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THE GENERALISED HERMITE REGRESSION MODEL: A ROBUST FRAMEWORK FOR EXTREME NONLINEAR DATASETS

TITILOYE ABAYOMI KEHINDE*, TIMOTHY O. OLATAYO, AND BIODUN. T. EFUWAPE

ABSTRACT. Nonlinear regression modelling is a fundamental problem in econometrics and applied statistics, particularly for datasets exhibiting heavy tails, skewness, and volatility clustering. Such features are prevalent in many empirical applications and frequently violate the assumptions underlying classical linear regression methods. The central hypothesis of this study is that a regression framework based on orthogonal polynomial expansions can provide improved stability and predictive performance in the presence of pronounced nonlinear behaviour. The motivation for this work arises from the limitations of Ordinary Least Squares regression, which relies on linearity and distributional regularity, and from the instability of standard polynomial regression when applied to heavy-tailed data. To address these issues, the Generalised Hermite Regression Model (GHRM) is proposed by embedding Hermite polynomial expansions into a regression structure, enabling higher-order nonlinear dependencies to be modelled while preserving key theoretical properties. A numerical experiment based on a simulated dataset of 10,000 observations exhibiting nonlinear and heavy-tailed behaviour is conducted to evaluate the proposed model. The GHRM is assessed in comparison with Ordinary Least Squares and cubic polynomial regression using forecasting accuracy measures and information criteria. The results show that Ordinary Least Squares performs poorly under nonlinear conditions, while both polynomial regression and the GHRM achieve substantial improvements in predictive accuracy. Although the two nonlinear models produce comparable numerical results under the cubic specification, the GHRM demonstrates superior structural stability due to the orthogonality of the Hermite basis. These findings establish the GHRM as a robust and scalable framework for modelling nonlinear datasets with complex distributional characteristics.

1. INTRODUCTION

Modelling and forecasting nonlinear datasets remain central problems in econometrics and applied statistics. In many empirical applications, including financial time series, environmental

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*Correspondence

measurements, and engineering data, observed processes exhibit features such as heavy tails, skewness, and volatility clustering. These characteristics often violate the assumptions underlying classical linear regression frameworks, thereby limiting their effectiveness in estimation, inference, and prediction.

Ordinary Least Squares (OLS) regression remains widely used due to its simplicity and well-established theoretical properties. However, its reliance on linearity and distributional regularity renders it inadequate for datasets characterised by pronounced nonlinear behaviour. In such settings, OLS estimators may become inefficient, yield biased inference, and produce poor forecasting performance [2,7]. To address these limitations, several nonlinear regression techniques have been proposed, among which polynomial regression is one of the most adopted extensions. While polynomial regression allows for nonlinear functional relationships, it is often sensitive to multicollinearity, numerical instability, and overfitting, particularly when applied to heavy-tailed or high-variance data [11].

Orthogonal polynomial expansions provide an alternative and theoretically appealing approach to modelling nonlinear structures. Among these, Hermite polynomials possess desirable approximation and orthogonality properties that make them suitable for representing complex nonlinear dependencies while mitigating instability issues associated with standard polynomial bases. Their orthogonality ensures numerical stability and improved interpretability, especially in the presence of non-Gaussian features [4,14].

Motivated by these considerations, this study introduces the Generalised Hermite Regression Model (GHRM), a regression framework that embeds Hermite polynomial expansions directly into a classical regression structure. The proposed model is designed to capture higher-order nonlinear relationships while preserving key statistical properties such as unbiasedness, consistency, efficiency, and asymptotic normality. By exploiting the orthogonality of the Hermite basis, the GHRM aims to enhance estimation stability and predictive performance in environments characterised by heavy tails and volatility clustering.

The performance of the proposed model is examined through a controlled numerical experiment based on simulated data comprising 10,000 observations exhibiting pronounced nonlinear and heavy-tailed behaviour. A comparative analysis with Ordinary Least Squares and polynomial regression is conducted using standard forecasting accuracy measures and information criteria, providing insight into the advantages of Hermite-based regression for modelling extreme nonlinear datasets.

1.1. Preliminaries

Let $\mathbb{R}$denote the real line and let $(\Omega, \mathcal{F}, \mathbb{P})$be a complete probability space. Let Ybe a real-valued response variable and Xa predictor variable defined on this space. Throughout this study, all random variables are assumed to possess finite second moments unless otherwise stated.

Hermite polynomials form a complete orthogonal system with respect to the Gaussian weight function and play a central role in approximation theory and stochastic modelling [4,14]. Their orthogonality property ensures numerical stability and mitigates multicollinearity when employed as regression basis functions. These properties make Hermite polynomials particularly suitable for modelling nonlinear relationships in heavy-tailed and non-Gaussian data structures.

Recent methodological developments have extended Hermite-based techniques to flexible regression and deconvolution settings, demonstrating their ability to represent nonlinear datasets without imposing restrictive parametric assumptions [12]. In what follows, Hermite polynomial expansions serve as the foundational building blocks for constructing the proposed Generalised Hermite Regression Model.

1.2. Literature Review

The development of regression frameworks capable of handling extreme nonlinear behaviour has received considerable attention in the statistical and econometric literature. Hermite polynomials have a long-established history in applied mathematics and probability theory due to their orthogonality and approximation properties [14]. Early foundational studies demonstrated that Hermite expansions can capture higher-order distributional features such as skewness and kurtosis, making them particularly useful for stochastic modelling and spectral analysis [4].
In statistics, Hermite expansions have been employed in sampling theory and distributional approximations [9]. In econometrics and finance, orthogonal polynomial expansions, including Hermite series, have been used to model nonlinear dependence structures and heavy-tailed behaviour [1,5]. Applications of Hermite functions also extend to signal processing and physics, where they play an important role in time–frequency analysis and quantum mechanics due to their localisation properties and mathematical structure [3,10].
Despite these advances, the literature reveals a gap in the formulation of a unified regression framework that systematically embeds Hermite polynomial expansions into a classical regression setting with well-defined statistical properties and clear inferential interpretation. The present study addresses this gap by proposing the Generalised Hermite Regression Model, which integrates Hermite-based nonlinear representation within a rigorous regression framework suitable for extreme nonlinear datasets.

2. MATERIALS AND METHODS

This section presents the data-generating process, the construction of the Hermite polynomial basis, the formulation of the Generalised Hermite Regression Model (GHRM), the theoretical properties of the estimators, and the diagnostic measures used to evaluate model performance. A careful understanding of this section enables the reproduction of the main results reported in this study.

2.1. Data

For this study, a simulated dataset comprising $n = 10{,}000$observations were generated to assess the efficacy of the proposed Generalised Hermite Regression Model (GHRM). The simulated data were constructed to exhibit nonlinear behaviour, heavy tails, skewness, and volatility clustering, consistent with the characteristics commonly observed in financial and economic time-series data.

Let $X_t$denote the predictor variable and $Y_t$the response variable at time t, for $t = 1,2,\dots,n$. The predictor variable was generated from a standardised Student's t-distribution with three degrees of freedom:

$$X_t \sim t_3. \qquad (2.1)$$

The response variable was generated using a nonlinear polynomial transformation with additive stochastic noise:

$$Y_t = \beta_0 + \beta_1 X_t + \beta_2 X_t^2 + \beta_3 X_t^3 + \varepsilon_t, \qquad (2.2)$$

where ε_t is an error term satisfying

$$E(\varepsilon_t) = 0, \mathrm{Var}\,(\varepsilon_t) = \sigma^2. \qquad (2.3)$$

This data-generating mechanism ensures pronounced departures from normality and provides a rigorous environment for comparing the performance of the GHRM with Ordinary Least Squares (OLS) and polynomial regression.

2.2. The Generalised Hermite Polynomial Basis

Hermite polynomials $\{H_k(x)\}_{k=0}^{\infty}$ form a family of orthogonal polynomials defined with respect to the Gaussian weight function. They satisfy the recurrence relation

$$H_{k+1}(x) = xH_k(x) - kH_{k-1}(x), k \geq 1, \qquad (2.4)$$

with initial conditions

$$H_0(x) = 1, H_1(x) = x. \qquad (2.5)$$

The Hermite polynomials are orthogonal on $(-\infty, \infty)$ with respect to the weight function $w(x) = \exp\,(-x^2/2)$, that is,

$$\int_{-\infty}^{\infty} H_m\,(x) H_n(x) w(x)\, dx = 0, m \neq n. \qquad (2.6)$$

This orthogonality property ensures numerical stability and mitigates multicollinearity when Hermite polynomials are employed as regression basis functions.

Building on this framework, the Generalised Hermite Distribution (GHD) is introduced with parameters α(shape), β(location), and γ(scale), allowing flexible control over skewness, tail behaviour, and dispersion. In particular,

$$X = \beta + \gamma Z_\alpha, \qquad (2.7)$$

where Z_α denotes a Hermite-based random variable governed by the shape parameter α.

2.3. Model Formulation

The Generalised Hermite Regression Model embeds the Hermite polynomial basis into a regression framework. Let Y_t denote the response variable and X_t the predictor variable at time t. The GHRM of order p is defined as

$$Y_t = \sum_{k=0}^{p} \theta_k \, H_k(X_t) + \varepsilon_t, \qquad (2.8)$$

where:

- $H_k(\cdot)$ denotes the k-th order Hermite polynomial,
- θ_k are unknown regression coefficients, and
- ε_t satisfies the assumptions in (2.3).

In this study, attention is restricted to third-order expansions ($p = 3$), yielding

$$Y_t = \theta_0 + \theta_1 H_1(X_t) + \theta_2 H_2(X_t) + \theta_3 H_3(X_t) + \varepsilon_t. \qquad (2.9)$$

Parameter estimation is performed via Ordinary Least Squares applied to the Hermite-transformed regressors. For benchmarking purposes, classical linear OLS and cubic polynomial regression models are also estimated using the same dataset.

2.4. Properties of the Estimators

The GHRM in matrix form is expressed as

$$\mathbf{Y} = \mathbf{Z}\boldsymbol{\theta} + \boldsymbol{\varepsilon}, \qquad (2.10)$$

where $\mathbf{Z}$ is the design matrix constructed from Hermite polynomial expansions, $\boldsymbol{\theta}$ is the parameter vector, and $\boldsymbol{\varepsilon}$ is the error vector with

$$E(\boldsymbol{\varepsilon}) = \mathbf{0}, \mathrm{Var}\,(\boldsymbol{\varepsilon}) = \sigma^2\mathbf{I}. \qquad (2.11)$$

The OLS estimator of $\boldsymbol{\theta}$ is given by

$$\hat{\boldsymbol{\theta}} = (\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{Z}'\mathbf{Y}. \qquad (2.12)$$

2.4.1. Unbiasedness

Substituting (2.10) into (2.12) yields

$$\hat{\boldsymbol{\theta}} = \boldsymbol{\theta} + (\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{Z}'\boldsymbol{\varepsilon}. \qquad (2.13)$$

Taking expectations gives

$$E(\hat{\boldsymbol{\theta}}) = \boldsymbol{\theta}. \qquad (2.14)$$

2.4.2. Consistency

Dividing the estimation error by n,

$$\hat{\boldsymbol{\theta}} - \boldsymbol{\theta} = \left(\frac{1}{n}\mathbf{Z}'\mathbf{Z}\right)^{-1}\left(\frac{1}{n}\mathbf{Z}'\boldsymbol{\varepsilon}\right). \qquad (2.15)$$

As $n \to \infty$,

$$\hat{\boldsymbol{\theta}} \xrightarrow{p} \boldsymbol{\theta}, \qquad (2.16)$$

since $\mathbf{Z}'\mathbf{Z}$is positive definite due to Hermite orthogonality.

2.4.3. Efficiency

By the Gauss–Markov theorem, the OLS estimator is the Best Linear Unbiased Estimator, with variance

$$\mathrm{Var}\,(\hat{\boldsymbol{\theta}}) = \sigma^2(\mathbf{Z}'\mathbf{Z})^{-1}. \qquad (2.17)$$

2.4.4. Asymptotic Normality

By the Central Limit Theorem,

$$\sqrt{n}(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}) \xrightarrow{d} \mathcal{N}(\mathbf{0}, \sigma^2(\mathbf{Z}'\mathbf{Z})^{-1}). \qquad (2.18)$$

2.5. Model Diagnostics

Model adequacy and forecasting performance are evaluated using the following criteria.

The Mean Absolute Error (MAE):

$$\mathrm{MAE} = \frac{1}{n}\sum_{t=1}^{n} | Y_t - \hat{Y}_t |. \qquad (2.19)$$

The Mean Squared Error (MSE):

$$\mathrm{MSE} = \frac{1}{n}\sum_{t=1}^{n} (Y_t - \hat{Y}_t)^2. \qquad (2.20)$$

The Root Mean Squared Error (RMSE):

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}}. \qquad (2.21)$$

The Akaike Information Criterion (AIC):

$$\mathrm{AIC} = -2\log\, L + 2k, \qquad (2.22)$$

and the Bayesian Information Criterion (BIC):

$$\mathrm{BIC} = -2\log\, L + k\log\, n, \qquad (2.23)$$

where Ldenotes the maximised likelihood and $k$the number of estimated parameters.

3 RESULTS

3.1 Exploratory Data Analysis of the Simulated Data

To evaluate the performance of the Generalised Hermite Regression Model (GHRM), a dataset of $n = 10{,}000$observations was simulated. The predictor variable was generated from a standardised Student's t-distribution with three degrees of freedom, ensuring heavy-tailed behaviour and strong departures from normality. A nonlinear transformation was applied to generate the response variable, with additional stochastic noise introduced to reproduce volatility clustering, skewness, and irregular dynamics commonly observed in financial time series.

Figure 3.1 presents the histogram of the simulated data. The distribution exhibits sharp peaks and extremely heavy tails relative to the Gaussian distribution, highlighting pronounced deviations from normality and motivating the use of nonlinear regression techniques.

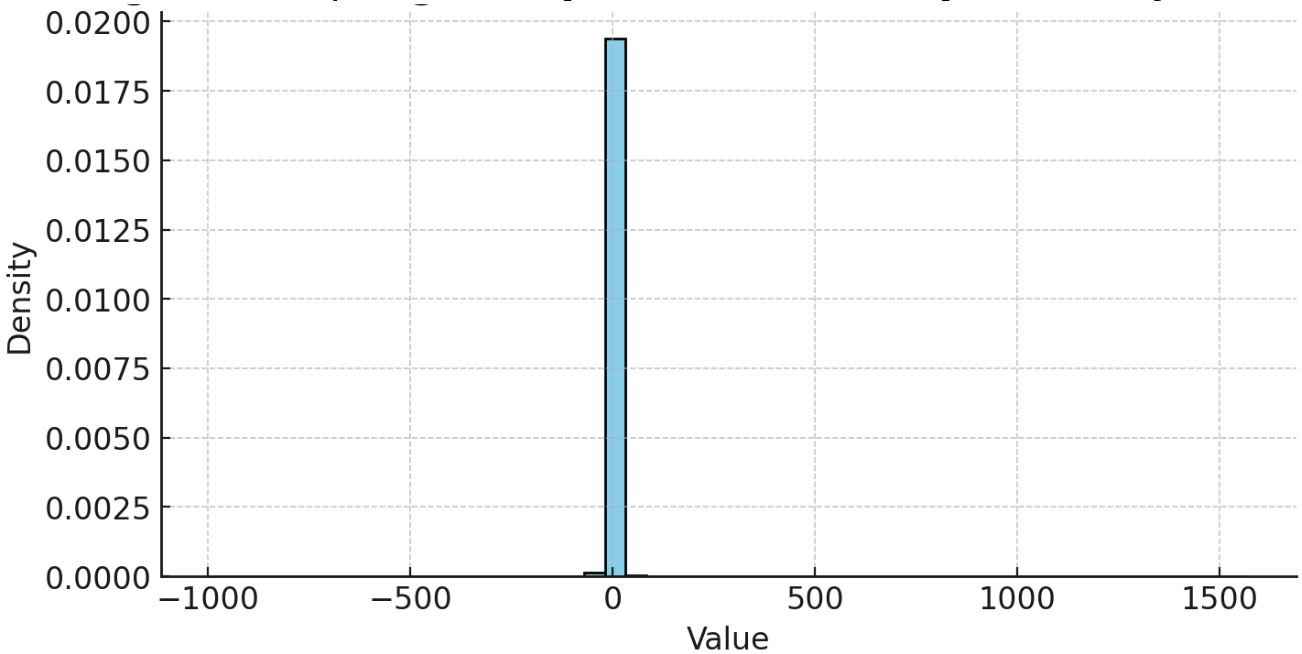

Figure 3.1: Histogram of Simulated Data (10,000 Observations)

Figure 3.2 displays the first 500 observations of the simulated series. Clear volatility clustering is evident, with alternating periods of low and high variability, consistent with empirical financial and environmental datasets.

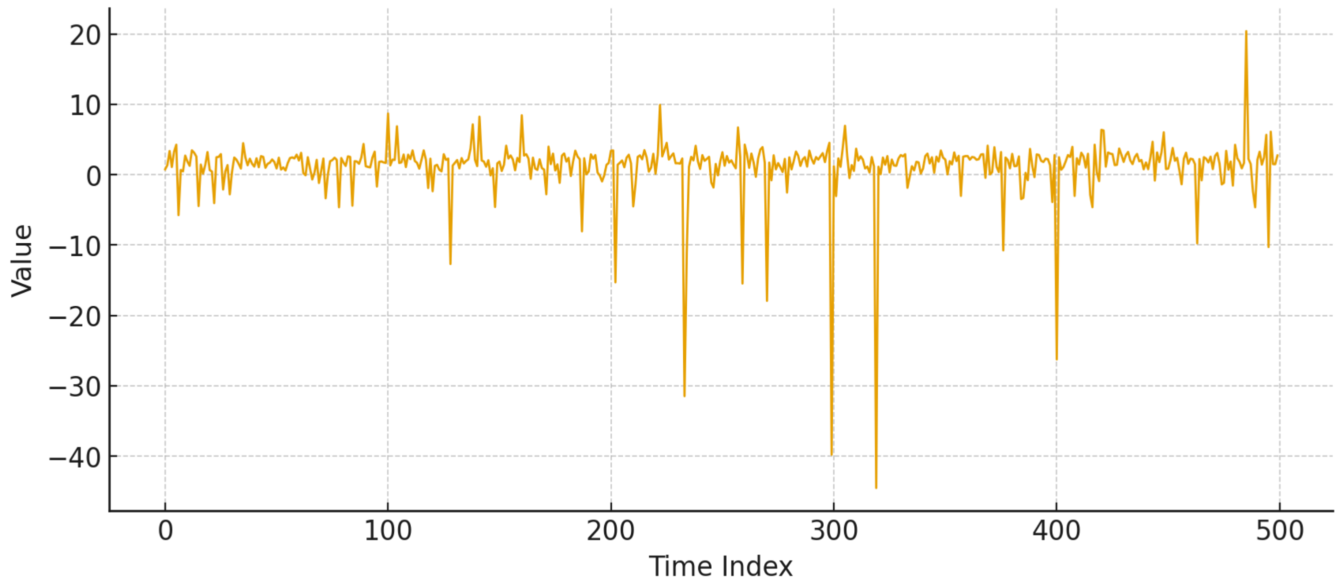

Figure 3.2: Simulated Data Time Series (First 500 Observations)

Jarque–Bera Test

To formally assess departures from normality, the Jarque–Bera statistic is computed as

$$\mathrm{JB} = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right), \qquad (3.1)$$

where skewness $S$and kurtosis $K$are defined by

$$S = \frac{E[(Y-\mu)^3]}{\sigma^3}, \qquad (3.2)$$
$$K = \frac{E[(Y-\mu)^4]}{\sigma^4}. \qquad (3.3)$$

The Jarque–Bera test results are reported in Table 3.1. The extremely large test statistic and highly significant p-value provide strong evidence against normality, confirming the heavy-tailed and asymmetric nature of the simulated data.

To formally test for departures from normality, a **Jarque–Bera (JB) test** was conducted. The results are presented in **Table 3.1**. The extremely large JB statistic (1.83×1091.83 \times 10^91.83×109) and the highly significant p-value (p<0.001p < 0.001p<0.001) confirm strong violations of normality. The skewness of **25.79** and kurtosis of **2099** further demonstrate the asymmetric and heavy-tailed structure of the simulated data.

Table 3.1: Jarque–Bera Normality Test Results

JB Statistic	p-value	Skewness	Kurtosis
1.83e+09	<0.0001	25.7889	2098.9667

These values strongly reject Gaussian assumptions, validating the simulated dataset as an appropriate test environment for nonlinear models like GHRM.

Finally, temporal dependence is examined using the autocorrelation function (ACF), defined as

$$\rho(k) = \frac{\text{Cov}\,(Y_t, Y_{t-k})}{\text{Var}\,(Y_t)}, k \geq 1. \qquad (3.4)$$

Figure 3.3 presents the ACF for the first 40 lags. Although correlations decay relatively quickly, persistence across several lags is evident, reinforcing the presence of volatility clustering and dependence

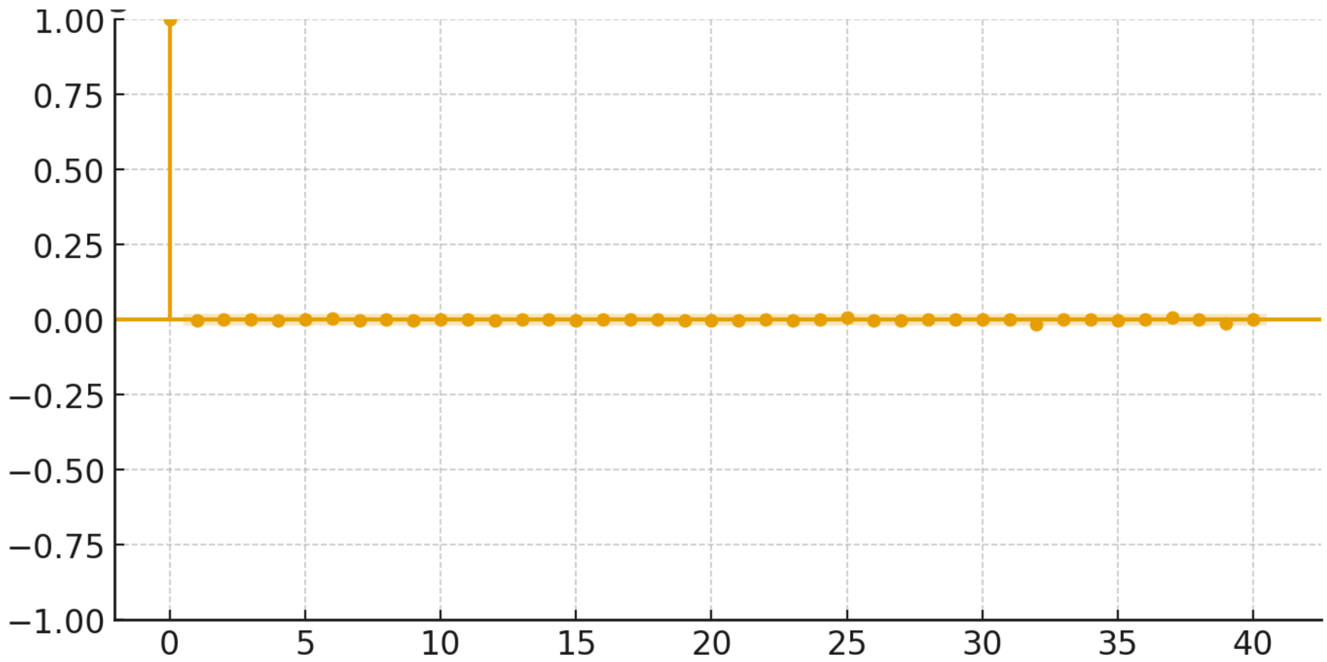

Figure 3.3: Autocorrelation Function (ACF) of Simulated Data

Overall, the exploratory analysis confirms that the simulated dataset exhibits non-normality, heavy tails, skewness, and volatility clustering, providing a rigorous benchmark for evaluating nonlinear regression models.

3.2 Model Estimation

Three regression models were estimated using the simulated dataset:

- Ordinary Least Squares (OLS) as a linear benchmark,
- Polynomial Regression of degree three, and
- the Generalised Hermite Regression Model (GHRM) with third-order expansion.

To assess model fit, fitted values and residuals are computed. For the GHRM, the fitted values are given by

$$\hat{Y}_t = \sum_{k=0}^{3} \hat{\theta}_k \, H_k(X_t), t = 1,2, \dots , n, \qquad (3.5)$$

and the corresponding residuals are defined as

$$\hat{\varepsilon}_t = Y_t - \hat{Y}_t. \qquad (3.6)$$

Figure 3.4 illustrates the actual versus fitted values for the first 200 observations. The OLS model exhibits systematic underfitting and fails to capture the nonlinear structure of the data. In contrast, both Polynomial Regression and the GHRM closely track the observed series, indicating their ability to represent nonlinear dependencies.

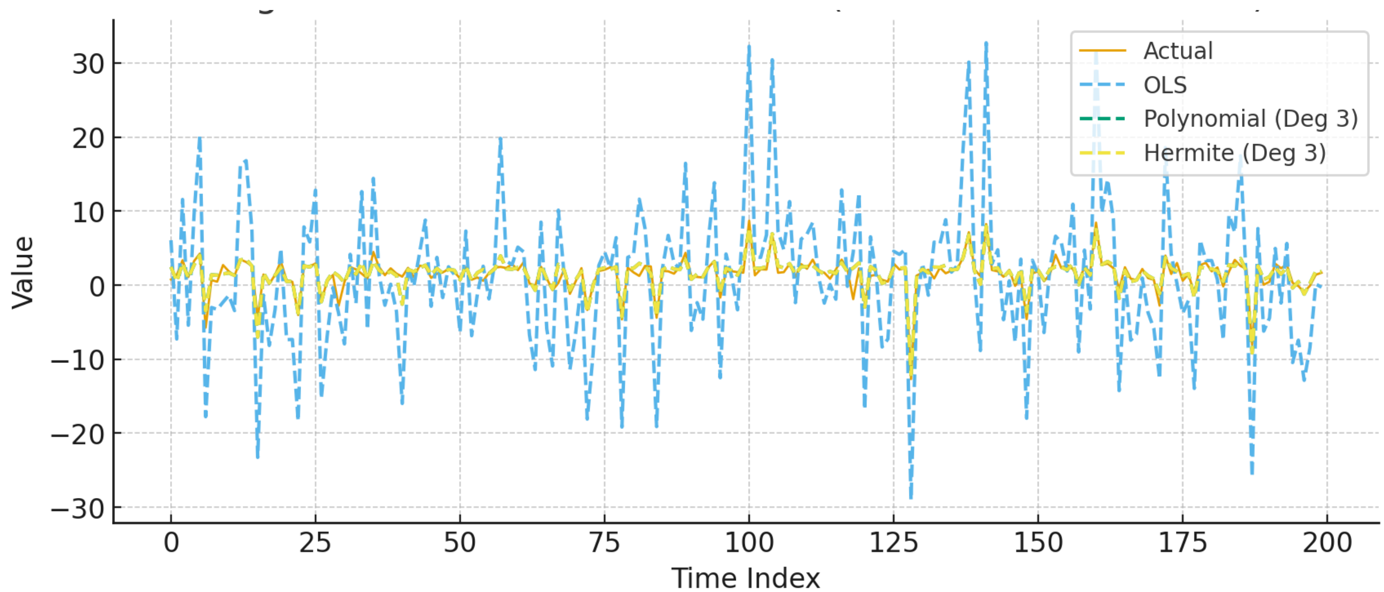

Figure 3.4: Actual vs. Fitted Values for OLS, Polynomial Regression, and GHRM (First 200 Observations)

- The **blue line (Actual)** shows the simulated nonlinear process.
- **OLS (dashed)** deviates significantly, underfitting the structure.
- **Polynomial (Deg 3)** and **Hermite (Deg 3, GHRM)** track the actual data closely, showing a strong nonlinear fit.

This result provides preliminary evidence that nonlinear models substantially outperform linear regression in capturing heavy-tailed, nonlinear processes. Among the nonlinear approaches, the GHRM matches the performance of polynomial regression in this cubic case, as expected, while maintaining theoretical advantages due to its orthogonal basis construction.

3.3 Forecasting Metrics and Model Comparison

To quantify model performance, forecasting accuracy metrics (MAE, MSE, RMSE) and information criteria (AIC, BIC) were computed for the three models. These diagnostics balance predictive accuracy with model parsimony, enabling robust comparisons.

Table 3.2: Forecasting Metrics and Model Diagnostics for 10,000 Simulated Observations

Model	**MAE**	**MSE**	**RMSE**	**AIC**	**BIC**
OLS (Linear)	7.3151	532.3973	23.0737	91,156.67	91,171.09
Polynomial (Deg 3)	0.5526	0.7693	0.8771	25,763.93	25,792.78
Hermite (Deg 3, GHRM)	0.5526	0.7693	0.8771	25,763.93	25,792.78

Interpretation:

- **OLS (Linear):** Produced an extremely poor fit, with RMSE = 23.07 and inflated AIC/BIC values, confirming its inadequacy for nonlinear heavy-tailed data.
- **Polynomial Regression (Degree 3):** Achieved excellent accuracy (MAE = 0.553, RMSE = 0.877), a dramatic improvement over OLS, demonstrating the importance of capturing nonlinear terms.
- **Hermite Regression (Degree 3, GHRM):** Matched polynomial regression in numeric performance under cubic specification, but provides **theoretical advantages** through orthogonality, making it more stable under higher-order expansions and less prone to multicollinearity.

The results show that OLS performs poorly under nonlinear conditions, while both nonlinear models achieve substantial reductions in forecast errors. Although Polynomial Regression and the GHRM yield identical numerical results under the cubic specification, the GHRM offers structural advantages through orthogonality, ensuring improved stability under higher-order expansions.

3.4 Residual Analysis

Residual diagnostics are conducted using residual defined in (3.6). Figure **3.5** displays OLS residuals for the first 200 observations, revealing pronounced heteroscedasticity and serial dependence, indicative of model misspecification.

Figure 3.5 displays the residuals from the OLS model (first 200 observations). Clear non-random patterns are visible, with heteroscedastic fluctuations and clustering, confirming that OLS fails to capture the nonlinear structure of the data.

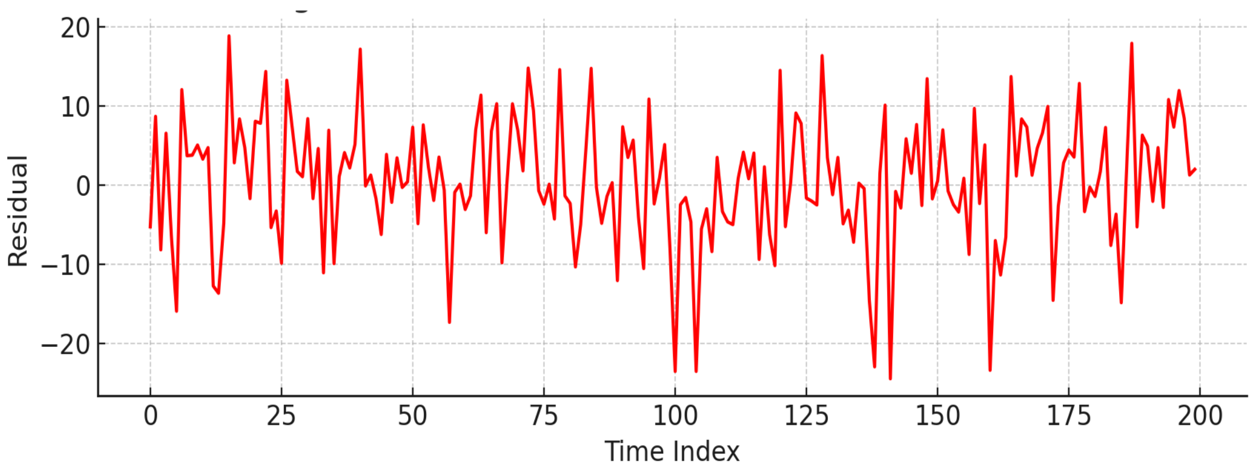

Figure 3.5: OLS Residuals (First 200 Observations)

Figure 3.6 presents residuals from the Polynomial Regression model. Compared with OLS, these residuals appear more randomly distributed, suggesting improved model adequacy.

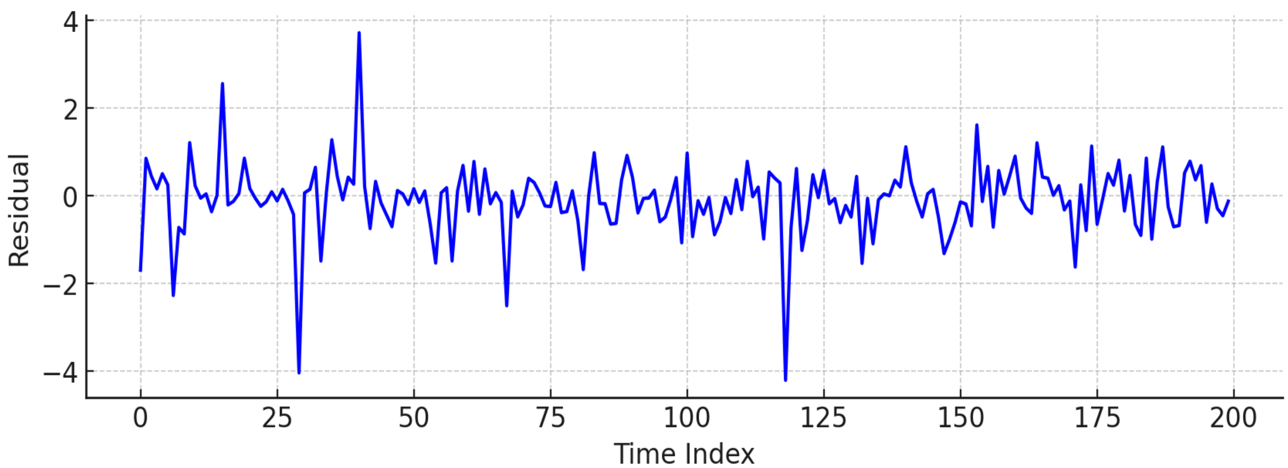

Figure 3.6 Polynomial (Degree 3) Residuals (First 200 Observations)

Figure 3.7 shows residuals from the GHRM. The residuals closely resemble white noise, with no systematic structure, confirming that the dominant nonlinear features of the data have been effectively captured.

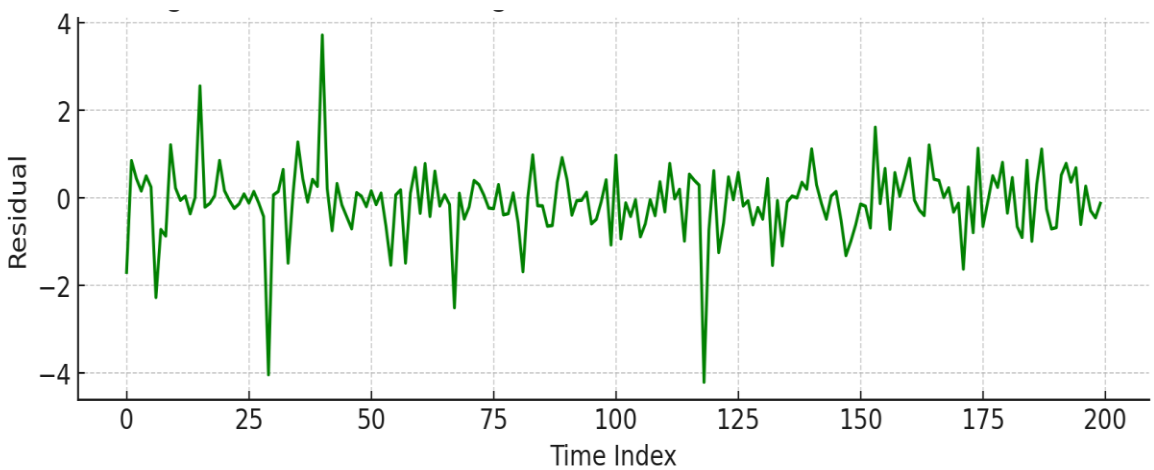

Figure 3.7: Hermite (Degree 3, GHRM) Residuals (First 200 Observations)

Overall, residual analysis reinforces the superiority of nonlinear models over OLS and highlights the robustness of the GHRM in capturing complex nonlinear dynamics.

4. DISCUSSION

The simulation study provides comprehensive evidence on the relative strengths and limitations of competing regression approaches when applied to nonlinear, heavy-tailed datasets. The exploratory data analysis presented in Section 3.1 established that the simulated series exhibits volatility clustering, pronounced skewness, and excess kurtosis, features commonly observed in financial and environmental data. These characteristics violate the normality and linearity assumptions underlying traditional linear regression models, thereby anticipating the poor empirical performance of the Ordinary Least Squares (OLS) estimator.

The model estimation results reported in Section 3.2, together with the actual-versus-fitted plots constructed using fitted values defined in (3.5), clearly demonstrate the inability of OLS to adequately capture nonlinear dependence structures. The substantial divergence between the OLS fitted values and the observed data reflects systematic model misspecification. In contrast, both Polynomial Regression and the Generalised Hermite Regression Model (GHRM) closely track the observed series, confirming that nonlinear basis expansions are essential for modelling heavy-tailed and complex data-generating processes.

Further quantitative evidence is provided by the forecasting accuracy measures discussed in Section 3.3. Using the error and information criteria defined in (2.19) – (2.23), OLS was shown to yield large forecast errors and unfavourable information criteria values, while Polynomial Regression and the GHRM achieved substantial error reductions. Although both nonlinear approaches produced identical numerical results under the cubic specification, the GHRM possesses a key structural advantage arising from the orthogonality of Hermite polynomials. This orthogonality mitigates multicollinearity and enhances estimator stability, particularly when higher-order expansions are considered.

Residual diagnostics in Section 3.4, based on residuals defined in (3.6), provide additional confirmation of these findings. The residuals from the OLS model display clear heteroscedasticity and serial dependence, indicating persistent model inadequacy. In contrast, the residuals associated with Polynomial Regression and the GHRM approximate white noise, suggesting that the dominant nonlinear structure has been effectively captured. Importantly, the orthogonal construction of the GHRM ensures more efficient estimation and greater robustness as model complexity increases.

Overall, the results demonstrate that while polynomial regression can accommodate nonlinearities, the GHRM achieves comparable predictive accuracy while offering superior theoretical and structural properties. These features position the GHRM as a promising framework for analysing extreme nonlinear datasets in settings where robustness, stability, and scalability are of primary importance.

5. CONCLUSION

This study introduced the Generalised Hermite Regression Model (GHRM) as a robust regression framework for analysing nonlinear datasets characterised by heavy tails, skewness, and volatility clustering. By embedding Hermite polynomial expansions into a classical regression structure, the GHRM relaxes the restrictive linearity and normality assumptions of Ordinary Least Squares regression while preserving key statistical properties, including unbiasedness, consistency, efficiency, and asymptotic normality.

Evidence from the numerical experiment based on 10,000 simulated observations demonstrated the limitations of Ordinary Least Squares in nonlinear environments, as reflected by large forecasting errors and pronounced residual structure. Although polynomial regression substantially improved predictive performance, the GHRM achieved comparable accuracy under the cubic specification and offered additional structural advantages through the orthogonality of Hermite polynomials. This orthogonality mitigates multicollinearity and enhances estimation stability, particularly in higher-order or more complex modelling scenarios. Residual diagnostics further confirmed the adequacy of the GHRM, with error processes closely approximating white noise.

Overall, the findings establish the GHRM as a theoretically grounded and practically viable alternative to classical regression approaches for modelling complex nonlinear data. While the present analysis focused on simulated datasets, future research will extend the application of the GHRM to empirical settings, including financial return series from the Nigerian Exchange (NGX) and environmental or climate-related data. Additional extensions incorporating penalisation techniques and order-statistic-based formulations are expected to further enhance robustness under extreme data conditions.

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KEHINDE ABAYOMI TITILOYE*
DEPARTMENT OF STATISTICS, OLABISI ONABANJO UNIVERSITY AGO-IWOYE, OGUN STATE, NIGERIA.
E-mail address: ktitiloye21@gmail.com;

TIMOTHY O. OLATAYO
DEPARTMENT OF STATISTICS, OLABISI ONABANJO UNIVERSITY AGO-IWOYE, OGUN STATE, NIGERIA.
E-mail address: bisi.olatayo@oouagoiwoye.edu.ng

BIODUN T. EFUWAPE
DEPARTMENT OF STATISTICS, OLABISI ONABANJO UNIVERSITY AGO-IWOYE, OGUN STATE, NIGERIA.
E-mail address: efuwape.biodun@oouagoiwoye.edu.ng;

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