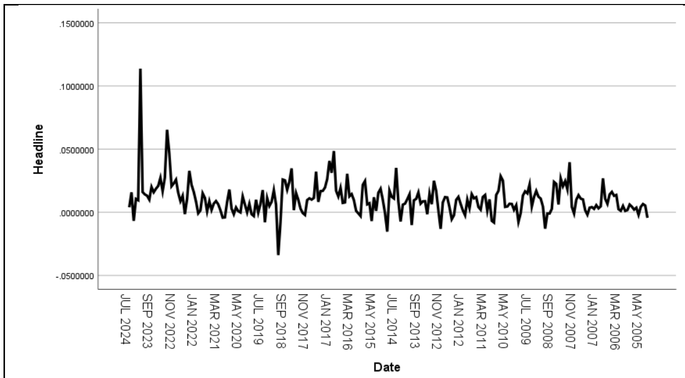
	
Regular item inflation rate	Vegetables and fruits inflation rate

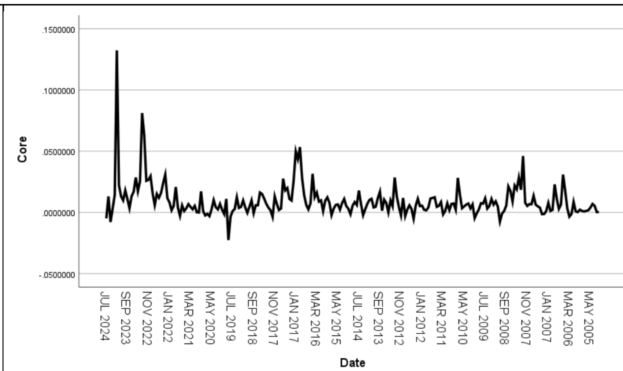
Figure [1] histogram and distribution curve for inflation rates

The monthly time series data of inflation rates from 2005 to 2024 in Figure (2) shows the trends for each of the following: first, headline inflation rate which is a significant spike around 2022, generally stable with occasional fluctuations throughout the period. Second, Core Inflation Rate which Similar spike observed around 2022, but more stable over the years compared to headline inflation. Third, Regulated Item Inflation Rate Which Demonstrates periodic spikes and dips, with more variability compared to core and headline rates, reflecting changes in regulated prices. Finally, Vegetables and Fruits Inflation Rate which Highly volatile with frequent sharp increases and decreases, reflecting seasonal and external market impacts.

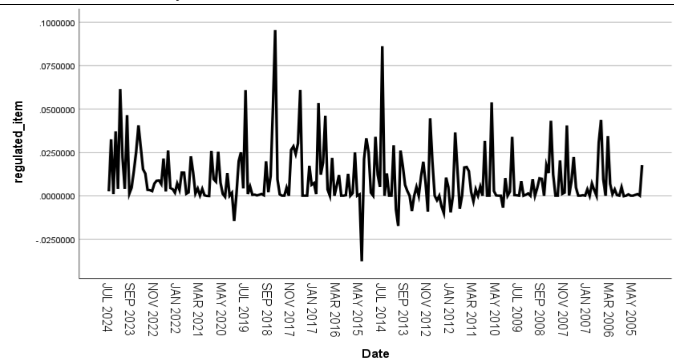
Overall, while core and headline rates show stability with some notable spikes, regulated items and food-related inflation exhibit more volatility.



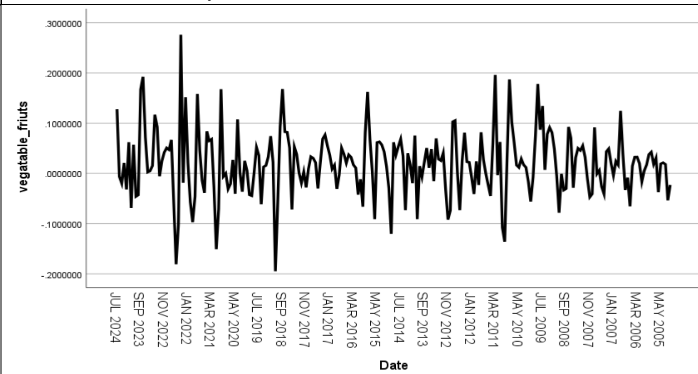
Monthly Headline inflation rate from 2005 to 2024



Monthly Core inflation rate from 2005 to 2024



Monthly Regular item inflation rate from 2005 to 2024



Monthly Vegetables and fruits inflation rate from 2005 to 2024

Figure [2] Monthly time series data of inflation rates from 2005 to 2024

Based on the Value at Risk (VaR) analysis for different inflation rates at various confidence levels, the Table (2) shows that Fruits and vegetables inflation rates carry the most risk across all models and confidence levels, reflecting their inherent volatility. Regulated items also show significant risk, while headline and core inflation rates are more stable. Different models provide varying risk estimates, with EWMA showing the lowest and Quantile VaR the highest.

Table [2] value at risk for three models at 90%, 95% and 99 % confidence levels

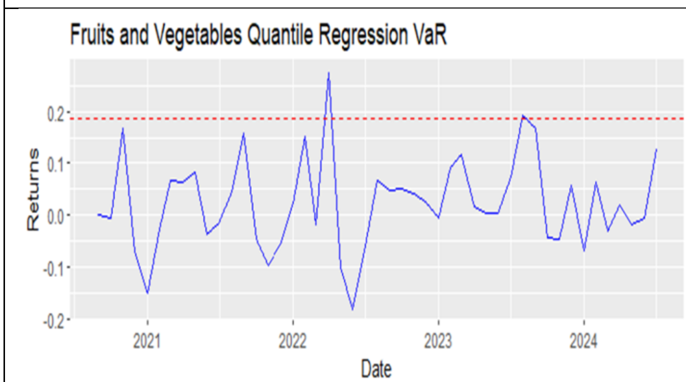
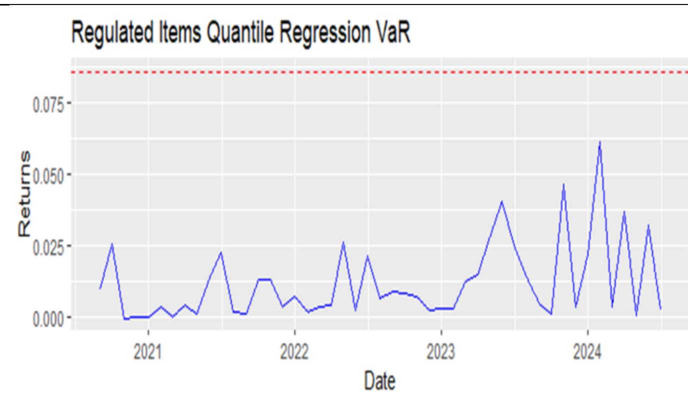
Valu At Risk	Inflation rate			
	Headline	Core	Regulated Items	Fruits and Vegetables
Confidence level				
α =1%				
Quantile VAR	0.04065	0.04995	0.08616	0.18718
EWMA VAR	0.0004767535	0.0005962334	0.0010151102	0.0082511909
t-GARCH VAR	0.01785413	0.01758788	0.02726364	0.12029804
α =5%				
Quantile VAR	0.02687	0.02812	0.04373	0.10269
EWMA VAR	0.0003809258	0.0002501004	0.0009201569	0.0171805102
t-GARCH VAR	0.007781450	0.006082288	0.010710000	0.067370540
α =10%				
Quantile VAR	0.02428	0.01797	0.03081	0.08184
EWMA VAR	0.0002626367	0.0003284564	0.0005592096	0.0045454623
t-GARCH VAR	0.003715707	0.002517081	0.006033537	0.045566307

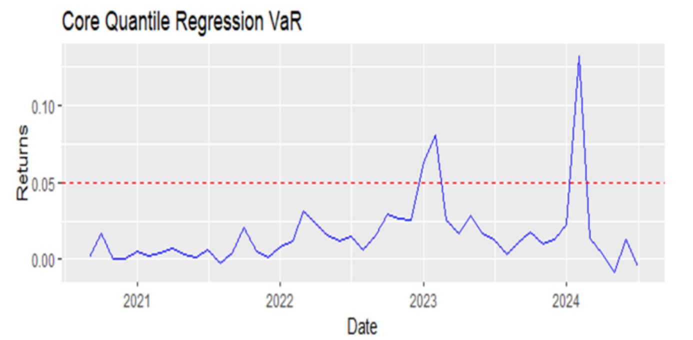
Also, to evaluate the estimated VARs we use plotting as shown in Figure (3) for Quantile, EWMA and t-GARCH Values At Risk at α =1%.

The quantile regression VaR figures indicate Fruits and vegetables Values often exceed the VaR threshold, indicating significant risk and volatility. Regulated items, core, and headline inflation show more stability, with headline inflation being the least volatile, which indicate the more accuracy of estimating for VAR using quantile regression

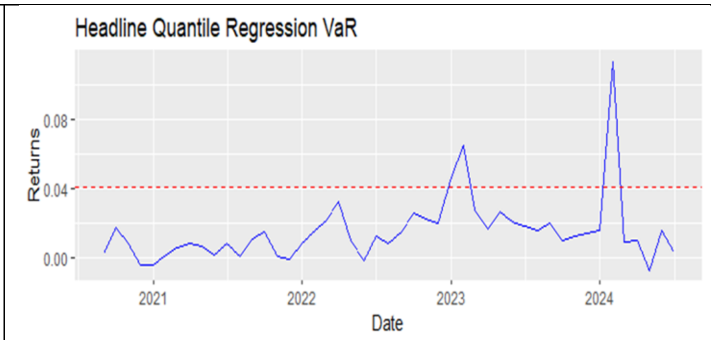
Based on the EWMA VaR figures using test data the values of almost all inflation rates exceed the estimated VaR threshold, which may indicate to low accuracy of estimating VARs using EWMA model

Finally, the t-GARCH model effectively captures volatility, especially for fruits and vegetables, where risk is higher. Its ability to align with actual peaks suggests it is relatively accurate in forecasting periods of increased risk. For stable categories like core and headline inflation, the model provides consistent and reliable estimates

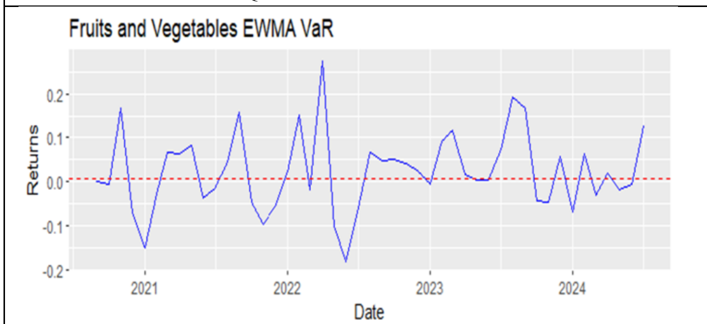
<table>
<tr><td colspan="2">α =1%</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>Quantile VAR = 0.18718</td><td>Quantile VAR =0.08616</td></tr>
</table>



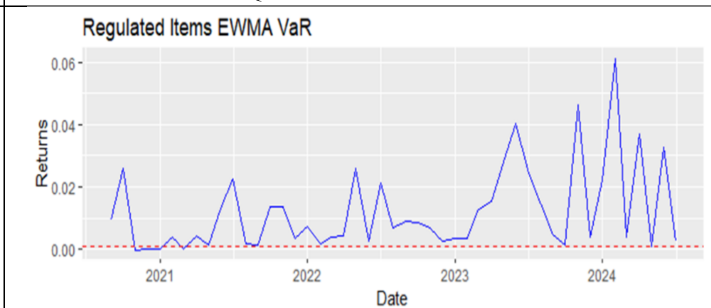
Quantile VAR = 0.04995



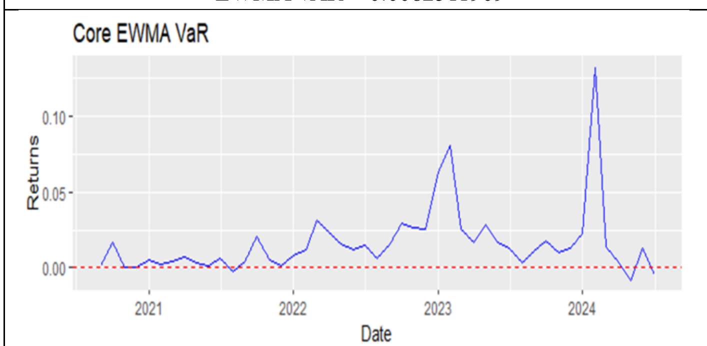
Quantile VAR = 0.04065



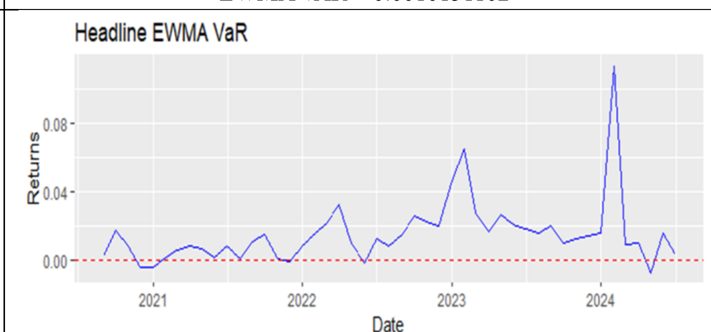
EWMA VAR = 0.0082511909



EWMA VAR = 0.0010151102



EWMA VAR =0.0005962334



EWMA VAR = 0.0004767535

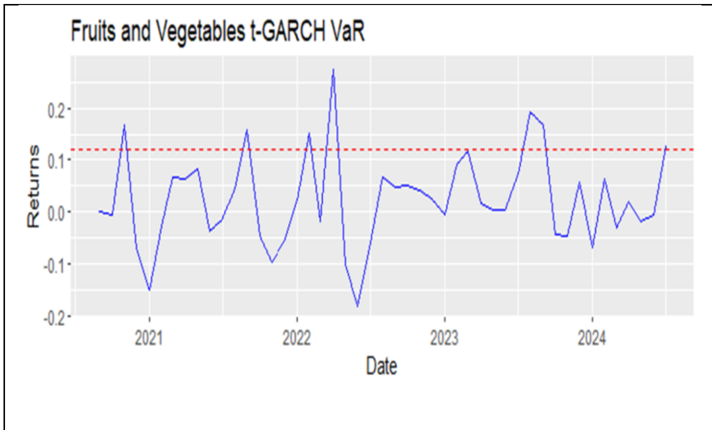
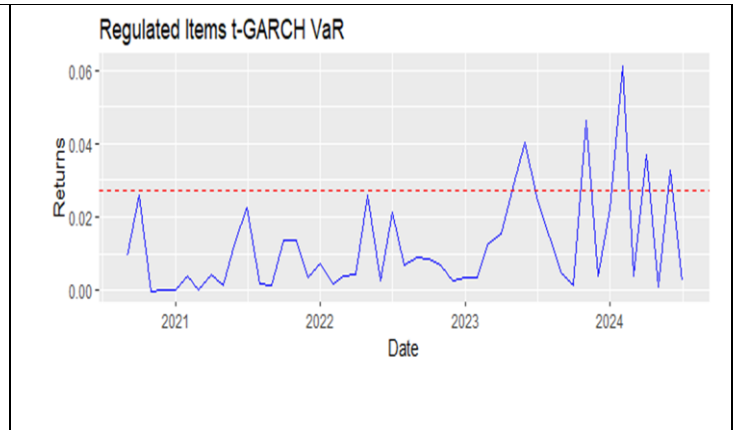
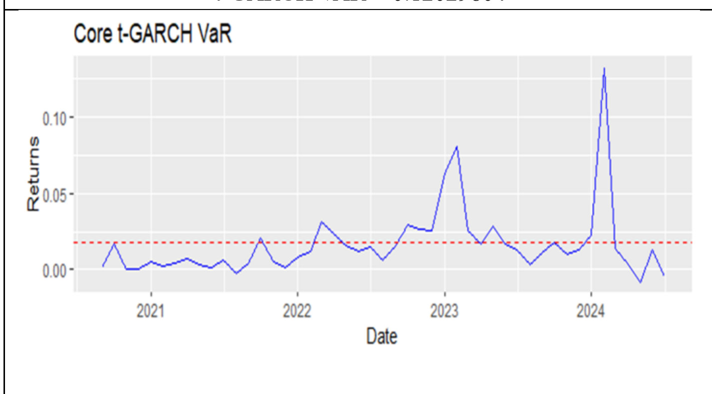
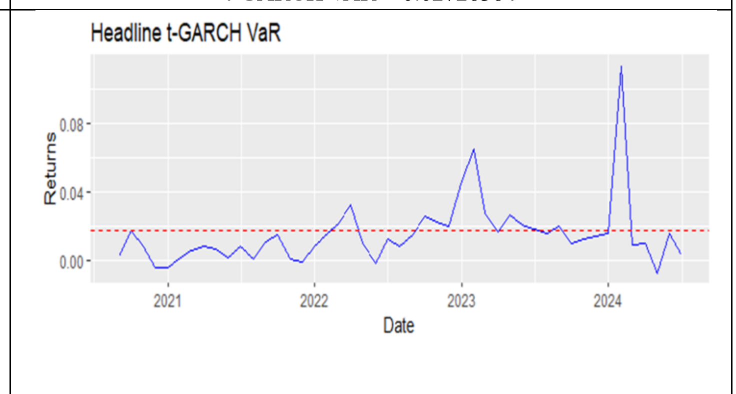
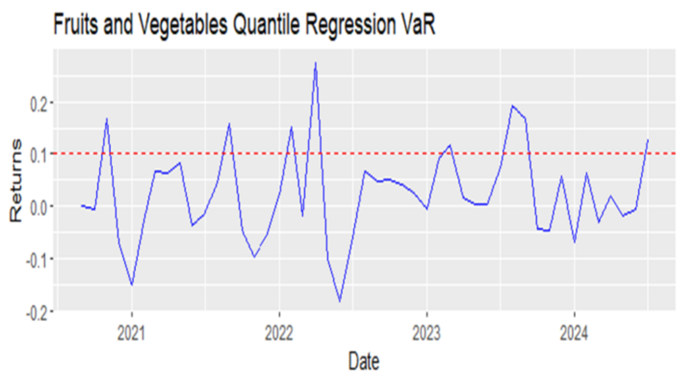
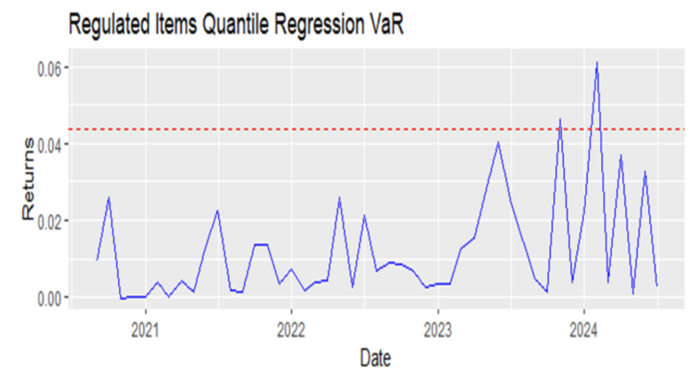
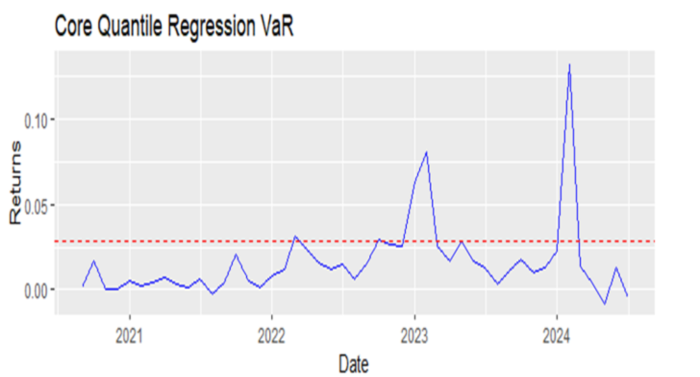
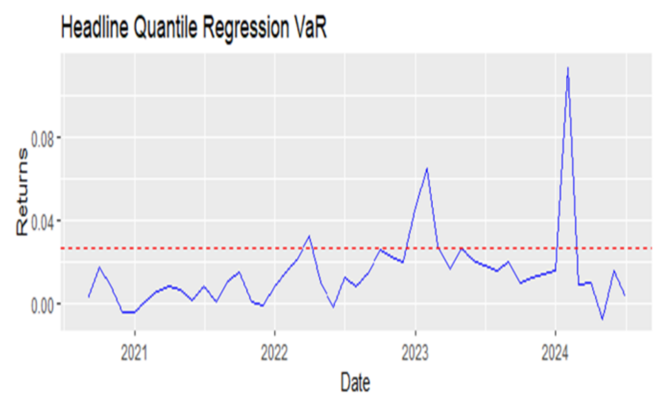
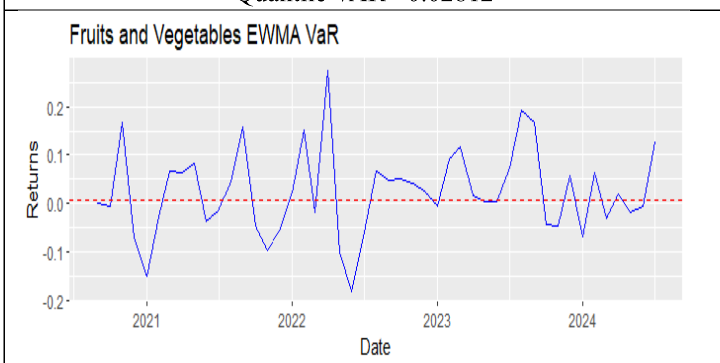
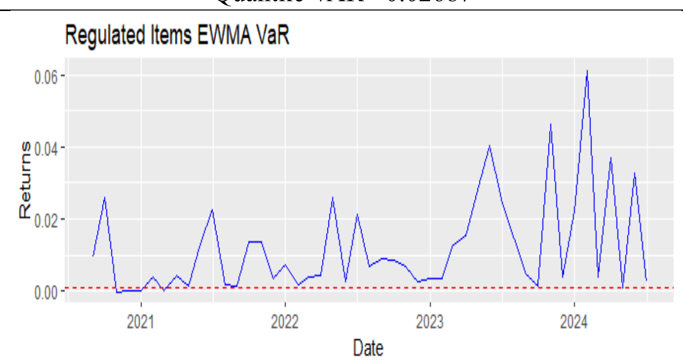
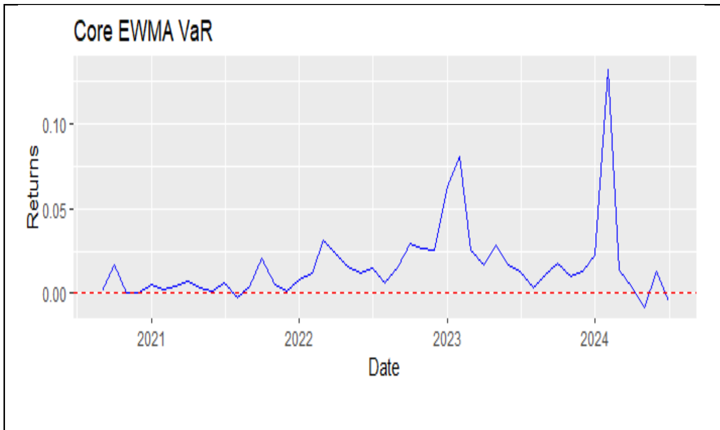
	
t-GARCH VAR = 0.12029804	t-GARCH VAR = 0.02726364
	
t-GARCH VAR = 0.01758788	t-GARCH VAR = 0.01785413

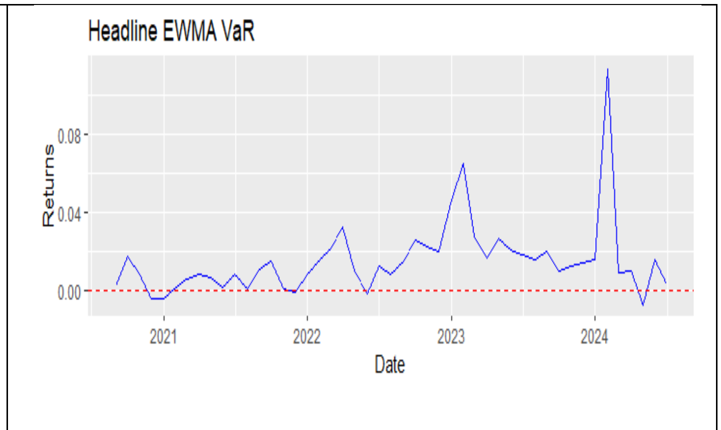
Figure [3]: Quantile, EWMA and t-GARCH Values At Risk at α =1%

Also, as we illustrated in previous figure, we replot Quantile, EWMA and t-GARCH Values At Risk at different confidence level with α =5%. As shown in Figure (4), which generally shows that different models lead to wide different VaR time series for the same returns series at different confidence levels.

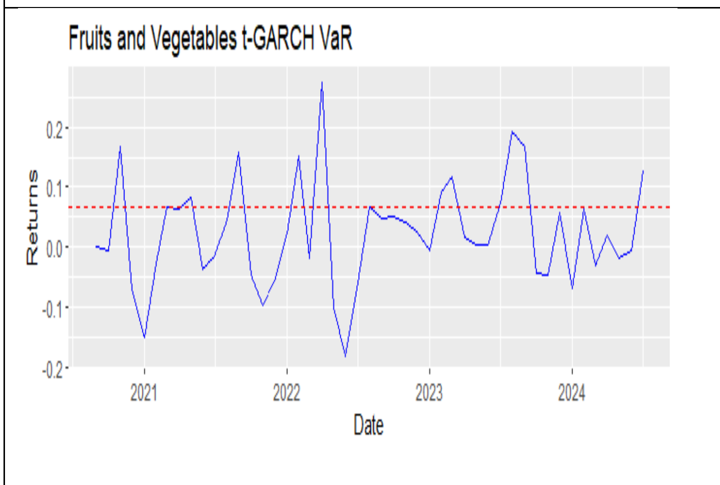
<table>
<tr><td colspan="2">α =5%</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>Quantile VAR =0.10269</td><td>Quantile VAR =0.04373</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>Quantile VAR =0.02812</td><td>Quantile VAR =0.02687</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>EWMA VAR = 0.0171805102</td><td>EWMA VAR =0.0009201569</td></tr>
</table>



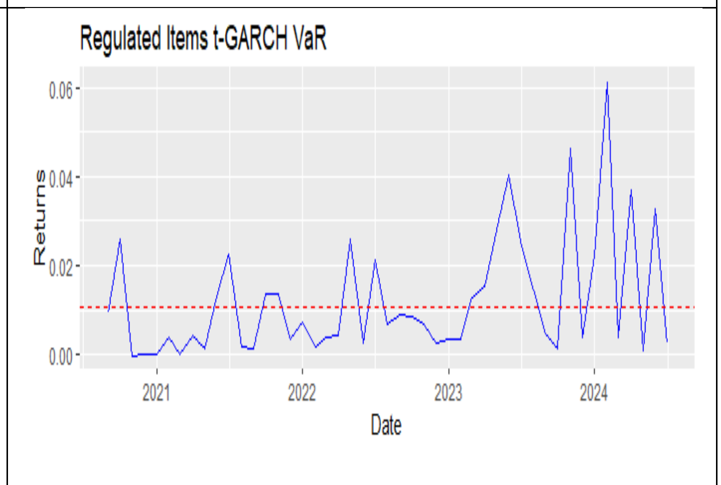
EWMA VAR =0.0002501004



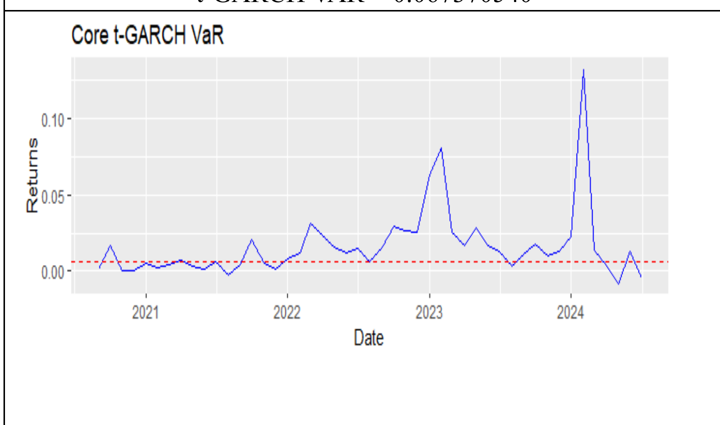
EWMA VAR =0.0003809258

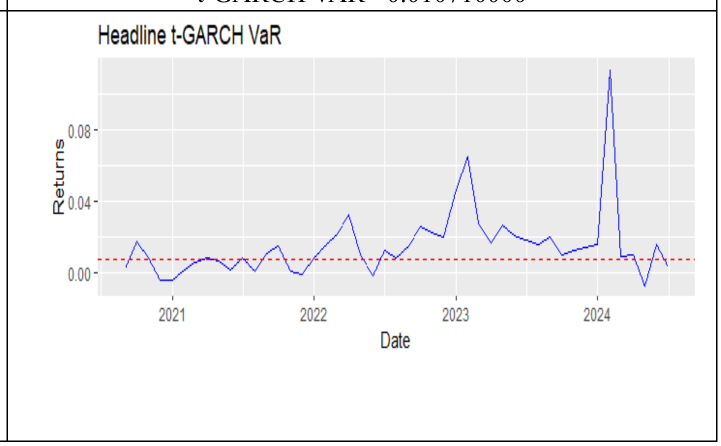


t-GARCH VAR = 0.067370540



t-GARCH VAR =0.010710000



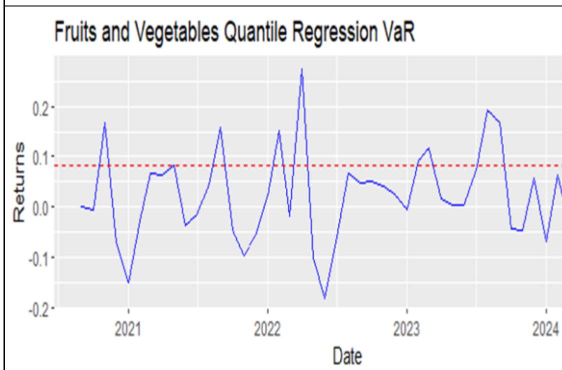
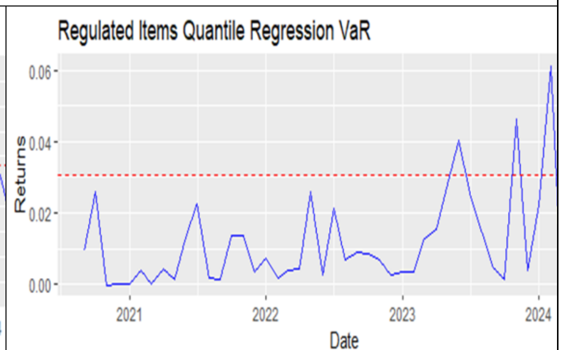


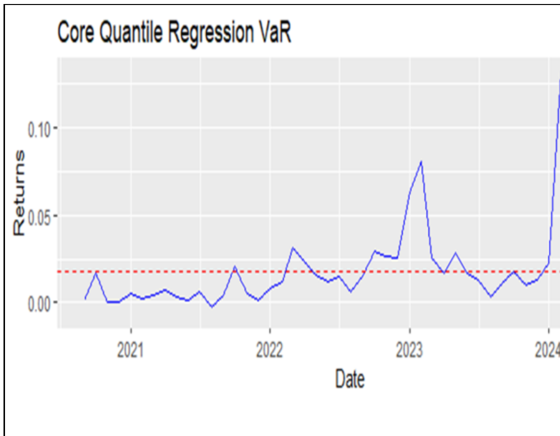
t-GARCH VAR = 0.006082288	t-GARCH VAR = 0.007781450

Figure[4]: Quantile, EWMA and t-GARCH Values At Risk at α =5%

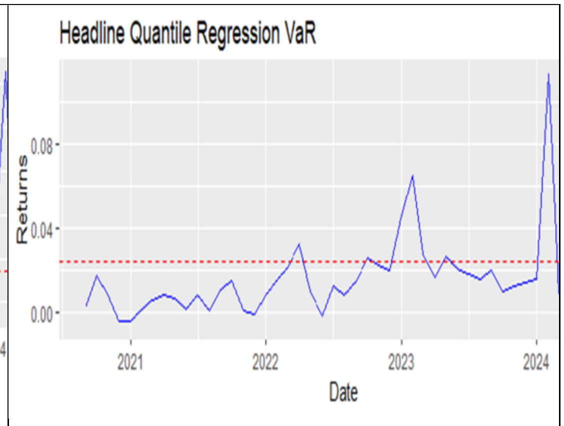
For more indications we also represent Quantile, EWMA and t-GARCH Values at Risk at different confidence level with α =10%. As shown in Figure (5), which generally leading us to models comparisons using Back-testing approach which will be illustrated in Table (3)

In general, and according to the three figures at three levels of confidence we can conclude that EWMA Var is a poor method for estimating Var, while t-GARCH Var considers a moderate efficient in estimating VaR. Finally, quantile regression VaR is the most efficient measure in estimating VaR, but we need to be sure by testing accuracy for each model at different levels of confidence

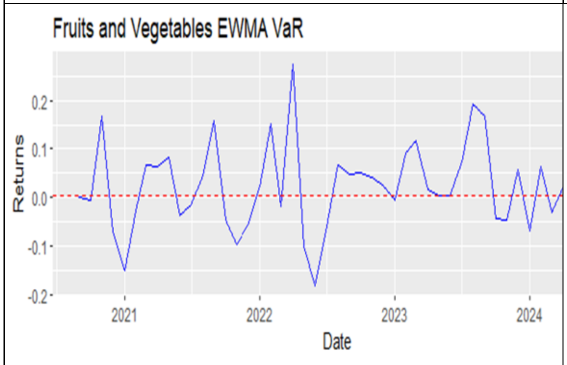
α =10%	
	
Quantile VAR =0.08184	Quantile VAR = 0.03081



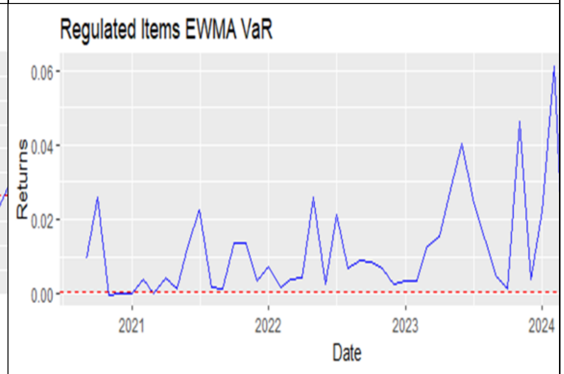
Quantile VAR = 0.01797



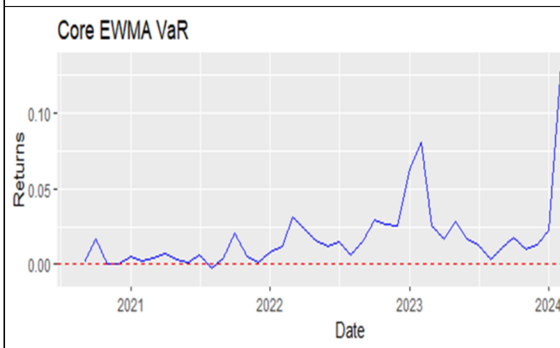
Quantile VAR = 0.02428



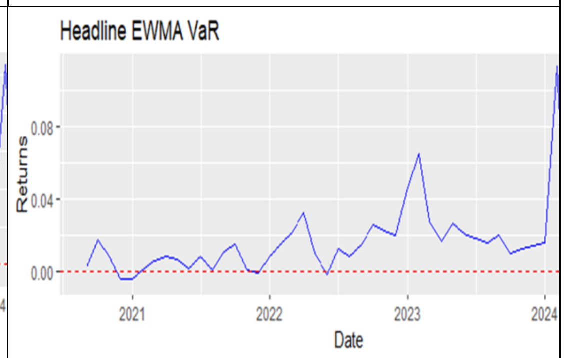
EWMA VAR =0.0045454623



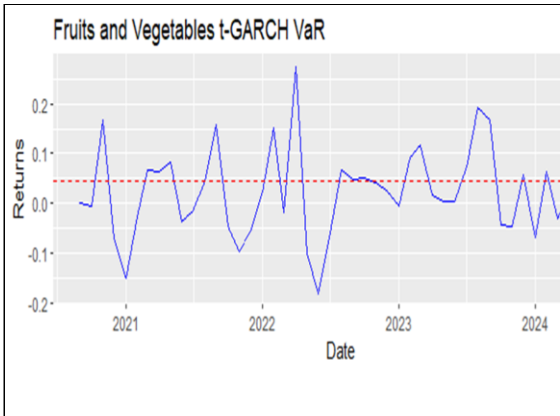
EWMA VAR =0.0005592096



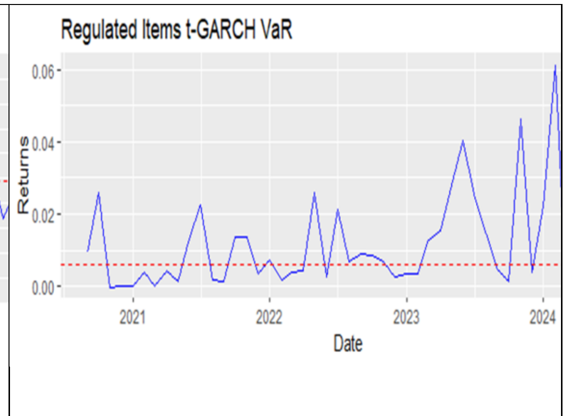
EWMA VAR =0.0003284564



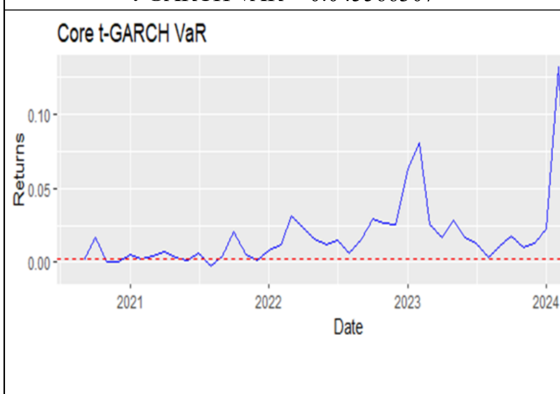
EWMA VAR =0.0002626367



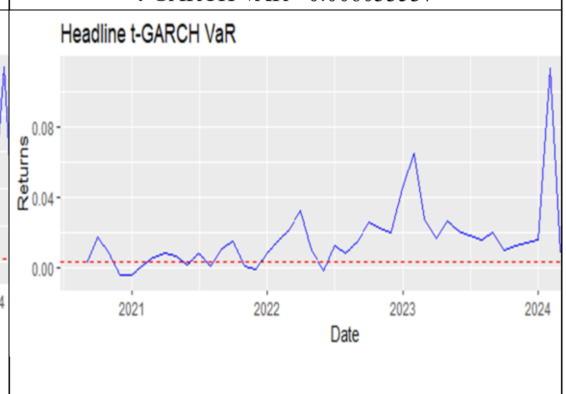
t-GARCH VAR = 0.045566307



t-GARCH VAR =0.006033537



t-GARCH VAR =0.002517081



t-GARCH VAR = 0.003715707

Figure[5]: Quantile, EWMA and t-GARCH Values At Risk at α =10%

We use Violations indictors to test the performance of each VaR model using as shown in Table (3) and Kupiec's Test as shown in Table (4) which revealed distinct performance characteristics for each model.

Quantile VaR Showed low violation rates, particularly at the 1% confidence level, indicating strong performance in capturing extreme events. Consistent accuracy across different inflation categories, with slightly higher violation rates at higher confidence levels. While t-GARCH VaR: Demonstrated balanced performance, with moderate violation rates. Effective in handling volatility clustering, especially at higher confidence levels, making it a reliable choice for variable market conditions.

Finally, EWMA VaR Exhibited high violation rates across all categories and confidence levels, suggesting an underestimation of risk. Most violations occurred at the 1% confidence level, raising concerns about its responsiveness to volatility.

Table [3] Violation indicator test for accuracy at 90%, 95% and 99 % confidence levels

Violations indictors test		Inflation rate			
		Headline	Core	Regulated Items	Fruits and Vegetables
Confidence level					
α = 1%					
Violations	Quantile VAR	3	3	0	2
Violation Rate		0.06382979	0.06382979	0	0.04255319
Violations	EWMA VAR	42	44	47	30
Violation Rate		0.893617	0.9361702	1	0.6382979
Violations	t-GARCH VAR	3	10	1	1
Violation Rate		0.06382979	0.212766	0.0212766	0.0212766
Confidence level					
α = 5%					
Violations	Quantile VAR	6	6	2	8
Violation Rate		0.1276596	0.1276596	0.04255319	0.1702128
Violations	EWMA VAR	42	44	47	27
Violation Rate		0.893617	0.9361702	1	0.5744681
Violations	t-GARCH VAR	7	19	6	6
Violation Rate		0.1489362	0.4042553	0.1276596	0.1276596
Confidence level					
α = 10%					
Violations	Quantile VAR	7	13	5	10
Violation Rate		0.1489362	0.2765957	0.106383	0.212766
Violations	EWMA VAR	42	44	47	27
Violation Rate		0.893617	0.9361702	1	0.5744681
Violations	t-GARCH VAR	11	23	12	8
Violation Rate		0.2340426	0.4893617	0.2553191	0.1702128

We note that from Table (4) low p-value (e.g., < 0.05) Suggests rejecting the null hypothesis, meaning the model does not accurately predict the expected number of violations. While, high p-value refers to Fails to reject the null hypothesis, indicating the model's predictions are consistent with the observed data.

The p-values for Headline and Core for Quantile VAR at confidence level $\alpha = 1\%$, are low (0.0128), indicating potential model inadequacy at this level. While, Regulated Items and Fruits and Vegetables have higher p-values (0.3311 and 0.0952), suggesting better model fit.

All p-values For EWMA VAR are 0, showing significant deviations from expected violations, suggesting model failure almost at the different levels for confidence.

Headline and Core show significant p-values in t-GARCH VAR at $\alpha = 1\%$ which is (0.0128, very low for Core), indicating poor fit. While, Regulated Items and Fruits and Vegetables p-values are higher, suggesting a better fit.

These results suggest that model adequacy varies significantly with the choice of model and variable. Quantile and t-GARCH models offer some reliability, while EWMA consistently underperforms. Adjustments or alternative models might be needed for better accuracy.

Table[4]: Kupiec's Test for testing significance accuracy

Kupiec's Test		Inflation rate			
		Headline	Core	Regulated Items	Fruits and Vegetables
Confidence level					
α = 1%					
Quantile VAR	Likelihood Ratio (LR) statistic	6.2019376	6.2019376	0.9447316	2.7835492
	p-value	0.012761053	0.01276105	0.33106397	0.09523690
EWMA VAR	Likelihood Ratio (LR) statistic	355.0796	383.0018	432.8860	215.1391
	p-value	0.00	0.00	0.00	0.00
t-GARCH VAR	Likelihood Ratio (LR) statistic	6.2019376	44.1928814	0.4561052	0.4561052
	p-value	1.276105e-02	2.975609e-11	1 4.994499e-01	1 4.994499e-01
Confidence level					
α = 5%					
Quantile VAR	Likelihood Ratio (LR) statistic	4.25498596	4.25498596	0.05766383	9.04759184
	p-value	0.039135272	0.039135272	0.810227197	0.002630411
EWMA VAR	Likelihood Ratio (LR) statistic	220.29920	241.61869	281.59883	99.71188
	p-value	0.00	0.00	0.00	0.00
t-GARCH VAR	Likelihood Ratio (LR) statistic	6.482939	53.288510	4.254986	4.254986
	p-value	1.089147e-02	2.879919e-13	6 3.913527e-02	6 3.913527e-02
Confidence level					
α = 10%					
Quantile VAR	Likelihood Ratio (LR) statistic	1.10425641	11.59905189	0.02088674	5.19413285
	p-value	0.2933338943	0.0006598545	0.8850879135	0.0226632593
EWMA VAR	Likelihood Ratio (LR) statistic	162.61551	180.94614	216.44300	64.44462
	p-value	0.000000e+03	0.000000e+003	0.000000e+004	9.992007e-16
t-GARCH VAR	Likelihood Ratio (LR) statistic	7.096014	45.841662	9.235528	2.174480
	p-value	7.725556e-03	1.282074e-11	2.373640e-03	1.403169e-01

6 conclusion

In this paper, we explored the efficacy of different VaR models in capturing inflationary trends in Egypt. Our analysis encompassed Quantile Regression, EWMA, and t-GARCH models, each evaluated for their accuracy and reliability across multiple confidence levels.

The LR statistic and its associated p-value provide a quantitative measure of a model's performance in predicting risk. They help determine whether the model's assumptions align with the real-world data, guiding decisions on model selection and risk management strategies.

Quantile Regression Proved effective in capturing extreme inflationary movements, with lower violation rates at higher confidence levels, which demonstrated robust performance, particularly in volatile categories such as fruits and vegetables. Also, t-GARCH Model Offered a balanced approach by effectively handling volatility clustering. Moderate violation rates across categories highlight its suitability for dynamic market conditions.

EWMA Model Exhibited high violation rates, indicating potential underestimation of risk, which is Less responsive to sudden shifts in inflation, suggesting limitations in highly volatile environments.

The findings underscore the importance of using Quantile Regression in evaluated VaR model based on specific market characteristics and risk management goals. Which contributes valuable insights into risk management strategies for inflation in Egypt, aiding policymakers and financial analysts in making informed decisions.

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الانحدار الكمي لتقدير القيمة المعرضة للمخاطر في معدل التضخم المصري: تحليل مقارن مع نماذج المتوسطات المتحركة المرجحة الاسية EWMA ونماذج الانحدار الذاتي الشرطية المعممة t-GARCH

المستخلص :

تبحث هذه الورقة في فعالية نماذج الانحدار الكمي، ومتوسط التحرك الموزون أسيًا(EWMA) ، و t-GARCH في تقدير قيمة المخاطرة (VaR) لمعدل التضخم في مصر. من خلال التحليل التجريبي والاختبارات العكسية، نُظهر أن الانحدار الكمي يتفوق على النماذج الأخرى من حيث الدقة والموثوقية في التقاط المخاطر الطرفية. من خلال نمذجة الكميات مباشرة من توزيعات العوائد، يوفر الانحدار الكمي إطارًا قويًا لتقدير قيمة المخاطرة، مما يعالج بشكل فعال عدم الخطية والقيم المتطرفة في البيانات المالية. تُمكّن قدرة النموذج على تقدير الكميات مباشرة من فهم دقيق للحركات التضخمية القصوى. تشير نتائجنا إلى أن الانحدار الكمي هو أداة متفوقة لإدارة المخاطر، حيث يقدم مزايا كبيرة في الدقة والقدرة على التكيف مقارنة بالطرق التقليدية، مما يوفر رؤى قيمة لمديري المخاطر وصناع السياسات.

الكلمات المفتاحية:

الانحدار الكمي، القيمة المعرضة للخطر (VaR)، EWMA، t-GARCH، الاختبار الخلفي