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Volatility and Dependence Dynamics between Money Market Funds and Kenyan Treasury Bills: An Integrated Egarch–Copula–Dcc-Garch Analysis

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**Volatility and Dependence Dynamics between Money
Market Funds and Kenyan Treasury Bills: An
Integrated Egarch–Copula–Dcc-Garch Analysis**

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Abstract

Purpose: Money Market Funds (MMFs) and Treasury Bills occupy an important position in Kenya's short-term investment market, yet their risk characteristics and interaction are not adequately described by measures that consider volatility or dependence in isolation. This study examines the volatility dynamics and dependence structure between an anonymized Kenyan MMF and 91-day, 182-day and 364-day Treasury Bills using an integrated EGARCH–copula–DCC-GARCH framework.

Methodology: The analysis uses 140 matched monthly observations covering November 2014 to July 2026. Preliminary diagnostics were conducted to assess distributional characteristics, stationarity and conditional heteroskedasticity. Competing GARCH family models were established and compared using Akaike Information Criterion, with student-t innovations used to accommodate heavy tailed distributions. Copula models were then applied to standardized residuals transformed using Probability Integral Transform, followed by DCC-GARCH models to examine time varying conditional correlations across the three Treasury Bill maturities.

Findings: Preliminary results indicate non-normal return distributions, excess kurtosis and significant ARCH effects across all four series. Among the competing symmetric and asymmetric GARCH specifications, EGARCH provides the lowest Akaike Information Criterion for each series. Student-t innovations are used to accommodate the heavy-tailed distributions. Significant asymmetric volatility effects are found for the MMF, 91-day and 364-day Treasury Bill series, while the evidence for asymmetry in the 182-day series is weaker. After filtering the marginal dynamics and applying the Probability Integral Transform, the copula analysis indicates weak residual dependence, with the independence copula providing the final representation and Kendall's tau of approximately 0.072. No meaningful lower- or upper-tail dependence is identified after accounting for the marginal volatility processes. The DCC-GARCH results add an important dynamic dimension: conditional correlations remain generally weak but vary over time and across maturities. The 364-day Treasury Bill has the largest short-run DCC adjustment coefficient (0.188), indicating greater responsiveness of its relationship with MMFs to new information.

Unique Contribution to Theory, Practice and Policy: The findings suggest that MMFs and Treasury Bills can provide diversification opportunities, but the strength of diversification is not fixed and should be assessed with regard to maturity and market conditions. The study contributes evidence from an emerging-market setting and demonstrates the value of combining marginal volatility, residual dependence and dynamic correlation models when analyzing short-term Kenyan financial assets.

Keywords: Money Market Funds, Treasury Bills, EGARCH, Copula, DCC-GARCH, Volatility, Dependence, Kenya

JEL Classification Codes: C32, C58, G11

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INTRODUCTION

Financial markets are characterized by changing levels of uncertainty, persistence in shocks and periods in which financial instruments move differently from their long-run patterns. These features are particularly relevant in emerging markets, where changes in monetary policy, liquidity conditions, inflation and investor behavior can affect short-term financial instruments. In Kenya, Money Market Funds (MMFs) operate within a regulatory and investment environment in which Government securities including Treasury Bills and treasury bonds, constitute an important component of collective investment portfolios. Consequently, the observed relationship between MMF performance and Treasury Bill returns may reflect not only market-based interactions but also the underlying asset allocation structure of MMFs. This structural connection provides an important economic context for examining the volatility and dependence between MMFs and Treasury Bills.

A central difficulty in financial modelling is that return variability is rarely constant. Volatility tends to cluster, so periods of relatively large movements may be followed by further large movements. The GARCH family provides a framework for modelling this conditional heteroskedasticity (Engle, 1982; Bollerslev, 1986). Asymmetric extensions such as EGARCH are particularly useful where the direction of a shock may alter its effect on conditional volatility. However, a univariate volatility model cannot by itself explain whether two financial assets move together after their own volatility processes have been accounted for.

Dependence modelling provides a complementary perspective. Copulas separate the marginal distributions of financial variables from their joint dependence structure, making it possible to examine nonlinear association without requiring the same marginal distribution for all assets (Sklar, 1959; Patton, 2006). In financial applications, this is useful because conventional correlation can conceal important features of dependence, especially when distributions are skewed or heavy-tailed. DCC-GARCH models provide a further complement by allowing conditional correlations to evolve over time (Engle, 2002).

Although these methods have been widely used in international financial markets, relatively little empirical work has brought them together to study Kenyan MMFs and Treasury Bills. Existing Kenyan applications have tended to focus on individual volatility processes, exchange rates, equities or broader financial conditions. This leaves a practical and methodological gap concerning whether the apparently close relationship between MMFs and government securities remains after marginal volatility is filtered out, and whether the residual relationship changes over time or across Treasury Bill maturities.

This study addresses that gap through a sequential framework. First, GARCH-family models are used to estimate the conditional volatility of the four-return series. Second, copulas are applied to standardized innovations to assess residual dependence. Third, DCC-GARCH is used to determine whether conditional correlation changes through time. The central contribution is therefore not simply the application of three statistical techniques, but their use as complementary stages that distinguish individual volatility from average residual dependence and from dynamic correlation. The two dependence approaches are complementary rather than redundant: copula models allow the dependence structure to capture nonlinear association and tail behavior, whereas DCC-GARCH focuses on the evolution of conditional linear correlation over time.

The study is guided by three objectives:

- (i) To model the volatility dynamics of MMF and Treasury Bill returns using GARCH-family models
- (ii) To examine the dependence structure between MMF and Treasury Bill returns using copula models
- (iii) To examine the time-varying conditional relationship between MMFs and Treasury Bills using DCC-GARCH.

LITERATURE REVIEW

Money Market Funds and Government Securities

Money Market Funds (MMFs) are important components of short-term investment markets because they provide investors with relatively liquid vehicles for investing in short-term fixed-income instruments. Their behavior is closely linked to developments in money markets, interest rates, liquidity conditions and the availability of short-term securities. The importance of MMFs to financial stability has been highlighted in the international literature, particularly during periods of market stress. For example, Li et al. (2021) examined liquidity restrictions, investor runs and central bank interventions in money market funds, while Capota et al. (2021) assessed the effectiveness of the European Money Market Fund Regulation during the COVID-19 turmoil. More recently, Nikolaou (2025) examined the growth of MMFs during global monetary policy tightening cycles. These studies demonstrate the importance of understanding the behavior of MMFs within changing financial and liquidity conditions.

The relationship between MMFs and government securities is particularly relevant because Treasury Bills represent major short-term government instruments and form part of the investment environment in which MMFs operate. The Kenyan monetary policy transmission mechanism provides an additional channel through which movements in policy and money-market rates can affect Treasury Bill yields. Mahasi and Pokhariyal (2013) found evidence of transmission from Central Bank Rate (CBR) to treasury Bill rates in Kenya, while Alper and Yang (2016) documented strong volatility transmission from interbank rates to Treasury Bill rates and substantial persistence in short-term interest-rate volatility. These findings indicate that Kenyan short-term fixed-income instruments are linked through monetary policy and market environment. This provides an important local context for examining whether the observed relationship between MMFs and Treasury Bills remains after individual volatility dynamics have been filtered.

In Kenya, MMFs and government securities are important components of the short-term investment market, while regulatory reports continue to document developments in collective investment schemes and their allocation across financial assets. However the existing literature provides limited evidence on the statistical dependence between MMF performance and Treasury Bill movements when Treasury Bills are distinguished according to maturity.

GARCH Models and Financial Volatility

GARCH models have become standard tools for analyzing financial volatility because they allow conditional variance to depend on previous shocks and past conditional variance. Engle (1982) introduced the autoregressive conditional heteroskedasticity (ARCH) model to account for changing variance over time, while Bollerslev (1986) generalized the approach through the GARCH model. These developments established an important framework for modelling volatility clustering and persistence in financial time series.

Subsequent developments in the GARCH family have allowed models to capture features that cannot be adequately represented by the symmetric GARCH specification, including differences in the volatility response to positive and negative innovations. Such asymmetric specifications are particularly relevant for financial markets in which the direction of a shock may influence subsequent volatility differently. Sharma et al. (2021), for example, compared linear and nonlinear GARCH models in emerging-country financial markets, illustrating the continued relevance of GARCH-family models for volatility forecasting. In the Kenyan context, Wanjuki et al. (2024) similarly examined alternative GARCH-based models of financial market volatility, providing evidence of the application of conditional volatility models to Kenyan financial data.

Although these studies establish the usefulness of GARCH-family models for capturing financial volatility, volatility modelling alone does not explain how two financial instruments move together after their individual volatility dynamics have been accounted for. A separate framework is therefore required to investigate dependence between financial series.

Copula-Based Dependence Modelling

Copula methods provide a flexible framework for modelling dependence separately from the marginal behavior of individual variables. The theoretical foundation was established by Sklar (1959), who showed that a multivariate distribution can be represented in terms of its marginal distributions and a copula describing their dependence structure. This separation is particularly useful in financial applications because individual assets may have different marginal distributions while still exhibiting dependence.

Patton (2006) demonstrated the usefulness of copula methods for modelling asymmetric dependence in financial markets, while Jondeau and Rockinger (2006) developed a Copula-GARCH framework in which conditional volatility is modelled separately before dependence is estimated through a copula. Their approach is particularly relevant to the present study because it demonstrates how marginal volatility dynamics and cross-series dependence can be analyzed jointly without imposing the same distributional structure on all series.

The flexibility of copula models has also supported their application to financial risk and portfolio analysis. Bernardi and Catania (2018) considered portfolio optimization under flexible dynamic dependence modelling, while Ndlovu and Chikobvu (2024) applied a GARCH-EVT-Copula framework to dependence and portfolio risk involving Bitcoin and the South African Rand. Melo-Velandia et al. (2025) further demonstrate the application of copula-based methods to financial dependence and systemic risk during stress episodes. More broadly, recent evidence from African financial markets also indicates the importance of modelling changing connections among financial assets rather than relying solely on conventional linear dependence measures (Dankwah et al., 2025).

Despite these developments, copula analysis generally provides a description of dependence over the modelling period and does not, by itself, provide the same information as a dynamic conditional correlation model about how dependence evolves through time. This motivates the complementary use of DCC-GARCH.

The distinction between the two approaches is important for the present study. DCC-GARCH models the evolution of conditional correlation within a specified multivariate volatility structure, whereas copula models separate the marginal distributions from the joint dependence structure and can accommodate alternative forms of nonlinear and tail dependence. The two methods therefore provide complementary information rather than competing measures: the

copula stage evaluates the residual dependence structure after marginal filtering, while the DCC-GARCH stage examines how conditional correlation changed through time. Using both approaches allows analysis to distinguish the overall residual dependence structure from its dynamic correlation behavior.

Dynamic Conditional Correlation and Time-Varying Dependence

The Dynamic Conditional Correlation (DCC-GARCH) model of Engle (2002) extends multivariate volatility modelling by allowing conditional correlations to change over time. Unlike a static correlation coefficient, DCC-GARCH can identify periods in which the relationship between two financial series becomes stronger or weaker. This is important for portfolio management because diversification benefits may vary according to prevailing market conditions.

The use of dynamic dependence models has become increasingly relevant in emerging and African financial markets, where relationships among assets may change in response to domestic and international financial conditions. Hafner and Linton (2010) further demonstrate the importance of modelling multivariate volatility efficiently when analyzing relationships across financial series. Recent African-market evidence also supports the broader relevance of dynamic dependence modelling for understanding interactions between regional financial assets and global market factors (Dankwah et al., 2025).

However, DCC-GARCH and copula models address related but distinct aspects of dependence. DCC-GARCH focuses on the evolution of conditional correlations, whereas copulas provide a more flexible representation of the dependence structure after accounting for the marginal distributions. Consequently, using the two approaches together can provide a more complete assessment of financial dependence than relying on either method independently.

Research Gap

The literature reviewed above reveals three related gaps. First, much of the financial volatility literature focuses on modelling the behavior of individual assets using GARCH-family models, without examining whether the remaining dependence between assets persists after their individual volatility dynamics have been filtered. Second, copula-based studies demonstrate the usefulness of flexible dependence modelling, but relatively few applications combine copula analysis with a separate examination of the time variation in conditional correlations. Third, the Kenyan literature remains comparatively limited regarding the joint behavior of Money Market Funds and government securities, particularly when Treasury Bills are differentiated by maturity.

The contextual gap is important because the relationship between an MMF and a 91-day, 182-day or 364-day Treasury Bill may not be identical. Differences in maturity may be associated with different responses to changes in interest rates, liquidity conditions and market information. Treating Treasury Bills as a single homogeneous asset class may therefore conceal maturity-specific volatility and dependence dynamics.

This study addresses these gaps by integrating three complementary components within a single empirical framework. First, GARCH-family models are used to capture the conditional volatility dynamics of the MMF and each Treasury Bill maturity. Second, copula methods are used to examine the dependence structure after the marginal volatility processes have been accounted for. Third, DCC-GARCH is used to determine whether the conditional relationship between the MMF and each Treasury Bill maturity changes over time. The analysis therefore

distinguishes between individual volatility dynamics, average residual dependence and time-varying conditional co-movement.

The study further extends the existing Kenyan evidence by considering three Treasury Bill maturities, 91-day, 182-day and 364-day rather than focusing on a single maturity. This allows the analysis to determine whether volatility and dependence characteristics differ across maturities and provides a more detailed assessment of the interaction between MMFs and government securities in the Kenyan short-term investment market.

METHODOLOGY

Data and Sample

The study employed secondary financial market data covering the period from November 2014 to July 2026. MMF observations were obtained from an anonymized Money Market Fund, while Treasury Bill observations were obtained from Central Bank of Kenya government securities records. Four series were analyzed: the Money Market Fund (MMF), 91-day Treasury Bill (TB91), 182-day Treasury Bill (TB182), and 364-day Treasury Bill (TB364).

The source data were available at different frequencies and therefore required harmonization before statistical modelling. The MMF observations were available at a higher frequency than the Treasury Bill observations, while Treasury Bill observations were reported according to auction dates. The series were therefore converted to a common monthly modelling frequency and matched by month across the four instruments. The initial matched dataset contained 141 monthly observations. One observation was subsequently removed because of a missing TB182 value, resulting in 140 complete matched observations for the empirical analysis.

The use of three Treasury Bill maturities allows the analysis to distinguish between maturity-specific volatility and dependence dynamics rather than treating government securities as a homogeneous short-term asset class.

Return Construction

For the MMF, the available observations were reported at daily frequency as annualized rates. These rates were converted to effective daily returns using

$$r_d = \left(1 + \frac{R}{100}\right)^{1/365} - 1,$$

Where R denotes the reported annualised MMF rate. The resulting daily effective returns were then compounded within each week to obtain weekly MMF returns. Weekly aggregation was used to harmonise the daily MMF observations with the timing of the Treasury Bill observations and to facilitate consistent matching of the two series over time.

For Treasury Bills, the reported annualized yields were converted into effective holding-period returns using

$$R_T = \left(1 + \frac{R}{100}\right)^{T/365} - 1,$$

Where R denotes the reported annualised Treasury Bill yield and T represents the maturity of the Treasury Bill in days. The transformation was applied separately to the 91-day, 182-day and 364-day Treasury Bills, thereby preserving the maturity-specific characteristics of the instruments while expressing the series on a comparable return basis.

The weekly MMF returns were subsequently matched with the corresponding Treasury Bill observations and aggregated to the monthly frequency. This produced a common monthly dataset for the MMF, 91-day Treasury Bill, 182-day Treasury Bill and 364-day Treasury Bill series. After matching and removal of the incomplete observation, the final dataset comprised 140 monthly observations covering November 2014 to July 2026.

The resulting monthly return series were used in the subsequent volatility, dependence and dynamic correlation analyses.

Preliminary Analysis

The preliminary analysis examined the distributional properties, stationarity and conditional heteroskedasticity of the four-return series. Descriptive statistics were calculated to assess the central tendency, dispersion, skewness and kurtosis of the observations. The Jarque–Bera test was used to assess departures from normality.

Stationarity was examined using the Augmented Dickey–Fuller (ADF), Phillips–Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. Using complementary tests provided a more robust assessment because the null hypotheses differ across the procedures. The presence of conditional heteroskedasticity was assessed using the ARCH-LM test. Rejection of the null hypothesis of no ARCH effects provided empirical justification for modelling conditional volatility.

Conditional mean specifications were identified before estimating the volatility models. Competing GARCH-family specifications were subsequently estimated and compared primarily using the Akaike Information Criterion (AIC), with residual diagnostic tests used to assess model adequacy.

EGARCH Volatility Modelling

The conditional volatility of each series was modelled using competing GARCH-family specifications. Symmetric GARCH, Exponential GARCH (EGARCH) and GJR-GARCH models were considered. EGARCH was selected where it provided the lowest AIC together with satisfactory diagnostic performance. Unlike the conventional GARCH specification, EGARCH models the logarithm of conditional variance and therefore permits the response of volatility to differ according to the sign and magnitude of innovations without imposing non-negativity restrictions directly on the variance parameters.

The general EGARCH specification is given by

$$\log(\sigma_t^2) = \omega + \sum_{j=1}^q \beta_j \log(\sigma_{t-j}^2) + \sum_{i=1}^p \alpha_i \left(\frac{|\varepsilon_{t-i}|}{\sigma_{t-i}} - E \left[\frac{|\varepsilon_{t-i}|}{\sigma_{t-i}} \right] \right) + \sum_{i=1}^p \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}},$$

Where σ_t^2 is the conditional variance, ω is the intercept, α_i captures the magnitude effect of innovations, β_j measures volatility persistence, and γ_i captures the asymmetric response of volatility to positive and negative innovations.

Student- t innovations were assumed in the final volatility models to accommodate the heavy-tailed characteristics identified in the preliminary analysis. The selected conditional mean specifications were incorporated into the final EGARCH models. The MMF model used an ARFIMA (1,0,1) mean structure, TB91 and TB182 used ARFIMA (1,0,0), while TB364 used ARFIMA (4,0,0).

Model adequacy was evaluated using Ljung–Box tests applied to standardized residuals and squared standardized residuals, ARCH-LM tests for remaining conditional heteroskedasticity, sign-bias tests for possible unmodelled asymmetry, and Nyblom stability statistics for parameter stability. These diagnostics were used jointly to determine whether the fitted models adequately captured the conditional mean and volatility dynamics.

Copula Dependence Modelling

After fitting the marginal EGARCH models, the standardized residuals were transformed using the Probability Integral Transform (PIT) to obtain approximately uniform variables. This procedure separates the marginal volatility dynamics from the subsequent dependence analysis.

The dependence structure between the MMF and each Treasury Bill maturity was then examined using alternative copula specifications. Gaussian, Student- t , Clayton, Frank and Gumbel copulas were considered, with the independence copula included as the benchmark specification for the absence of residual dependence.

Copula models were compared primarily using the Akaike Information Criterion. Kendall's tau was used to quantify the strength and direction of dependence, while lower- and upper-tail dependence coefficients were examined where applicable to assess whether extreme movements in the MMF and Treasury Bill series tended to occur jointly.

The copula stage therefore provides information that cannot be obtained from the marginal volatility models alone. Specifically, it assesses the dependence remaining between the series after their individual conditional mean and volatility dynamics have been filtered out.

Dynamic Conditional Correlation Modelling

To examine whether the relationship between the MMF and Treasury Bills changes over time, DCC-GARCH models were estimated separately for the MMF–TB91, MMF–TB182 and MMF–TB364 pairs.

The conditional covariance matrix is represented as

$$H_t = D_t R_t D_t,$$

Where D_t is a diagonal matrix containing the conditional standard deviations obtained from the univariate volatility models and R_t is the time-varying conditional correlation matrix.

The DCC dynamics are specified as

$$Q_t = (1 - a - b)\bar{Q} + az_{t-1}z'_{t-1} + bQ_{t-1},$$

Where Q_t is the time-varying quasi-correlation matrix, $\bar{Q}$ is the unconditional correlation matrix of the standardized residuals, and z_t denotes the vector of standardized residuals. The parameter a measures the short-run response of conditional correlation to new information, while b measures the persistence of the conditional correlation process.

The DCC analysis complements the copula analysis by distinguishing between average dependence and time-varying co-movement. Thus, even where the residual dependence is weak on average, DCC-GARCH can identify whether the conditional relationship becomes stronger or weaker during particular periods. This distinction is particularly relevant for assessing diversification characteristics across the three Treasury Bill maturities.

RESULTS

Descriptive and Preliminary Results

Series	Mean	SD	Skewness	Kurtosis
MMF	0.0081	0.001877	1.0226	3.9490
TB91	0.0072	0.002149	1.8205	5.7247
TB182	0.0080	0.002082	1.4276	4.8780
TB364	0.0086	0.001860	1.4942	5.2804

All four series recorded positive average monthly returns. The distributions were positively skewed and had kurtosis above three, indicating departures from normality and relatively heavy tails. The Jarque–Bera test rejected normality for every series at the 1% level. These findings support the use of Student-t innovations in the volatility models.

Series	ADF p	PP p	KPSS p
MMF	0.4755	0.0633	0.1000
TB91	0.5002	0.4452	0.0535
TB182	0.4608	0.5219	0.1000
TB364	0.4757	0.5094	0.1000

The stationarity tests produced mixed evidence. The ADF and Phillips–Perron tests did not reject the unit-root null at the 5% level, whereas the KPSS results did not reject the stationarity null. Given this mixed evidence, the stationarity findings are interpreted cautiously and alongside the observed distributional and volatility diagnostics rather than relying on a single test in isolation.

Series	ARCH-LM χ^2	p-value
MMF	120.76	$<2.2 \times 10^{-16}$
TB91	109.92	$<2.2 \times 10^{-16}$
TB182	113.49	$<2.2 \times 10^{-16}$
TB364	114.15	$<2.2 \times 10^{-16}$

The ARCH-LM results strongly reject constant conditional variance for all four series. This provides direct empirical support for modelling volatility as time-varying rather than treating the return variance as fixed.

Selection and Interpretation of Volatility Models

Series	sGARCH AIC	EGARCH AIC	GJR-GARCH AIC
MMF	-11.8469	-11.8750	-11.8209
TB91	-13.5682	-13.6091	-12.6937
TB182	-13.3046	-13.3174	-12.6696
TB364	-13.1495	-13.9403	-13.0037

EGARCH produced the lowest AIC for every series. The result indicates that allowing the conditional variance to respond asymmetrically provides a better statistical representation of the observed return dynamics than the symmetric benchmark or GJR-GARCH alternatives. The finding is particularly relevant for financial instruments that may respond differently to shocks of different signs.

Series	Key volatility result	Asymmetry
MMF	$\beta=0.6668, p<0.001$	$\gamma=0.8486, p=0.0012$; significant
TB91	$\beta=0.8501, p<0.001$	$\gamma=1.7916, p=0.0118$; significant
TB182	$\beta=0.7804, p<0.001$	$\gamma=1.5573, p=0.1568$; not significant
TB364	$\beta=0.6935, p<0.001$	$\gamma=2.7914, p=0.0060$; significant

Volatility persistence was statistically significant across all four series, as indicated by the significant β parameters ($p<0.001$). The asymmetry parameter was statistically significant for the MMF, TB91 and TB364 series, but not for TB182. This indicates that the volatility responses to shocks of different signs were statistically different for the MMF, TB91 and TB364 series, whereas no statistically significant asymmetric response was detected for TB182. Thus, the evidence supports asymmetric volatility for three of the four series rather than suggesting that asymmetry is a universal feature across all maturities. The TB182 result further demonstrates that the inclusion of an asymmetric volatility specification does not, by itself, imply the presence of statistically significant asymmetry in every series.

The Student-t shape parameters were statistically significant across the fitted models, consistent with the heavy-tailed behavior identified in the preliminary analysis. Post-estimation diagnostics showed no remaining ARCH effects: the ARCH-LM p-values were 0.9624, 0.9787, 0.8908 and 0.8463 for MMF, TB91, TB182 and TB364, respectively. Squared-residual Ljung–Box tests were also insignificant. Some residual serial dependence remained in the MMF and TB182 mean equations, but this did not translate into remaining conditional heteroskedasticity.

Residual Dependence: Copula Results

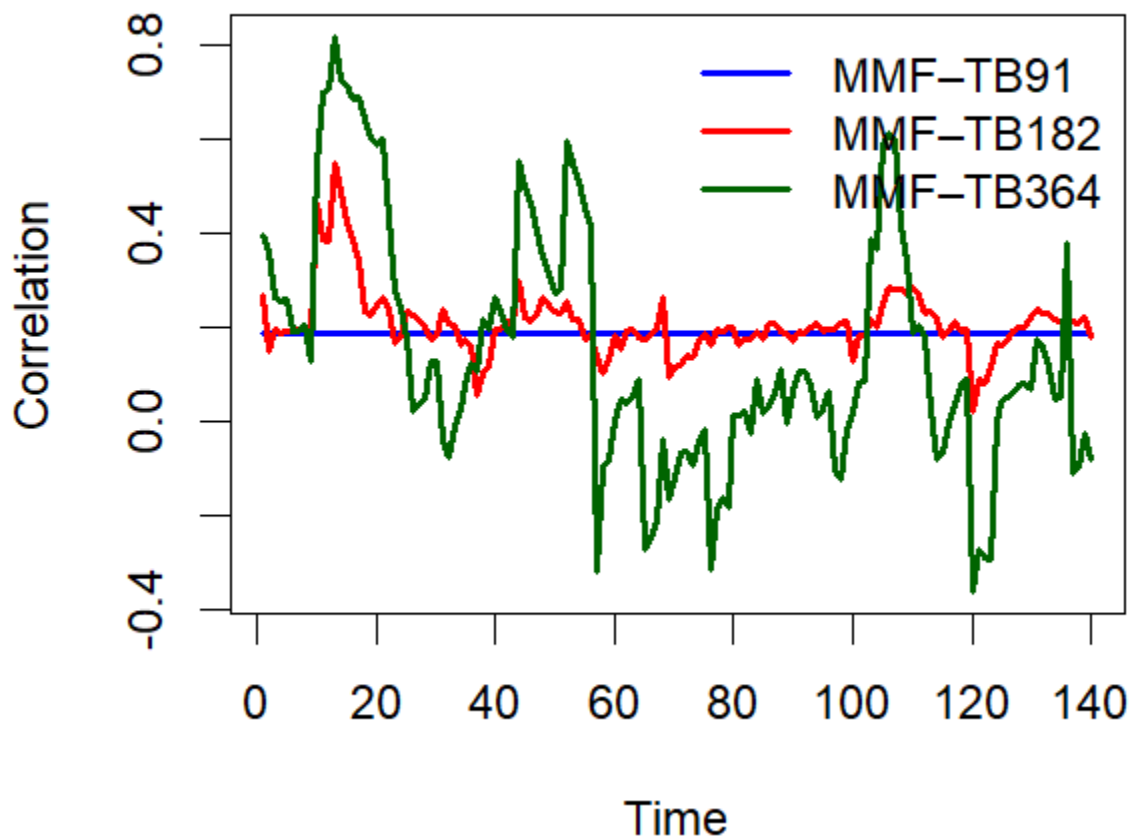
After the marginal EGARCH models were fitted, standardized residuals were transformed through the PIT and used for dependence analysis. The final interpretation of the copula stage indicates that the independence copula provides the preferred representation of residual dependence. Kendall's tau was approximately 0.072, indicating only weak positive rank dependence after the marginal mean and volatility dynamics had been removed. There was no evidence of meaningful lower- or upper-tail dependence in the filtered series.

This result is substantively important. The MMF and Treasury Bill series can display apparent co-movement at the raw-return level without implying strong residual dependence. Once each series is allowed to have its own conditional mean and volatility process, the remaining association is small. The evidence therefore points to a relationship in which much of the observed co-movement can be explained by the individual dynamics of the instruments rather than by a strong common dependence structure.

Dynamic Conditional Correlation

Pair	dcc a1	dcc b1	AIC
MMF–TB91	0.000	0.905	-23.968
MMF–TB182	0.058	0.692	-24.478
MMF–TB364	0.188	0.747	-24.675

Dynamic Correlation between MMF and Treas



The results reveal clear differences in the dynamics of conditional dependence across Treasury Bill maturities. For the MMF-TB91 pair, the short-run adjustment coefficient is essentially zero ($\alpha_1=0.000$), while the persistence coefficient is relatively high ($\beta_1=0.905$). This indicates that although the conditional correlation is highly persistent once established, it shows virtually no immediate response to new information in the DCC process. The MMF-TB182 pair exhibits a moderate short-run adjustment ($\alpha_1=0.058$) and lower persistence ($\beta_1=0.692$), suggesting a more gradual evolution of conditional dependence.

The most notable result is observed for the MMF-TB364 pair. It has the largest short-run adjustment coefficient among the three maturities ($\alpha_1=0.188$), together with substantial persistence ($\beta_1=0.747$). This indicates that the conditional relationship between MMFs and 364-day Treasury Bills responds more strongly to new information while still retaining considerable dependence on its previous state. The increasingly larger α_1 values across TB91, TB182 and TB364 therefore indicate that the responsiveness of MMF-Treasury Bill dependence is not uniform across maturities.

These findings are important because they demonstrate that the dependence structure cannot be adequately characterized by a single unconditional or static correlation measure. Even where average residual dependence is weak, the conditional relationship can evolve over time and respond differently to market information. In particular, the 364-day Treasury Bill exhibits the greatest short-run sensitivity of conditional dependence to new information, whereas the 91-day Treasury Bill exhibits almost no short-run DCC adjustment.

The DCC results therefore provide a maturity-specific dimension to the dependence structure between MMFs and government securities. Rather than treating Treasury Bills as a homogeneous asset class, the analysis shows that the dynamics of their relationship with MMFs differ according to maturity. This is a key contribution of the study because it identifies not only whether dependence exists, but also how the dependence adjusts over time across different maturities. The finding is particularly relevant for investors and portfolio managers because the diversification and risk-transmission characteristics of MMFs may vary depending on the maturity of the government security considered.

Taken together with the copula results, the evidence suggests that weak average residual dependence should not be interpreted as evidence of a completely stable relationship. The copula analysis characterizes the overall dependence structure after filtering the individual series for their own dynamics, while the DCC-GARCH analysis demonstrates that the remaining conditional relationship varies over time and exhibits different adjustment behavior across maturities. The combination of these approaches therefore provides a more complete representation of MMF-Treasury Bill dependence than a static correlation analysis alone.

Discussion

The results provide three connected insights. First, the four-return series have materially different distributional features from a normal, constant-variance process. Positive skewness, excess kurtosis and strong ARCH effects indicate that volatility modelling is necessary. The superior AIC performance of EGARCH across all four series further suggests that a flexible volatility specification is useful for these Kenyan short-term instruments.

Second, asymmetric volatility is not uniform across maturities. Significant asymmetry appears for the MMF, 91-day and 364-day Treasury Bill series, whereas the 182-day Treasury Bill does not show statistically significant evidence of an asymmetric response. This pattern cautions against imposing a common shock-response mechanism on all short-term fixed-income instruments. The maturity-specific result is one of the useful empirical features of the study.

Third, dependence is considerably weaker after the marginal processes are filtered. The independence copula and low Kendall's tau suggest that the apparent relationship between the instruments should not be interpreted as strong residual integration. At the same time, DCC-GARCH demonstrates that dependence is not static. This distinction between weak average dependence and time-varying conditional correlation is central to the interpretation of the study.

For portfolio management, the results imply that MMFs and Treasury Bills may offer diversification opportunities because their residual dependence is weak. However, the diversification benefit should not be treated as constant. The stronger short-run responsiveness of the MMF-TB364 relationship suggests that longer-maturity Treasury Bills may respond differently to changing market information than shorter maturities. Portfolio construction should therefore account for maturity as well as prevailing market conditions.

For risk managers and policymakers, the findings illustrate the value of separating three questions: how volatile each instrument is, how strongly the filtered innovations depend on one another, and whether their conditional correlation changes through time. A single correlation coefficient cannot answer all three questions. The integrated framework used here provides a more informative statistical description of the Kenyan short-term fixed-income market.

Conclusion

This study examined the volatility and dependence dynamics between an anonymized Kenyan Money Market Fund and 91-day, 182-day and 364-day Treasury Bills using an integrated EGARCH–copula–DCC-GARCH framework. Based on 140 matched monthly observations, the analysis found non-normality, heavy tails and strong ARCH effects in all four series. EGARCH was preferred to the competing volatility specifications, and significant asymmetric responses were identified for MMF, TB91 and TB364, while TB182 showed weaker evidence of asymmetry.

After filtering the marginal mean and volatility processes, residual dependence was weak. The independence copula provided the final interpretation, with Kendall's tau of approximately 0.072 and no meaningful tail dependence. The DCC-GARCH analysis nevertheless showed that conditional correlations varied over time. The 364-day Treasury Bill had the largest short-run adjustment coefficient, indicating greater sensitivity of its relationship with MMFs to new information.

The main implication is that MMFs and Treasury Bills should not be treated as either completely independent or permanently integrated. Their residual dependence is weak on average, but their conditional relationship changes over time and differs across maturities. The integrated modelling framework therefore provides a more complete basis for evaluating diversification and risk in Kenya's short-term investment market.

Limitations and Future Research

The study is subject to several limitations. The sample contains 140 matched observations, which restricts the ability to identify very short-lived changes in volatility and dependence. The analysis also covers only MMFs and three Treasury Bill maturities and therefore does not represent the entire Kenyan financial market. In addition, the models do not explicitly incorporate macroeconomic variables such as policy rates, inflation, exchange rates or liquidity conditions, so changes in dependence cannot be attributed to particular economic drivers. Finally, the findings are historical and may change as financial and monetary conditions evolve.

Future studies could use higher-frequency matched data to examine short-run reactions around major economic events. The analysis could also be extended to equities, corporate bonds and longer-term government securities. Time-varying copulas and alternative multivariate volatility models such as BEKK-GARCH and GO-GARCH could provide additional evidence on changing dependence. Incorporating macroeconomic variables would further help explain the economic mechanisms underlying volatility and co-movement.

Declarations

Ethics approval and Consent to Participate

The study used secondary financial data and did not involve human participants or personally identifiable information.

Data Availability

The study used MMF data obtained from an anonymized Money Market Fund and Treasury Bill data from Central Bank of Kenya government securities records. Availability of the underlying proprietary MMF observations is subject to the data provider's permissions.

Conflict of Interest

The author declares no conflict of interest.

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