African Journal of Mathematics and Statistics Studies
ISSN: 2689-5323
Volume 9, Issue 2, 2026 (pp. 1-10)
www.abjournals.org

ADDRESSING MULTICOLLINEARITY AND HETEROSCEDASTICITY: A REVIEW OF LINEAR ESTIMATORS AND THEIR POTENTIAL APPLICATION IN SEMs

Okeke Ngozi Christy*, Olanrewaju Samuel Olayemi, and Zubair Mohammed Anono.

Department of Statistics, Faculty of Science, University of Abuja, Abuja, Nigeria.

*Corresponding Author's Email: ngoziokeke674@gmail.com

Cite this article:

Okeke, N. C., Olanrewaju, S. O., Zubair, M. A. (2026), Addressing Multicollinearity and Heteroscedasticity: A Review of Linear Estimators and Their Potential Application in SEMs. African Journal of Mathematics and Statistics Studies 9(2), 1-10. DOI: 10.52589/AJMSS-U4L17Q9N

Manuscript History

Received: 3 Mar 2026

Accepted: 1 Apr 2026

Published: 21 Apr 2026

ABSTRACT: *Simultaneous Equation Models (SEMs) represent an essential category of statistical models where dependent variables are determined not only by independent variables but also by other dependent variables within the system. This characteristic implies that the explanatory variables may be interrelated with the dependent variables, reflecting equilibrium mechanisms commonly found in economic models. For example, in a standard supply and demand model, both the quantity supplied and the quantity demanded are influenced by the market price. However, it is also possible for producers to adjust their prices based on observed consumer demand, illustrating the bidirectional relationships in SEMs. The presence of Multicollinearity and Heteroscedasticity in a model is often problematic during estimation, especially when the system of equations is complex, as is the case of SEM. This paper provides a detailed literature review under the linear regression model on the two assumption violators (Multicollinearity and Heteroscedasticity). Multicollinearity, a situation where explanatory variables in a regression model are highly correlated, remains a fundamental challenge in statistical analysis, particularly when dealing with complex datasets. When multicollinearity occurs, it becomes difficult to isolate the individual effects of predictor variables, often leading to inflated standard errors, unstable parameter estimates, and reduced statistical power. Another significant challenge in estimating linear regression model is the presence of heteroscedasticity, where the variance of the error terms is not constant across observations. Heteroscedasticity violates one of the key assumptions of the OLS method, leading to inefficient and biased estimates of the regression parameters. To address this issue, heteroscedasticity-consistent estimators, such as White's robust standard errors and the Generalized Method of Moments (GMM), have been developed (Pérez-Sánchez et al., 2021). These methods provide more reliable estimates in the presence of heteroscedasticity by accounting for the varying error variances. However, when Multicollinearity and Heteroscedasticity co-exist in the model (whether a linear or simultaneous equation model), estimation is usually very cumbersome.*

KEYWORDS: Simultaneous Equation Models, Multicollinearity, Heteroscedasticity, Elastic-net, GMM.

Article DOI: 10.52589/AJMSS-U4L17Q9N
DOI URL: https://doi.org/10.52589/AJMSS-U4L17Q9N

INTRODUCTION

Regression analysis is a widely used statistical method that aims to model the relationship between a dependent variable, denoted as "y," and a set of explanatory or independent variables, commonly represented as X. This method is fundamental in many areas of research, particularly in economics, social sciences, and natural sciences, where the goal is to understand how changes in one or more explanatory variables affect the outcome variable. The regression model essentially quantifies the strength and nature of these relationships, allowing researchers to make predictions and inferences about the underlying data-generating processes (Tarka, 2017).

The simplest form of regression is the linear regression model, where the dependent variable Y is assumed to be a linear function of one or more explanatory variables X. Mathematically, this can be expressed as:

$$Y_i = \beta_0 + \beta_1 X_i + \epsilon_i \quad (1)$$

where β_0 represents the intercept, β_1 is the slope or coefficient that measures the impact of the explanatory variable X_i on the dependent variable Y_i, and ϵ_i is the error term that captures all other factors affecting Y_i that are not included in the model. However, in many real-world applications, especially in economics and social sciences, the relationships between variables are often more complex and may involve multiple dependent variables that are simultaneously influenced by a common set of explanatory variables. In such cases, a simple linear regression model is insufficient, and more advanced models such as the simultaneous equations model (SEM) are employed. SEM is a generalization of regression analysis that allows for multiple interdependent equations, each representing a different aspect of the system being studied. Consider the equation below,

$$y_1^* = \alpha_1 y_2^* + \beta_1' X_1 + \epsilon_1 \quad (2)$$

$$y_2^* = \alpha_2 y_1^* + \beta_2' X_2 + \epsilon_2 \quad (3)$$

In these equations, y_1^* and y_2^* are the endogenous variables, meaning they are simultaneously determined. A change in y_2^* leads to a change in y_1^*, as seen in equation (2), and vice versa through equation (3). This interdependence creates a situation where each dependent variable is a function of the other, violating the assumption of exogeneity in typical regression models (Billor *et a*l. 2006) Thus, traditional estimation methods such as Ordinary Least Squares (OLS) cannot be applied to models with endogenous variables because the assumption of zero covariance between the disturbance term and independent variables is violated.

The estimation of the parameters in SEMs is more challenging than in standard linear regression models because the dependent variables appear on both sides of the equations, creating a system of interdependent relationships. This simultaneity introduces endogeneity, meaning that the explanatory variables are correlated with the error terms, which violates the assumptions of OLS and leads to biased and inconsistent estimates. To address this issue, specialized estimation techniques such as the Two-Stage Least Squares (2SLS) and Three-Stage Least Squares (3SLS) methods have been developed (Tarka, 2017). These methods provide consistent estimates by using instrumental variables to remove the endogeneity bias.

Article DOI: 10.52589/AJMSS-U4L17Q9N
DOI URL: https://doi.org/10.52589/AJMSS-U4L17Q9N

One of the key challenges in estimating linear regression model is the presence of multicollinearity, where the explanatory variables are highly correlated with each other (Umeh *et al.,*2016). Multicollinearity can lead to inflated standard errors for the estimated coefficients, making it difficult to determine the true impact of each explanatory variable on the dependent variable. Various methods, such as ridge regression and principal component analysis, have been proposed to address multicollinearity in linear regression model, but these methods often involve trade-offs between bias and variance. (Kibria, 2003). In the context of SEM, where there are multiple interdependent relationships between the variables, multicollinearity can significantly affect the accuracy and reliability of the parameter estimates. Heteroscedasticity refers to the presence of non-constant variance in the error terms of a regression model, which violates one of the key assumptions of classical linear regression. The presence of heteroscedasticity can lead to inefficient and biased estimates, resulting in incorrect statistical inferences (White, 1980). In economic and statistical models, particularly those dealing with cross-sectional and time-series data, heteroscedasticity often arises due to the changing scale of variables over time or across observations (Abdul-Hameed *et al*., 2021). This problem is particularly prevalent in large datasets where variability in response variables can differ across subpopulations (Long & Ervin, 2000).

REVIEWS ON MULTICOLLINEARITY

This section provides an overview of these advancements, highlighting the progress made in linear regression modeling and emphasizing the need for similar innovations in the context of simultaneous equation models (SEMs). Numerous authors have contributed significantly to the body of literature surrounding the detection, consequences, and mitigation of multicollinearity across various regression models.

Historically, ridge regression has been one of the earliest and most widely used techniques for addressing multicollinearity in regression models (Hoerl & Kennard, 1970). Ridge regression introduces a biasing constant to reduce the variance of the estimators at the cost of introducing some bias, thereby stabilizing estimates when the independent variables are highly correlated.

Several modified ridge regression approaches have been proposed to improve its performance in various contexts. For example, Kibria (2003) proposed a ridge regression estimator that improves upon the traditional ridge regression technique by incorporating a stochastic shrinkage factor. This modification resulted in better estimation accuracy when applied to multicollinear data.

Recent Developments in Multicollinearity Management

In recent years, researchers have proposed more sophisticated methods to address multicollinearity in regression analysis. Ahmad & Aslam (2021) introduced a two-parameter estimator designed specifically to combat the effects of multicollinearity within linear regression models. Their approach builds on the traditional ridge regression method by introducing an additional parameter that enhances the flexibility and adaptability of the estimator in the presence of multicollinear data. This two-parameter estimator has demonstrated improved performance compared to classical techniques such as ordinary least squares (OLS) and traditional ridge regression in simulation studies.

Article DOI: 10.52589/AJMSS-U4L17Q9N
DOI URL: https://doi.org/10.52589/AJMSS-U4L17Q9N

Building on this foundation, Lukman *et al. (2024)* extended the two-parameter framework by modifying the K L estimator for use in Poisson regression models. This adaptation was motivated by the need to address multicollinearity in count data models, a context where traditional methods often fail to perform adequately. The results of their study showed that the modified KL estimator significantly reduced bias and improved the efficiency of parameter estimates in Poisson models with multicollinear data.

Abidoye *et al. (2021)* proposed another innovative solution to multicollinearity with their Almost Unbiased Two-Parameter (AUTP) estimator. The AUTP estimator introduces two parameters to control bias and variance more effectively than traditional estimators. Through a comprehensive comparative analysis of the OLS estimator, the two-parameter estimator, and the AUTP estimator. Abidoye *et al. (2021)* demonstrated that the AUTP estimator achieves unbiased parameter estimation under conditions of multicollinearity. Their work highlights the importance of striking a balance between bias and variance to achieve optimal estimation in regression models.

Similarly, Lukman *et al. (2024)* introduced a new biased estimator based on a combination of one and two-parameter estimators. This hybrid approach was shown to outperform traditional OLS estimators in scenarios involving high levels of multicollinearity. Lukman and his colleagues demonstrated that their estimator provides a robust alternative for researchers dealing with complex datasets where multicollinearity is a significant concern.

Iterative Methods and Robust Estimation Techniques

In addition to new parametric approaches, researchers have also explored iterative methods to handle multicollinearity more effectively. Karakoca (2022) introduced an iterative ridge estimator that combines the strengths of ridge regression with an iterative optimization process. This method involves repeatedly updating the ridge estimator until convergence is achieved, resulting in more stable and accurate parameter estimates in the presence of multicollinearity. The iterative nature of this approach allows it to adapt to the specific structure of the data, making it a powerful tool for addressing multicollinearity in complex models. However, the application of this method to SEMs remains largely unexplored.

Owolabi *et al. (2022)* proposed a two-parameter ridge-type estimator that builds on the traditional ridge regression technique by incorporating a second parameter to control for multicollinearity more effectively. Their work demonstrated that the two-parameter ridge-type estimator significantly reduces bias and improves the accuracy of parameter estimates compared to traditional ridge regression. This technique has shown great promise in linear regression models, but further research is needed to assess its applicability in SEMs.

Robust estimation techniques have also gained traction as a way to handle multicollinearity and other data-related challenges simultaneously. Jegede *et al*. (2022) developed the Robust Jackknife Kibria Lukman M-Estimator, which combines robust estimation techniques with the jackknife method to address both multicollinearity and the presence of outliers in the data. The robust nature of this estimator makes it particularly useful in real-world applications where data may be contaminated by outliers or other anomalies. While this estimator has been shown to perform well in linear regression models, its use in SEMs remains an open area of research**.**

Article DOI: 10.52589/AJMSS-U4L17Q9N
DOI URL: https://doi.org/10.52589/AJMSS-U4L17Q9N

Stochastic and Restricted Estimators

Another emerging area of research involves the use of stochastic and restricted estimators to handle multicollinearity in regression models. Arumairajan *et al.* (2017) proposed a stochastic restricted two-parameter estimator that incorporates stochastic restrictions into the estimation process. This method is designed to handle multicollinearity in situations where additional prior information is available, making it a highly flexible and adaptable approach. The use of stochastic restrictions allows the estimator to leverage external information to improve the accuracy of parameter estimates, particularly in cases where multicollinearity is severe.

Abidoye *et al*. (2022) introduced an unbiased Modified Two-Parameter Estimator that also incorporates prior information into the estimation process. Their approach is based on the idea that incorporating external knowledge about the structure of the data can help mitigate the effects of multicollinearity. By using prior information to inform the estimation process, the Modified Two-Parameter Estimator provides a powerful tool for addressing multicollinearity in linear regression models. However, like many of the other techniques discussed in this section, its application in SEMs has not been explored.

Applications in Simultaneous Equation Models (SEMs)

While significant progress has been made in addressing multicollinearity in single-equation regression models, much less attention has been paid to the issue in the context of SEMs. SEMs are used to model complex relationships between multiple endogenous and exogenous variables, and they often involve multiple equations that must be estimated simultaneously. The complexity of SEMs, combined with the presence of multicollinearity, presents unique challenges that cannot always be addressed using traditional methods designed for single-equation models.

Existing methods for SEM estimation, such as Two-Stage Least Squares (2SLS), Three-Stage Least Squares (3SLS), Full Information Maximum Likelihood (FIML), and Instrumental Variables (IV), are often effective but limited in their ability to handle multicollinearity. These techniques are designed to address issues related to endogeneity and omitted variable bias, but they are not always sufficient when the explanatory variables are highly correlated. As a result, there is a clear need for new estimation techniques that can handle multicollinearity within the SEM framework.

Reviews on Heteroscedasticity

In SEMs, heteroscedasticity is particularly problematic because the error terms in different equations may have different variances, and these variances may be correlated with the explanatory variables. There is a need to address this issue within SEMs. The presence of heteroscedasticity can lead to inefficient and biased estimates, resulting in incorrect statistical inferences (White, 1980). In economic and statistical models, particularly those dealing with cross-sectional and time-series data, heteroscedasticity often arises due to the changing scale of variables over time or across observations (Abdul-Hameed *et al*., 2021). This problem is particularly prevalent in large datasets where variability in response variables can differ across subpopulations (Long & Ervin, 2000).

The classical assumption of homoscedasticity, which assumes constant variance, underpins many standard econometric techniques. When heteroscedasticity is present, ordinary least

Article DOI: 10.52589/AJMSS-U4L17Q9N
DOI URL: https://doi.org/10.52589/AJMSS-U4L17Q9N

African Journal of Mathematics and Statistics Studies
ISSN: 2689-5323
Volume 9, Issue 2, 2026 (pp. 1-10)

squares (OLS) estimators remain unbiased but no longer have the smallest variance among linear estimators. In such cases, the standard errors of the regression coefficients can be misleading, leading to incorrect conclusions about hypothesis tests and confidence intervals.

Early work on detecting heteroscedasticity includes statistical tests such as the Goldfeld-Quandt test (Goldfeld and Quandt, 1965), which focuses on splitting the sample and testing for changes in variability. A systematic relationship between the residuals and the predictors (Abdul-Hameed *et al*., 2021), developed a modified Breusch-Pagan test for heteroscedasticity in the presence of outliers. The modified test is obtained by substituting non-robust components in the Breusch-Pagan test with robust procedures which makes the modified Breusch-Pagan test to be unaffected by outliers. This method further advanced the detection heteroscedasticity in linear model especially when the model is contaminated with outliers. White (1980) introduced a general test for heteroscedasticity that does not require any assumptions about the specific form of heteroscedasticity.

Classical Methods for Addressing Heteroscedasticity

Several classical methods have been developed to address heteroscedasticity, ensuring that statistical models can produce reliable estimates even in the presence of non-constant variance. One common approach is to transform the dependent variable to stabilize variance (Wooldridge, J. M., 2020). For instance, applying a logarithmic or square root transformation can mitigate the effects of heteroscedasticity when the variability of the dependent variable increases with its magnitude.

Another widely used method is the application of weighted least squares (WLS), where observations are weighted by the inverse of their variance. WLS adjusts the contribution of each observation in proportion to its variance, reducing the influence of observations with larger variances and thus improving the efficiency of parameter estimates (Greene, W. H., 2018). The success of WLS depends on accurately estimating the error variance, which can be challenging in practice.

In cases where heteroscedasticity is present, but its form is unknown, robust standard errors can be used. White (1980), heteroscedasticity-consistent standard errors (HCSE) adjust the standard errors of OLS estimates without altering the coefficient estimates themselves. This approach remains one of the most popular techniques for correcting heteroscedasticity in applied econometrics because it does not require strong assumptions about the form of heteroscedasticity.

Various statistical tests are employed to detect heteroscedasticity before applying corrective measures. The Breusch-Pagan test is one such method, where the squared residuals from the OLS regression are regressed on the independent variables to test for a systematic relationship between the residuals and the predictors (Abdul-Hameed *et al.,* 2021). If this relationship is significant, it suggests the presence of heteroscedasticity. Similarly, the White test extends this approach to allow for a broader range of possible heteroscedasticity forms (White, 1980).

While these classical methods remain relevant, their effectiveness can be limited in models that exhibit more complex forms of heteroscedasticity. Moreover, in large datasets with a high degree of variability, classical methods such as WLS may suffer from issues of multicollinearity among the weighted variables, which introduces further complications.

 Article DOI: 10.52589/AJMSS-U4L17Q9N
DOI URL: https://doi.org/10.52589/AJMSS-U4L17Q9N

Recent Developments in Heteroscedasticity Management

Recent developments in addressing heteroscedasticity have focused on creating more flexible and efficient estimators that can handle both heteroscedasticity and other complications such as multicollinearity or endogeneity. Rauf *et al.* (2024) propose a set of heteroscedasticity correction measures within the stochastic frontier analysis (SFA) model. They highlight that when both the random error and the technical efficiency error exhibit heteroscedasticity, traditional assumptions of homoscedasticity lead to inefficient estimates. Their proposed correction measures for the random error (HCRE), technical efficiency error (HCTE), and both (HCRTE) significantly improve the efficiency of parameter estimates when heteroscedasticity is present in SFA models. Their Monte Carlo simulations show that the HCRTE consistently produces the most efficient estimates in terms of mean squared error (MSE) when heteroscedasticity affects both error components.

Bodunwa and Fasoranbaku (2020) also explore recent methods to address heteroscedasticity in linear models using optimal design approaches. They propose a D-optimal design in a linear model with two explanatory variables in the presence of heteroscedasticity. Their sequential method for deriving D-optimal designs improves parameter estimation efficiency and demonstrates better performance with real-world datasets. Moreover, they compare three weighted least squares correction methods for heteroscedasticity and find that the method tagged HCW1 outperforms other correction approaches in terms of efficiency.

In another significant development, Onifade and Olanrewaju (2020) conducted extensive Monte Carlo simulations to compare the performance of different heteroscedasticity detection tests in generalized linear models (GLMs). They evaluate tests such as the Breusch-Godfrey test, the White test, and the Glejser test under various heteroscedasticity structures, including linear, quadratic, and exponential forms. Their findings indicate that the Park and Glejser tests are the most reliable in detecting heteroscedasticity in specific forms of the error structure, with the White test performing well across different sample sizes and error variances.

Quevedo and Vining (2022) introduced an innovative approach for online monitoring of nonlinear profiles using a Gaussian process model with heteroscedasticity. They developed a Shewhart chart that uses the Gaussian process to make real-time adjustments to the profile, reducing the need for post-hoc corrections. This method is particularly useful in industrial settings where monitoring processes in real-time is crucial for quality control.

Cui *et* (2023) proposed a robust approach to handling heteroscedasticity, error serial correlation, and slope heterogeneity in large panel datasets. Their method, which integrates pooled iterated principal component (IPC) estimators with a panel heteroscedasticity and autocorrelation consistent (PHAC) variance matrix, offers a significant advancement in managing heteroscedasticity in models with interactive effects. Their approach is particularly valuable for applied researchers working with large, complex datasets, where traditional methods for correcting heteroscedasticity may fall short.

Simultaneous Management of Multicollinearity and Heteroscedasticity

Addressing both multicollinearity and heteroscedasticity simultaneously is crucial for obtaining reliable estimates in SEMs. In practice, these two problems often occur together, particularly in large and complex datasets, making it essential to use estimation techniques that can handle both issues concurrently. Recent advancements in the field have introduced several

Article DOI: 10.52589/AJMSS-U4L17Q9N
DOI URL: https://doi.org/10.52589/AJMSS-U4L17Q9N

new estimators that aim to improve the handling of multicollinearity and heteroscedasticity in linear regression model. Dar & Chand (2023) developed an improved heteroscedasticity-consistent ridge estimator that addresses both multicollinearity and heteroscedasticity by incorporating a regularization term that penalizes large coefficients while allowing for non-constant variance in the error terms. This estimator has shown great promise in simulation studies, where it consistently outperformed traditional linear regression model estimators.

Amalare et al. (2023) combined the strength of the Generalized Ridge Estimator (GRE) and the Ordinary Ridge Estimator (ORE) respectively to combat heteroscedasticity and multicollinearity jointly in the linear regression model.

In addition to developing robust estimation techniques, proper model specification is critical for ensuring the reliability of SEM estimates. Dent and Geweke, (1980) stressed the importance of comprehensive specification analysis in SEMs, which includes tests for exogeneity, identification, and normalization. Proper specification ensures that the model is correctly identified and that the estimated parameters are meaningful. Multicollinearity and heteroscedasticity can exacerbate identification problems in SEMs, making specification analysis an essential step in the estimation process.

Moreover, Hansen *et al. (2014)* highlighted the value of tests for endogeneity, exogeneity, and weak instruments in enhancing the robustness of SEM estimates. These tests help to identify potential sources of bias in the estimation process, allowing researchers to apply appropriate corrections, such as using instrumental variables or system methods like 3SLS, to obtain more reliable parameter estimates.

CONCLUSION

While significant progress has been made in developing robust estimators for multicollinearity and heteroscedasticity in linear regression model, there is still much work to be done, particularly in the context of SEMs. Future research should focus on developing new estimators that can handle both problems individually and simultaneously while maintaining computational efficiency and ease of interpretation. There is a need for more comprehensive simulation studies to evaluate the performance of these estimators under various conditions, including small sample sizes, high-dimensional data, and non-normal distributions.

Empirical validation of these new estimators is also essential. While simulation studies provide valuable insights into the theoretical properties of estimators, real-world data often present additional challenges that cannot be fully captured in a simulated environment. Applying these new estimators to real-world datasets across different domains, such as economics, finance, and the social sciences, will be an important step in demonstrating their practical effectiveness and generalizability.

The literature on multicollinearity and heteroscedasticity in linear regression model highlights the importance of using robust estimation techniques and comprehensive diagnostic testing to ensure the reliability of parameter estimates. However, further research is needed to refine these techniques and explore new methods for addressing the complex interplay between multicollinearity and heteroscedasticity in SEM estimation.

Article DOI: 10.52589/AJMSS-U4L17Q9N
DOI URL: https://doi.org/10.52589/AJMSS-U4L17Q9N

REFERENCES

Abdul-Hameed, A. B., & Matanmi, O. G. (2021). A modified Breusch–Pagan test for detecting heterosedasticity in the presence of outliers. *Pure and applied mathematics journal,*10(6), 139-149. https://doi.org/10.11648/jpamj.20211006.13" 13.

Abidoye A. O, Ajayi I. M, Adewale F. L., Ogunjobi J. O. (2021). Unbiased Modified Two-Parameter Estimator for the Linear Regression Model. *Journal of Scientific Research*, 4(3):785-95.https://doi.org/10.3329/jsr.v14i3.58234.

Arumairajan, S., Wijekoon, P., 2017. Modified Almost Unbiased Liu Estimator in Linear Regression Model. *Commun. Math. Stat.* **5,** 261–276 https://doi.org/10.1007/s40304-017-0111-z.

Amalare A. A., Ayinde K., & Ononuga K**.** (2023). Parameter estimation of linear regression model with multicollinearity and heteroscedasticity problems. *The Journals of the Nigerian Association of Mathematical Physics*, *65*,207216. https://nampjournals.org.ng/index.php/home/article/view/49

Aslam, M., & Ahmad, S. (2020). The modified Liu-ridge-type estimator: a new class of biased estimators to address multicollinearity. *Communications in Statistics - Simulation and Computation*. doi:10.1080/03610918.2020.1806324.

Bodunwa, O. A., & Fasoranbaku, O. K. (2020). D-optimal design in linear model with different heteroscedasticity structures. *International Journal of Statistics and Probability*, *9*(2),7-

Dar, I. S., & Chand, S. (2023). Improved heteroscedasticity-consistent ridge estimators for linear regression with multicollinearity. *Iranian Journal of Science*, 47(5), 1593-1604.

Dent, W., & Geweke, J. (1980). On specification in simultaneous equation models. *In Evaluation of Econometric Models Academic Press* (pp. 169-196). http://www.nber.org/books/kmen80-1

Dorugade, A. V. (2016). Improved ridge estimator in linear regression with multicollinearity, heteroscedastic errors and outliers. *Journal of Modern Applied Statistical Methods*,15, 362-381. doi:10.22237/jmasm/1478002860.

Guowei Cui, Kazuhiko Hayakawa, Shuichi Nagata & Takashi Yamagata (2023) A Robust Approach to Heteroscedasticity, Error Serial Correlation and Slope Heterogeneity in Linear Models with Interactive Effects for Large Panel Data, Journal of Business & Economic Statistics, 41:3, 862-875. https://doi.org/10.1080/07350015.2022.2077349.

Goldfeld, S. M., & Quandt, R. E. (1965). Some tests for homoscedasticity. *Journal of the American statistical Association*, *60*(310), 539-547. https://doi.org/10.1080/01621459.1965.10480811.

Greene, W. (2018) Econometric Analysis. 8th Edition, *Pearson Education Limited, London*.

Hansen, Christian & Kozbur, Damian. (2014). Instrumental variables estimation with many weak instruments using regularized JIVE. *Journal of Econometrics*. 182. DOI:10.1016/j.jeconom.2014.04.022.

Hoerl, A. E., & Kennard, R. W. (1970). Ridge Regression: Biased Estimation for Nonorthogonal Problems. *Technometrics*, *12*(1), 55–67. https://doi.org/10.2307/1267351.

Jegede, S. L. Lukman, A. F., Keyinde, A. O, Ayinde, K. (2022). Jackknife Kibria-Lukman M-Estimator: Simulation and Application. (2022). *Journal of the Nigerian Society of Physical Sciences*, *4*(2), 251-264. https://doi.org/10.46481/jnsps.2022.664.

Komlos, J, 2020. "Multicollinearity in the Presence of Errors-in-Variables Can Increase the Probability of Type-I Error," *Journal of Economics and Econometrics, Economics and*

Article DOI: 10.52589/AJMSS-U4L17Q9N
DOI URL: https://doi.org/10.52589/AJMSS-U4L17Q9N

Econometrics Society, vol. 63(1), pages 1-17.

Karakoca, A. (2022). A New Type Iterative Ridge Estimator: Applications and Performance Evaluations. Journal of Mathematics. 2022. DOI:10.1155/2022/3781655.

Kibria, B. G. (2003). Performance of some new ridge regression estimators. *Communications in Statistics-Simulation and Computation*. 32(2):419-35. https://doi.org/10.1081/SAC-120017499

Kibria, B. G. & Shipra, B. (2019). A simulation study on the size and power Properties of some ridge regression Tests. Applications and Applied Mathematics: *An International Journal (AAM)* 14.2: 7. https://digitalcommons.pvamu.edu/aam/vol14/iss2/7.

Long, J. S. & Ervin, L. H. (2000). Using heteroscedasticity consistent standard errors in the linear regression model. *The American Statistician*, *54*(3), pp.217-224. https://doi.org/10.1080/00031305.2000.10474549.

Lukman, A. F., Mohammed, S., Olaluwoye, O., & Farghali, K. A. (2024) Robust Negative Binomial Regression via the Kibria–Lukman Strategy: Methodology and Application." *Mathematics* 12.18: 2929. doi:10.1016/j.sciaf.2023.e01566.

L'Ecuyer, P. (2012). Random number generation, in Handbook of Computational Statistics. *Springer Handbooks of Computational Statistics*. 35-71. DOI:10.1007/978-3-642-21551-3_3.

Owolabi, A. T, Kayode A, Olusegun O. A. (2022) A Modified Two Parameter Estimator with Different Forms of Biasing Parameters in the Linear Regression Model.). *African Scientific Reports*, *1*(3), 212–228. https://doi.org/10.46481/asr.2022.1.3.62.

Pérez-Sánchez, B., González, M., Perea, C., & López-Espín, J. J. (2021). A New Computational Method for Estimating Simultaneous Equations Models Using Entropy as a Parameter Criteria. *Mathematics*, *9*(7), 700. https://doi.org/10.3390/math9070700

Quevedo, A. V., & Vining, G. G. (2022). Online monitoring of nonlinear profiles using a Gaussian process model with heteroscedasticity. *Quality Engineering*, *34*(1), 58-74. DOI:10.1080/08982112.2021.1998530.

Rauf, R. I., Hamidu, B. A., Kikelomo, B. O., Kayode, A., & Olusegun, A. O. (2024). Heteroscedasticity correction measures in stochastic frontier analysis. *The Annals of the University of Oradea*, *33*(1st), 155. https://www.sdiarticle5.com/review-history/121987.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Journal of the Econometric Society*: 817-838. https://doi.org/10.2307/1912934.

Wooldridge, J. M. (2020). *Introductory econometrics: A modern approach (7th ed.). Cengage Learning.*

Umeh, E. U., Awopeju, K. A., & Ajibade, F. B. (2016). Detection of Multicollinearity Using Min-Max and Point-Coordinates Approach. *American Journal of Theoretical and Applied Statistics*, *4*(6), 640. https://doi.org/10.11648/J.AJTAS.20150406.36