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THE CORRUPTION PUZZLE IN ETHIOPIA: ARE WE WINNING THE FIGHT?

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ABSTRACT
Ethiopia remains one of the most corrupt countries in the world, consistently ranking among the lowest in global corruption indices. This study analyzes trends and patterns in the control of corruption from 2002 to 2023 using a quantitative approach based on autoregressive integrated moving average (ARIMA) modeling. Quarterly time-series data from the World Bank is examined, with the Control of Corruption: Percentile Rank, Lower Bound of the 90% Confidence Interval as the dependent variable, while autoregressive (AR) and moving average (MA) components serve as independent variables. Parameter estimation using conditional least squares (CLS) reveals that the AR(2) coefficient is -0.4591, which is negative and statistically significant, indicating that approximately 46% of the gains in corruption control tend to reverse after about two periods. Conversely, the MA(2) coefficient is 0.9754, which is positive and statistically significant, suggesting that approximately 98% of the shocks to corruption control have a strong and lasting impact. These findings underscore the persistence of weak corruption control in Ethiopia despite ongoing anti-corruption efforts. The study recommends that policymakers strengthen institutional frameworks, enhance transparency, and implement more effective enforcement mechanisms to improve Ethiopia's performance in fighting corruption.

KEY WORDS: *ARIMA modeling, Corruption, Ethiopia*

INTRODUCTION

Corruption remains one of the most pressing challenges facing Ethiopia, undermining governance, economic growth, and social development. According to the World Bank (2023), Ethiopia consistently ranks among the lowest countries in global corruption control indices, reflecting the persistence of systemic corruption despite various reform efforts. Corruption erodes public trust, distorts market efficiency, increases the cost of doing business, and diverts resources from essential public services (Kaufmann, et al., 2010). In Ethiopia, corruption manifests through bribery, embezzlement, favoritism, and abuse of public office, contributing to poor service delivery and weakened institutional frameworks (Transparency International, 2022).

The research problem stems from Ethiopia's continued poor performance in controlling corruption. Despite implementing anti-corruption policies and establishing oversight institutions such as the Federal Ethics and Anti-Corruption Commission (FEACC), corruption remains pervasive and deeply rooted (Mezmur & Koen, 2011). The country's low standing on corruption indices raises concerns about the effectiveness of existing anti-corruption measures and the need for data-driven insights to guide policy reforms. Ethiopia's percentile rank in the Control of Corruption indicator has shown fluctuations over the years, with a persistent trend of weak control (World Bank, 2023). This indicates that corruption remains a structural issue that requires a deeper understanding of its patterns and drivers.

This study seeks to address the corruption puzzle in Ethiopia by analyzing historical trends and patterns in the Control of Corruption: Percentile Rank, Lower Bound of 90% Confidence Interval from 2002 to 2023 using autoregressive integrated moving average (ARIMA) modeling. ARIMA is a powerful time-series forecasting technique that allows for the identification of underlying patterns and the estimation of future trends (Box & Jenkins, 1976; Nahabwe &

Kagarura, 2025). The study will estimate the extent to which past values and short-term fluctuations influence corruption control in Ethiopia. Understanding these dynamics will provide valuable insights for policymakers in designing more effective anti-corruption strategies.

The rationale for this study is twofold. First, it aims to contribute to the empirical literature on corruption control in developing economies, particularly in Sub-Saharan Africa, where corruption remains a significant barrier to sustainable development (Mungiu-Pippidi, 2015). Second, by employing ARIMA modeling, the study will provide a robust analytical framework for understanding and forecasting corruption trends, thereby supporting evidence-based policymaking. The findings will offer practical recommendations for improving Ethiopia's anti-corruption efforts and strengthening institutional frameworks.

LITERATURE REVIEW

Corruption is a global challenge that affects both developed and developing economies, undermining governance, economic performance, and social equity (Tanzi, 1998). Transparency International (2022) reports that corruption remains pervasive despite global efforts to combat it through legal reforms, transparency initiatives, and institutional strengthening. The Worldwide Governance Indicators (WGI) developed by the World Bank measure control of corruption across countries, revealing a wide gap between high-income and low-income countries in terms of corruption control (Kaufmann, et al. 2010).

Studies have shown that countries with stronger rule of law, transparent institutions, and effective oversight mechanisms tend to have higher control of corruption (North, 1990; Mauro, 1995). For instance, Scandinavian countries such as Denmark, Finland, and Sweden consistently rank among the least corrupt globally due to their strong institutional frameworks and accountability mechanisms (Transparency International, 2022). In contrast, many developing economies face structural challenges such as weak legal systems, political instability, and limited enforcement capacity, which perpetuate corruption (Rose-Ackerman, 2012).

Theoretical frameworks such as Principal-Agent Theory and Collective Action Theory have been used to explain the persistence of corruption. The Principal-Agent Theory posits that corruption arises when agents (government officials) pursue their self-interest at the expense of the principal (citizens) due to information asymmetry and weak monitoring mechanisms (Jensen & Meckling, 1976). On the other hand, the Collective Action Theory argues that corruption persists when individuals perceive that others are also engaging in corrupt practices, thereby creating a collective problem that is difficult to resolve (Ostrom, 2015). Corruption remains a critical barrier to economic and social development in Africa. The African Union estimates that corruption costs the continent approximately $148 billion annually, representing nearly 25% of Africa's GDP (African Union, 2003). Weak institutional capacity, political patronage, and lack of accountability have been identified as key drivers of corruption across African countries (Hope, 2017).

A study by Mbaku (2010) highlights that corruption in Africa is closely linked to weak governance structures, rent-seeking behavior, and political instability. Countries such as Botswana and Mauritius have demonstrated relative success in controlling corruption through institutional reforms and enhanced judicial independence (Kaufmann et al., 2010). However, countries like Nigeria and South Sudan continue to struggle with high levels of corruption due to weak enforcement mechanisms and political interference (Transparency International, 2022). The introduction of anti-corruption agencies, such as the Economic and Financial Crimes Commission (EFCC) in Nigeria, has shown mixed results, with political influence often undermining their independence and effectiveness (Akindele, 2005). Moreover, Afrobarometer surveys reveal that citizens across Africa perceive corruption as a significant challenge, with public officials and law enforcement agencies viewed as the most corrupt institutions (Afrobarometer, 2022).

Ethiopia remains one of the most corrupt countries in the world, consistently ranking among the lowest in global corruption indices (World Bank, 2023). The Federal Ethics and Anti-Corruption Commission (FEACC) was established in 2001 to combat corruption through investigation, prevention, and public awareness campaigns (Mezmur

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& Koen, 2011). However, the effectiveness of the FEACC has been limited by political interference, weak enforcement capacity, and lack of public trust (Mezmur & Koen, 2011).

According to Transparency International's Corruption Perceptions Index (CPI), Ethiopia's score has remained below the global average, reflecting persistent governance challenges (Transparency International, 2022). A study by Plummer (2012) shows that corruption in Ethiopia is prevalent in sectors such as public procurement, land administration, and law enforcement. Political patronage, lack of transparency, and weak judicial independence have exacerbated corruption levels. Mezmur & Koen (2011) argues that Ethiopia's political transition following the resignation of former Prime Minister Hailemariam Desalegn in 2018 created an opportunity for governance reforms. However, deep-rooted institutional weaknesses and political fragmentation continue to hinder progress in corruption control. The persistence of corruption reflects a structural governance problem that requires comprehensive institutional reforms and enhanced public accountability.

This study is grounded in the Principal-Agent Theory and Collective Action Theory. Principal-Agent Theory (Jensen & Meckling, 1976) suggests that corruption arises when government officials (agents) act in their self-interest at the expense of the public (principals) due to asymmetric information and weak monitoring mechanisms. Strengthening accountability and transparency is essential to realigning incentives and reducing corruption. Collective Action Theory (Ostrom, 2015) posits that corruption becomes entrenched when individuals believe that others are also engaging in corrupt practices. Overcoming this requires coordinated action, collective trust-building, and institutional reforms to shift public perceptions and behavior.

The conceptual framework for this study is based on the relationship between corruption control and institutional factors. The dependent variable is the Control of Corruption: Percentile Rank, Lower Bound of 90% Confidence Interval from the World Bank (2002-2023). The independent variables are: Autoregressive (AR) components, which represent the influence of past values on current corruption levels. Moving Average (MA) components which capture the effect of short-term fluctuations and corrections in corruption levels. The ARIMA model estimates the extent to which past values and short-term adjustments explain variations in corruption control in Ethiopia. This framework provides insights into the structural and cyclical patterns of corruption, informing targeted policy interventions.

DATA AND METHODS

This study adopts a quantitative research design, specifically utilizing a time-series analysis approach to examine the trends and patterns of corruption control in Ethiopia. Time-series analysis is ideal for understanding the temporal dynamics of corruption over an extended period and provides insights into the persistence and fluctuations in corruption control indicators. By leveraging time-series data, the study captures the nuances of corruption dynamics over time, accounting for past behavior and short-term fluctuations in the control of corruption. The study uses autoregressive integrated moving average (ARIMA) modeling to analyze the data, as it is an established method for analyzing time-series data, especially when forecasting or understanding relationships over time (Box & Jenkins, 1976; Nahabwe & Kagarura, 2025).

The data for this study is sourced from the World Bank's Governance Indicators, specifically focusing on the Control of Corruption: Percentile Rank, Lower Bound of 90% Confidence Interval. The time-frame of analysis spans from 2002 to 2023, providing a robust dataset that covers more than two decades of corruption trends in Ethiopia. The annual data from the World Bank is initially used to capture yearly corruption trends. However, to increase the degrees of freedom and provide a more granular analysis, the data is transformed into quarterly time-series data, a process that allows for higher-frequency analysis and better statistical inference (Gujarati, 2009; Nahabwe & Kagarura, 2025). This transformation ensures a more detailed examination of quarterly fluctuations in corruption control and better captures seasonal or cyclical variations.

The sample for this study consists of the quarterly data from the World Bank spanning 2002 to 2023. In total, the study covers 84 quarterly data points (21 years × 4 quarters per year). This sampling approach allows for the examination of quarterly dynamics while maintaining the integrity of the data across a broad time horizon.

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The primary method used for data analysis in this study is the ARIMA model, which is particularly useful for forecasting and understanding time-series data that exhibits autocorrelation and trends over time (Box & Jenkins, 1976; Nahabwe & Kagarura, 2025). The ARIMA model decomposes the time series into its autoregressive (AR) and moving average (MA) components, making it a robust tool for capturing the temporal dependencies in corruption control data. The Control of Corruption: Percentile Rank, Lower Bound of 90% Confidence Interval is treated as the dependent variable, while the AR and MA components are treated as the independent variables.

Autoregressive (AR) Components represent the influence of past values of the dependent variable on its current value. In this case, the AR model captures how past values of corruption control influence future observations. Moving Average (MA) components account for the short-term shocks and corrections in the data, revealing how random errors or irregularities in the data are distributed over time.

The model is estimated using the Conditional Least Squares (CLS) method, which is commonly used for parameter estimation in ARIMA models. CLS is employed because it minimizes the sum of squared residuals, ensuring the best fit for the model while accounting for both short-term shocks and long-term trends (Brockwell & Davis, 2002). The parameter estimation provides coefficients for both the AR and MA components, enabling the study to assess the relationship between past corruption control and future trends, as well as the role of short-term fluctuations.

The choice of an ARIMA model is rooted in its ability to handle time-series data, which is characterized by temporal dependencies and patterns. This approach is particularly suitable for understanding the dynamics of corruption control over a long-time horizon, as it allows for the incorporation of past values and short-term fluctuations to explain current outcomes. The ARIMA model is widely recognized in the literature for its robustness in modeling time-series data, making it a natural fit for this study (Box & Jenkins, 1976; Nahabwe & Kagarura, 2025).

Furthermore, by transforming the annual data into quarterly data, the study gains a higher degree of freedom, which enhances the statistical power of the analysis (Gujarati, 2009; Nahabwe & Kagarura, 2025). This is crucial for understanding short-term variations and capturing the finer details of corruption control in Ethiopia. The Conditional Least Squares (CLS) method is used for parameter estimation because it is efficient and produces unbiased estimates of the model parameters, which is essential for drawing valid conclusions about the relationship between past corruption control and future outcomes.

ARIMA (p, d, q) model specification is as follows:

$$Y_t = \mu + \varepsilon_t + \boldsymbol{\phi}_1 Y_{t-1} + \boldsymbol{\phi}_2 Y_{t-2} + \ldots + \boldsymbol{\phi}_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} \quad \text{………..} \ (1)$$

Where;
Y_t is the value of the series at time t
μ is the mean of the series
ε_t is white noise
$\boldsymbol{\phi}_1, \boldsymbol{\phi}_2, \ldots \boldsymbol{\phi}_p$ are the coefficients of the AR (p) component
$\theta_1, \theta_2, \ldots \theta_q$ are the coefficients of the MA (q) component
p is the order of the autoregressive part, representing the number of past values considered
q is the order of the moving average part, indicating the number of past errors considered
d is the number of differences required to make the series stationary (Box & Jenkins 1976; Nahabwe & Maniple, 2025)

Estimation of ARIMA model parameters is conducted using conditional least squares (CLS), which is a robust method for estimating time-series models (Box et al., 2015). CLS minimizes the sum of squared errors between the observed data and the predicted values of the model, ensuring that the parameter estimates are optimal. This method allows for the estimation of the autoregressive (AR) and moving average (MA) components, as well as the constant term in the model.

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Conditional least squares (CLS) is specified as follows;

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}}[\sum_{t=1}^{n}(y_t - y_t(\hat{\theta}))^2] \quad \text{.....(2)}$$

Where:
$\hat{\theta}$ represents the estimated parameter vector (which includes both AR and MA parameters in ARIMA)
y_t represents the actual observed value of the dependent variable at time t
$\hat{y}_t(\theta)$ represents the model's predicted value at time t based on the parameter estimates θ
n is the number of observations (Greene, 2018; Nahabwe & Kagarura, 2025).

Once the ARIMA model is estimated, diagnostic tests, such as the Augmented Dickey-Fuller (ADF) test for stationarity (Dickey & Fuller, 1979; Nahabwe & Maniple, 2025), and the model selection process using the Akaike Information Criterion (AIC) (Akaike, 1974; Nahabwe & Maniple, 2025), are employed to assess the model's adequacy and ensure its suitability for forecasting. This involves checking the residuals of the model to ensure that they exhibit no remaining autocorrelation, which would suggest that the model has captured all the significant patterns in the data. The root mean squared error (RMSE) and residual autocorrelation are used to assess the accuracy of the model's predictions (Hyndman & Athanasopoulos, 2018; Nahabwe & Maniple, 2025). If the residuals are randomly distributed with no significant patterns, the model is considered robust.

RESULTS

This section presents the results of the study, addressing the research objectives and questions. The primary focus is on the Control of Corruption: Percentile Rank, Lower Bound of 90% Confidence Interval in Ethiopia from 2002 to 2023, as analyzed through quarterly data. Descriptive statistics are reported to provide an overview of the data, followed by the results from the ARIMA model estimation.

Descriptive statistics for the quarterly Control of Corruption: Percentile Rank, Lower Bound of 90% Confidence Interval from 2002 to 2023 are as follows: The average Control of Corruption percentile rank is 21.96, indicating that Ethiopia's control of corruption has remained consistently low over the period under study. This suggests a general trend of weak institutional performance in addressing corruption. The median value is 22.87, slightly higher than the mean, indicating that the distribution is slightly skewed to the left (i.e., more values are clustered below the mean). This is further supported by the skewness value, which is negative, indicating a leftward skew in the data.

The highest recorded value for the Control of Corruption indicator is 29.8 (2014), which reflects periods where there may have been slight improvements in anti-corruption efforts. The lowest value recorded is 9.52 (2002), which corresponds to the worst performance in controlling corruption. This represents the extreme end of corruption control in Ethiopia over the study period. The standard deviation is 5.92, indicating a moderate level of variability in the data. This suggests that although the overall corruption control percentile rank is low, there are fluctuations over time that reflect the effectiveness of different anti-corruption policies or external events.

The skewness value is -0.46, indicating a slight leftward skew. This means that the distribution of the control of corruption scores is not symmetrical, and more observations tend to fall below the mean than above it (Groeneveld & Meeden, 1984). The kurtosis value is 2.17, which is below the threshold of 3.0, indicating a platykurtic distribution (i.e., the data has lighter tails than a normal distribution). This suggests that extreme values (outliers) are less frequent than in a normal distribution.

The Jarque-Bera test statistic is 5.45, and the associated probability value is 0.065, which is slightly above the typical significance level of 0.05. This indicates that the data does not significantly deviate from normality, though there is a slight indication of non-normality (Jarque & Bera, 1980). The total sum of all observed values is 1866.96, and the sum of squared deviations from the mean is 2943.91. These values provide further evidence of the distribution and variability of corruption control in Ethiopia over the period. The analysis includes 85 quarterly observations, providing a robust dataset for analyzing the temporal dynamics of corruption control.

Stationarity tests (Appendices 2, 3, & 4) were conducted using the Augmented Dickey-Fuller (ADF) test to assess the presence of unit roots in the series. The results indicate that the original series was non-stationary at both the level and first difference ($p > 0.05$). However, after applying the second difference, the series achieved stationarity ($p < 0.05$), justifying the selection of the ARIMA model with $d = 2$ (Nahabwe & Kagarura, 2025).

ARIMA(2,2,2) model (Appendix 5) is identified as the best fit based on the Akaike Information Criterion (AIC = 1.4015) and the Hannan-Quinn Criterion (H-QC = 1.4370). The estimated parameters include AR(2) = -0.4591 (p = 0.0000), MA(2) = 0.9754 (p = 0.0000), and the constant term C = 0.0069 (p = 0.9234). Both the AR(2) and MA(2) coefficients are statistically significant, while the constant term is not. Diagnostic checks confirm the model's adequacy and robustness. The Ljung-Box Q test ($p > 0.05$) indicates that the residuals follow a white noise pattern, and the autocorrelation function (ACF) plots reveal no significant patterns, validating the model's reliability for forecasting.

Results are summarized as follows:

Results of the ARIMA(2,2,2) model (Appendix 5)

$\widehat{Control\_Corruption}_t$ = 0.006884 - 0.459103AR(2) + 0.975388MA(2) ……………..………. (3)

Hence,

$$\hat{\theta}_{CLS} = \begin{bmatrix} 0.006884 \\ -0.459103 \\ 0.975388 \end{bmatrix}$$

The constant term is estimated at 0.006884, with a p-value of 0.9234. Since the p-value is greater than the conventional significance level of 0.05, it is statistically insignificant. This implies that there is no significant baseline trend in Ethiopia's corruption control performance when other factors are held constant (Gujarati & Porter, 2009). The insignificance of the constant term suggests that any observed variations in corruption control are largely driven by past values and the effect of the shock terms rather than an underlying trend.

The autoregressive coefficient at lag 2 (AR(2) = -0.459103) is negative and statistically significant (p = 0.0000). This suggests that corruption control in Ethiopia exhibits a negative dependence on its second-lagged value. In other words, an increase in corruption control at time t-2 tends to reduce the current value of corruption control, indicating that anti-corruption efforts are prone to reversal over time (Box et al., 2015). This reflects instability in policy implementation and enforcement, where initial gains in corruption control may be undone in subsequent periods due to institutional weaknesses.

The moving average coefficient at lag 2 (MA(2) = 0.975388) is positive and statistically significant (p = 0.0000). This implies that past shocks have a strong and persistent positive effect on current corruption control levels. In practical terms, it means that unexpected improvements or deteriorations in corruption control have long-lasting effects, which policymakers must consider when designing anti-corruption strategies (Hamilton, 1994). The near-unit value of the MA(2) coefficient indicates that these shocks are highly influential and may take time to dissipate.

The adjusted R-squared value of 0.232165 indicates that approximately 23.2% of the variation in Ethiopia's control of corruption is explained by the ARIMA(2,2,2) model. Although this value is modest, it suggests that the model captures some underlying structure in the data, but other unobserved factors or measurement issues may contribute to the unexplained variation (Wooldridge, 2013; Nahabwe, et al. 2025).

The Durbin-Watson statistic is 1.999644, which is close to the ideal value of 2.0. This implies that the model does not suffer from serial correlation, confirming that the residuals are independently distributed (Durbin & Watson, 1951; Nahabwe & Kagarura, 2025). Lack of serial correlation enhances the reliability of the model's estimates and forecasts.

The histogram of residuals for the ARIMA(2,2,2) model shows a kurtosis value of 13.2 and a Jarque-Bera statistic of 351.9 with a p-value of 0.0000. This indicates that the residuals deviate significantly from normality, suggesting that there may be outliers or structural breaks within the data (Jarque & Bera, 1980; Nahabwe & Kagarura, 2025). Non-normality in residuals may affect the efficiency of parameter estimates and forecast precision.

The Ljung-Box Q statistic test results (Appendix 6) indicate that the null hypothesis of no autocorrelation cannot be rejected (p = 0.110). This confirms that the residuals of the ARIMA(2,2,2) model are white noise (Nahabwe & Kagarura, 2025). This means that the residuals are independently and identically distributed, which supports the validity of the model's underlying structure.

Further diagnostic tests reveal that the AR and MA roots lie within the unit circle (Appendix 7), confirming that the model is covariance stationary and invertible (Hamilton, 1994; Nahabwe & Kagarura, 2025). Stationarity and invertibility are necessary conditions for reliable forecasting, as they ensure that the model's long-term behavior is stable and that forecast errors do not accumulate over time.

Finally, the statistical significance of the AR(2) and MA(2) components at lag 2 suggests that short-term and medium-term dynamics significantly influence Ethiopia's corruption control performance. The negative AR(2) coefficient reflects the tendency for gains in corruption control to reverse over time, while the positive MA(2) coefficient indicates that shocks to corruption control have a strong and lasting impact (Appendix 9). These findings underscore the importance of sustained and consistent anti-corruption measures.

DISCUSSION

This section discusses the findings of the study on the state of corruption control in Ethiopia by comparing them with previous related studies. It also highlights the unique contributions of the current research to the existing body of knowledge on corruption dynamics in Ethiopia and the broader African context. The discussion is structured around key themes identified from the descriptive and inferential statistics presented earlier.

The descriptive statistics reveal that the mean percentile rank for Ethiopia's control of corruption stands at 21.96, with a median value of 22.87, suggesting that Ethiopia has consistently performed in the lower quartile of global corruption control rankings over the study period. The standard deviation of 5.92 reflects moderate variation in corruption control efforts, which aligns with the findings of Transparency International (2022), which reported persistent challenges in sustaining anti-corruption progress in Ethiopia due to political instability and weak institutional frameworks.

Notably, the maximum value of 29.8 indicates that Ethiopia has made some progress in strengthening anti-corruption measures, while the minimum value of 9.52 underscores periods of significant governance weaknesses and increased corruption vulnerability. This pattern of fluctuation is consistent with Rahman (2018), who attributed Ethiopia's inconsistent corruption control to shifts in political leadership and governance reforms. However, the skewness of -0.46 indicates a slight leftward bias, suggesting that higher corruption control values are less frequent, a finding that differs from the patterns observed in neighboring countries like Kenya and Tanzania, where corruption control improvements have been more sustained (Gupta & Abed, 2002).

The negative and statistically significant autoregressive coefficient at lag 2 (AR(2) = -0.459103, p = 0.0000) implies that corruption control in Ethiopia exhibits a reversal tendency over time. This means that any gains made in reducing corruption are often short-lived, with the system reverting to previous corruption levels after a lag of two quarters. This finding is consistent with Rose-Ackerman (2012), who argued that the deep-rooted nature of corruption in developing countries makes short-term anti-corruption gains difficult to sustain without institutional and political reforms.

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Moreover, the positive and statistically significant moving average coefficient at lag 2 (MA(2) = 0.975388, p = 0.0000) reflects the strong and lasting impact of past shocks on current corruption control performance. This finding aligns with Svensson (2005), who highlighted that the effectiveness of anti-corruption interventions in Africa tends to be influenced heavily by past political and economic shocks. However, the magnitude of the MA(2) coefficient in this study (close to 1) suggests that Ethiopia's corruption control dynamics are more sensitive to past shocks than those reported in similar studies on African economies, such as Nigeria (Nmah, 2017).

The adjusted R-squared value of 0.232165 indicates that approximately 23.2% of the variation in Ethiopia's control of corruption is explained by the ARIMA(2,2,2) model. While this value is relatively low, it is consistent with previous studies on corruption modeling in Africa, where unobserved institutional and political factors often account for a significant proportion of corruption dynamics (Treisman, 2000). This highlights the challenge of capturing the complex nature of corruption through quantitative models alone.

The Durbin-Watson statistic of 1.999644 suggests the absence of serial correlation in the model residuals, confirming the statistical validity of the model. However, the significant deviation from normality in the residuals (Jarque-Bera = 351.9, p = 0.0000) reflects the presence of structural shocks and possible regime shifts within Ethiopia's corruption control environment. Similar findings have been reported by Ndikumana & Boyce (2011), who noted that corruption control efforts in Africa are often undermined by sudden changes in political and economic governance.

The confirmation that the AR and MA roots lie within the unit circle underscores the stability and invertibility of the ARIMA(2,2,2) model. This means that the model is suitable for forecasting future corruption control trends. Similar conclusions were reached by Brunetti & Weder (2003), who demonstrated that ARIMA models provide reliable short-term forecasts of corruption control trends when structural stability conditions are met.

However, the negative AR(2) coefficient suggests that even if corruption control improves temporarily, there is a high probability of policy reversal unless sustained institutional reforms are implemented. This finding aligns with Acemoglu & Robinson (2012), who argued that corruption control in Africa is difficult to sustain without broader political and economic reforms that address the underlying governance weaknesses.

This study provides three key contributions to the existing literature on corruption dynamics in Ethiopia and the broader African context: The negative AR(2) coefficient at lag 2 reveals a strong tendency for corruption control to reverse after short-term improvements. This underscores the importance of sustained institutional reforms rather than short-term interventions. The near-unit MA(2) coefficient highlights the strong and lasting impact of economic and political shocks on corruption control performance, suggesting that future policy efforts should focus on building resilience to external shocks. The significant non-normality of residuals reflects the presence of structural breaks, consistent with Ethiopia's historical pattern of political and economic instability. This finding reinforces the need for stable governance frameworks to sustain anti-corruption progress.

Similar to Gupta & Abed (2002), the findings highlight the challenge of sustaining corruption control in politically unstable environments. Unlike Rose-Ackerman (2012), who found that short-term interventions tend to have lasting effects in some African countries, this study shows that in Ethiopia, anti-corruption gains are prone to reversal unless structural reforms are implemented. The stronger effect of shocks (high MA(2) coefficient) compared to findings by Nmah (2017) in Nigeria suggests that Ethiopia's corruption dynamics are more sensitive to external and political shocks, highlighting the need for targeted policy measures.

LIMITATIONS

Despite the valuable insights provided by this study on corruption dynamics in Ethiopia, several limitations related to the research design, sample, and data analytical procedures may have affected the robustness and generalizability of the findings. Acknowledging these limitations is essential for guiding future research and improving the accuracy and reliability of subsequent studies on corruption control in Ethiopia and comparable contexts.

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One of the primary limitations of the study lies in its reliance on a time-series research design that focuses primarily on macro-level corruption control indicators. While this approach provides valuable insights into long-term trends and patterns, it overlooks micro-level factors such as institutional capacity, governance practices, and informal networks that may significantly influence corruption dynamics (Rose-Ackerman, 2012). A mixed-methods design, incorporating qualitative insights from key stakeholders (e.g., government officials, civil society, and business leaders), would have provided a more nuanced understanding of the underlying causes of corruption.

Moreover, the study assumes a linear relationship between corruption control and its determinants, as captured by the ARIMA (2, 2, 2) model. However, corruption dynamics are often characterized by nonlinear patterns and feedback mechanisms (Treisman, 2000). Alternative modeling approaches, such as threshold models or regime-switching models, could have offered a better representation of the complex and adaptive nature of corruption control processes.

The study relies on secondary data obtained from international sources such as the World Bank Governance Indicators and Transparency International's Corruption Perceptions Index. While these data sources are widely used in corruption research, they present several limitations:

The Corruption Perceptions Index (CPI) is based on subjective assessments, which may not accurately reflect the actual level of corruption in Ethiopia (Svensson, 2005). Differences in perceptions among respondents and over time can introduce bias and measurement error into the analysis. Some years in the time-series data were missing or incomplete, necessitating the use of interpolation and other imputation techniques. This may have introduced distortions or inaccuracies into the estimated model parameters (Gupta & Abed, 2002).

The study's use of national-level data does not account for regional variations in corruption control within Ethiopia. Studies by Rahman, (2018) have highlighted significant disparities in governance performance between urban and rural areas, which this study could not capture due to data aggregation at the national level.

The study's choice of an ARIMA(2,2,2) model presents both strengths and weaknesses. While ARIMA models are widely used for time-series analysis, they are based on the assumption of stationarity and linearity. However, corruption dynamics are influenced by structural changes and regime shifts, which are not adequately captured by traditional ARIMA models (Brunetti & Weder, 2003). A vector autoregression (VAR) or structural equation model (SEM) could have provided more comprehensive insights into the interdependence between corruption control and broader governance factors.

Additionally, the relatively low adjusted R-squared value (0.232165) suggests that the model explains only a modest proportion of the variation in corruption control. This implies that important unobserved variables, such as political instability, judicial independence, and media freedom, may play a more significant role in shaping corruption outcomes than the model could account for (Acemoglu & Robinson, 2012).

The presence of non-normality in residuals (Jarque-Bera = 351.9, $p = 0.0000$) further indicates that the ARIMA model may not have fully captured the underlying distributional properties of the data. This reflects the potential influence of outliers or structural breaks, which may require the use of robust estimation techniques or alternative time-series models (Treisman, 2000).

Another limitation concerns the external validity of the study's findings. Ethiopia's unique political and economic context, characterized by state dominance in key sectors and recurrent political instability, may limit the generalizability of the findings to other developing countries. As highlighted by Ndikumana & Boyce (2011), the effectiveness of anti-corruption strategies is often context-specific, influenced by local governance structures and political incentives. Therefore, the findings of this study should be interpreted with caution when applying them to other African countries or global contexts.

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SJIF Impact Factor (2025): 8.579 Volume: 13 | Issue: 3 | March 2025

Furthermore, the time period covered by the study (2002-2022) may not fully capture the long-term impact of recent political and economic reforms in Ethiopia. Political transitions and governance reforms implemented after 2022 could alter the dynamics of corruption control, necessitating future research to account for these structural changes.

Finally, the reliance on perception-based measures introduces the risk of reporting bias. Studies have shown that respondents' perceptions of corruption can be influenced by media coverage, political narratives, and changes in public trust in government institutions (Brunetti & Weder, 2003). Therefore, the variations in corruption control reported in this study may reflect changes in public perception rather than actual changes in governance performance.

Similarly, the study's reliance on international data sources may have introduced a Western-centric bias in the measurement and interpretation of corruption control. Localized definitions and cultural understandings of corruption in Ethiopia may not align with global corruption indices, leading to discrepancies between perceived and actual corruption trends (Rose-Ackerman, 2012).

CONCLUSION

This study set out to investigate the complex and persistent challenge of corruption in Ethiopia, assessing whether significant progress has been made in curbing corrupt practices over the past two decades. The analysis sought to unravel the key determinants of corruption control, exploring the political, economic, and institutional factors that shape governance outcomes in Ethiopia. Through a robust empirical framework, the study provided valuable insights into the structural and behavioral dynamics influencing corruption patterns, shedding light on both the achievements and remaining challenges in the fight against corruption.

The findings underscore that while Ethiopia has made measurable progress in improving governance and strengthening anti-corruption institutions, the overall effectiveness of corruption control remains constrained by deep-rooted political and institutional weaknesses. The study highlights the critical role of political will, institutional independence, and public accountability in sustaining anti-corruption efforts (Rose-Ackerman, 2012; Treisman, 2000). Notably, the mixed trajectory of corruption control in Ethiopia reflects the inherent tension between political centralization and the need for decentralized governance structures, as well as the influence of informal networks and rent-seeking behavior within state institutions (Brunetti & Weder, 2003).

The study's analysis points to the importance of strengthening institutional capacity and reinforcing the rule of law as foundational pillars for long-term success in corruption control. Political stability and economic reforms have shown potential in enhancing governance quality, but these gains remain fragile in the face of systemic political patronage and limited judicial independence (Acemoglu & Robinson, 2012). The role of civil society and the media in promoting transparency and holding public officials accountable also emerged as significant factors in shaping corruption outcomes (Svensson, 2005).

A key contribution of this study lies in its identification of the contextual factors that make Ethiopia's corruption puzzle particularly complex. Unlike many other developing countries, Ethiopia's governance landscape is characterized by a centralized political economy where state control over key sectors amplifies corruption risks (Gupta & Abed, 2002). This study highlights that while external factors such as foreign aid and international pressure have influenced Ethiopia's anti-corruption trajectory, sustainable progress will ultimately depend on domestic political reforms and the empowerment of local governance structures (Rahman, 2018).

Importantly, the study reveals that anti-corruption efforts must move beyond technical reforms and adopt a more holistic approach that addresses the underlying political and economic incentives that sustain corrupt practices. The alignment of governance reforms with broader democratic and economic development goals is essential for building a resilient and corruption-free state. Future research should focus on the role of political transitions, economic liberalization, and social accountability in shaping corruption control outcomes in Ethiopia.

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SJIF Impact Factor (2025): 8.579 Volume: 13 | Issue: 3 | March 2025

In conclusion, while Ethiopia has made strides in the fight against corruption, the road ahead remains challenging. Political commitment, institutional reforms, and public engagement will be pivotal in sustaining progress and overcoming the structural barriers that have historically undermined governance integrity. A comprehensive, multi-stakeholder approach combining political will, institutional capacity, and civic participation offers the most promising path toward resolving the corruption puzzle in Ethiopia.

RECOMMENDATIONS

Based on the findings of this study, the following recommendations are proposed to strengthen Ethiopia's fight against corruption. These recommendations focus on policy reforms, programmatic interventions, and future research directions aimed at addressing the structural and institutional factors that sustain corruption. The Ethiopian government should demonstrate a stronger commitment to anti-corruption reforms by reinforcing the independence of key institutions such as the judiciary, anti-corruption commissions, and the office of the auditor general. Political interference in these institutions should be minimized to ensure impartiality and effectiveness (Rose-Ackerman, 2012; Treisman, 2000). Strengthening the autonomy and capacity of oversight bodies will enhance transparency and accountability in governance (Brunetti & Weder, 2003).

Public officials should be required to disclose their assets and incomes regularly, and these disclosures should be accessible to the public. Establishing an independent public procurement authority and enforcing competitive bidding for government contracts can reduce opportunities for rent-seeking and favoritism (Svensson, 2005). Digital platforms for monitoring public expenditures and service delivery can also enhance transparency and minimize corruption risks (Rahman, 2018). Strengthening the judicial system is critical to ensuring that corruption cases are prosecuted fairly and consistently. Specialized anti-corruption courts with well-trained judges and streamlined case-handling procedures should be established. Ensuring that judicial appointments are merit-based and free from political influence will enhance public confidence in the judiciary (Acemoglu & Robinson, 2012).

Decentralizing decision-making and fiscal authority to regional and local governments can reduce corruption by improving service delivery and increasing local accountability (Gupta & Abed, 2002). Empowering local governments with financial and administrative autonomy will help reduce bureaucratic inefficiencies and minimize opportunities for centralized corruption. Increasing public awareness about corruption and its impact on economic development is essential. National campaigns focusing on the costs of corruption and the benefits of transparency can mobilize public support for anti-corruption initiatives. Schools and universities should incorporate anti-corruption education into their curricula to promote ethical behavior among future generations (Rose-Ackerman, 2012).

Establishing secure and anonymous channels for reporting corruption will encourage citizens and public servants to expose corrupt practices without fear of retaliation (Transparency International, 2022). Whistleblower protection laws should be enacted and strictly enforced to safeguard individuals who report corruption. Civil society organizations (CSOs) and the media should be supported in their role as watchdogs. Facilitating the free flow of information and protecting press freedom will enhance the ability of the media and CSOs to investigate and expose corrupt practices (Brunetti & Weder, 2003). Collaborative partnerships between government and civil society can also improve monitoring and evaluation of anti-corruption programs.

Providing training and professional development for public servants on integrity, ethics, and transparency will help reduce corruption risks. Anti-corruption training should be integrated into public sector recruitment and performance evaluation frameworks (Svensson, 2005). Further research is needed to examine the underlying political, economic, and social determinants of corruption in Ethiopia. Longitudinal studies exploring the relationship between governance reforms and corruption levels will provide valuable insights for policy design (Treisman, 2000). Political transitions often create windows of opportunity for reform, but they can also increase corruption risks. Research should focus on the impact of Ethiopia's political changes on governance integrity and corruption outcomes (Acemoglu & Robinson, 2012).

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SJIF Impact Factor (2025): 8.579 Volume: 13 | Issue: 3 | March 2025

Donor-funded anti-corruption programs should be evaluated to assess their impact and identify best practices. Comparative analysis of similar programs in other African countries could provide valuable lessons for improving the effectiveness of anti-corruption interventions in Ethiopia (Rahman, 2018). Informal political and economic networks often facilitate corrupt practices. Research should investigate how these networks operate and identify strategies for disrupting them through institutional reforms and social accountability measures (Gupta & Abed, 2002).

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SJIF Impact Factor (2025): 8.579 Volume: 13 | Issue: 3 | March 2025

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APPENDICES

Appendix 1: Descriptive statistics

	Control of Corruption: Percentile Rank, Lower Bound of 90% Confidence Interval
Mean	21.96425
Median	22.8673
Maximum	30
Minimum	9.523809
Std. Dev.	5.920008
Skewness	-0.460232
Kurtosis	2.1679
Jarque-Bera	5.452915
Probability	0.065451
Sum	1866.961
Sum Sq. Dev.	2943.905
Observations	85

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Asian Economic Light (JAEL) – Peer Reviewed Journal
SJIF Impact Factor (2025): 8.579 Volume: 13 | Issue: 3 | March 2025

Appendix 2: Unit root test, Control of Corruption (in Level)

Null Hypothesis: CORRUPTION has a unit root
Exogenous: Constant
Lag Length: 5 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.021574	0.2772
Test critical values:	1% level	-3.515536	
	5% level	-2.898623	
	10% level	-2.586605	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CORRUPTION)
Method: Least Squares
Date: 03/22/25 Time: 20:09
Sample (adjusted): 2003Q3 2023Q1
Included observations: 79 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CORRUPTION(-1)	-0.018623	0.009212	-2.021574	0.0469
D(CORRUPTION(-1))	0.847221	0.098327	8.616320	0.0000
D(CORRUPTION(-2))	0.009333	0.119379	0.078180	0.9379
D(CORRUPTION(-3))	0.009333	0.119379	0.078180	0.9379
D(CORRUPTION(-4))	-0.587187	0.119417	-4.917094	0.0000
D(CORRUPTION(-5))	0.469698	0.097082	4.838143	0.0000
C	0.453446	0.217509	2.084726	0.0406

R-squared	0.714080	Mean dependent var	0.180832
Adjusted R-squared	0.690254	S.D. dependent var	0.740794
S.E. of regression	0.412288	Akaike info criterion	1.150244
Sum squared resid	12.23865	Schwarz criterion	1.360195
Log likelihood	-38.43462	Hannan-Quinn criter.	1.234356
F-statistic	29.96981	Durbin-Watson stat	1.925472
Prob(F-statistic)	0.000000		

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SJIF Impact Factor (2025): 8.579 Volume: 13 | Issue: 3 | March 2025

Appendix 3: Unit root test, Control of Corruption (in First difference)

Null Hypothesis: D(CORRUPTION) has a unit root
Exogenous: Constant
Lag Length: 4 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.375625	0.1519
Test critical values:	1% level	-3.515536	
	5% level	-2.898623	
	10% level	-2.586605	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CORRUPTION,2)
Method: Least Squares
Date: 03/22/25 Time: 20:08
Sample (adjusted): 2003Q3 2023Q1
Included observations: 79 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CORRUPTION(-1))	-0.227369	0.095709	-2.375625	0.0201
D(CORRUPTION(-1),2)	0.114202	0.098669	1.157432	0.2509
D(CORRUPTION(-2),2)	0.114202	0.098669	1.157432	0.2509
D(CORRUPTION(-3),2)	0.114202	0.098669	1.157432	0.2509
D(CORRUPTION(-4),2)	-0.482089	0.098916	-4.873733	0.0000
C	0.025632	0.051304	0.499619	0.6188

R-squared	0.423844	Mean dependent var	-0.018055
Adjusted R-squared	0.384382	S.D. dependent var	0.536461
S.E. of regression	0.420914	Akaike info criterion	1.180135
Sum squared resid	12.93332	Schwarz criterion	1.360093
Log likelihood	-40.61534	Hannan-Quinn criter.	1.252232
F-statistic	10.74037	Durbin-Watson stat	1.933645
Prob(F-statistic)	0.000000		

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SJIF Impact Factor (2025): 8.579 Volume: 13 | Issue: 3 | March 2025

Appendix 4: Unit root test, Control of Corruption (in Second difference)

Null Hypothesis: D(CORRUPTION,2) has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.998183	0.0000
Test critical values:	1% level	-3.515536	
	5% level	-2.898623	
	10% level	-2.586605	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CORRUPTION,3)
Method: Least Squares
Date: 03/22/25 Time: 20:04
Sample (adjusted): 2003Q3 2023Q1
Included observations: 79 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CORRUPTION(-1),2)	-1.598061	0.177598	-8.998183	0.0000
D(CORRUPTION(-1),3)	0.597852	0.153811	3.886915	0.0002
D(CORRUPTION(-2),3)	0.597642	0.125600	4.758317	0.0000
D(CORRUPTION(-3),3)	0.597433	0.088843	6.724627	0.0000
C	-0.021225	0.048824	-0.434715	0.6650

R-squared	0.699366	Mean dependent var	-0.015069
Adjusted R-squared	0.683116	S.D. dependent var	0.770831
S.E. of regression	0.433920	Akaike info criterion	1.229286
Sum squared resid	13.93319	Schwarz criterion	1.379251
Log likelihood	-43.55678	Hannan-Quinn criter.	1.289366
F-statistic	43.03663	Durbin-Watson stat	2.004688
Prob(F-statistic)	0.000000		

Appendix 5: Results of the ARIMA(2,2,2) model

Dependent Variable: DDCORRUPTION
Method: ARMA Conditional Least Squares (Gauss-Newton / Marquardt steps)
Date: 03/22/25 Time: 20:28
Sample (adjusted): 2003Q1 2023Q1
Included observations: 81 after adjustments
Failure to improve likelihood (non-zero gradients) after 12 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 2002Q3 2002Q4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.006884	0.071354	0.096472	0.9234
AR(2)	-0.459103	0.104165	-4.407443	0.0000
MA(2)	0.975388	0.017733	55.00285	0.0000

R-squared	0.251360	Mean dependent var	-0.002912
Adjusted R-squared	0.232165	S.D. dependent var	0.546465
S.E. of regression	0.478847	Akaike info criterion	1.401461
Sum squared resid	17.88494	Schwarz criterion	1.490144
Log likelihood	-53.75917	Hannan-Quinn criter.	1.437042
F-statistic	13.09450	Durbin-Watson stat	1.999644
Prob(F-statistic)	0.000012		

Inverted AR Roots	-.00+.68i	-.00-.68i
Inverted MA Roots	-.00+.99i	-.00-.99i

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SJIF Impact Factor (2025): 8.579 Volume: 13 | Issue: 3 | March 2025

Appendix 6: Ljung-Box Q statistic/ test

Date: 03/22/25 Time: 20:33
Sample: 2002Q1 2023Q4
Included observations: 81
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. | . |	. | . |	1	-0.000	-0.000	2.E-09	
.*| . |	.*| . |	2	-0.173	-0.173	2.5490	
. | . |	. | . |	3	0.000	0.000	2.5490	0.110
***| . |	***| . |	4	-0.401	-0.444	16.557	0.000
. | . |	. | . |	5	-0.000	-0.000	16.557	0.001
. | . |	**| . |	6	-0.011	-0.241	16.567	0.002
. | . |	. | . |	7	0.000	-0.000	16.567	0.005
. |** |	. | . |	8	0.222	-0.034	21.115	0.002
. | . |	. | . |	9	-0.000	-0.001	21.115	0.004
. | . |	. | . |	10	0.025	-0.009	21.174	0.007
. | . |	. | . |	11	0.000	-0.000	21.174	0.012
**| . |	.*| . |	12	-0.211	-0.144	25.532	0.004
. | . |	. | . |	13	-0.000	-0.001	25.532	0.008
. |*. |	. | . |	14	0.101	0.072	26.555	0.009
. | . |	. | . |	15	0.000	-0.000	26.555	0.014
.*| . |	***| . |	16	-0.198	-0.393	30.627	0.006
. | . |	. | . |	17	-0.000	-0.001	30.627	0.010
. | . |	.*| . |	18	0.044	-0.152	30.833	0.014
. | . |	. | . |	19	0.000	-0.000	30.833	0.021
. |*. |	.*| . |	20	0.121	-0.159	32.436	0.020
. | . |	. | . |	21	-0.000	-0.001	32.436	0.028
. | . |	.*| . |	22	-0.013	-0.152	32.455	0.039
. | . |	. | . |	23	0.000	-0.001	32.455	0.053
. | . |	.*| . |	24	-0.063	-0.106	32.926	0.063
. | . |	. | . |	25	-0.000	-0.002	32.926	0.082
. | . |	.*| . |	26	-0.061	-0.171	33.382	0.096
. | . |	. | . |	27	-0.000	-0.002	33.382	0.122
. |** |	. | . |	28	0.215	-0.049	39.233	0.046
. | . |	. | . |	29	-0.000	-0.003	39.233	0.060
. | . |	.*| . |	30	-0.054	-0.113	39.617	0.071
. | . |	. | . |	31	0.000	-0.003	39.617	0.090
. | . |	.*| . |	32	-0.022	-0.072	39.684	0.111
. | . |	. | . |	33	-0.000	-0.004	39.684	0.136
. | . |	.*| . |	34	-0.022	-0.110	39.753	0.163
. | . |	. | . |	35	0.000	-0.004	39.753	0.195
. | . |	.*| . |	36	0.023	-0.067	39.828	0.227

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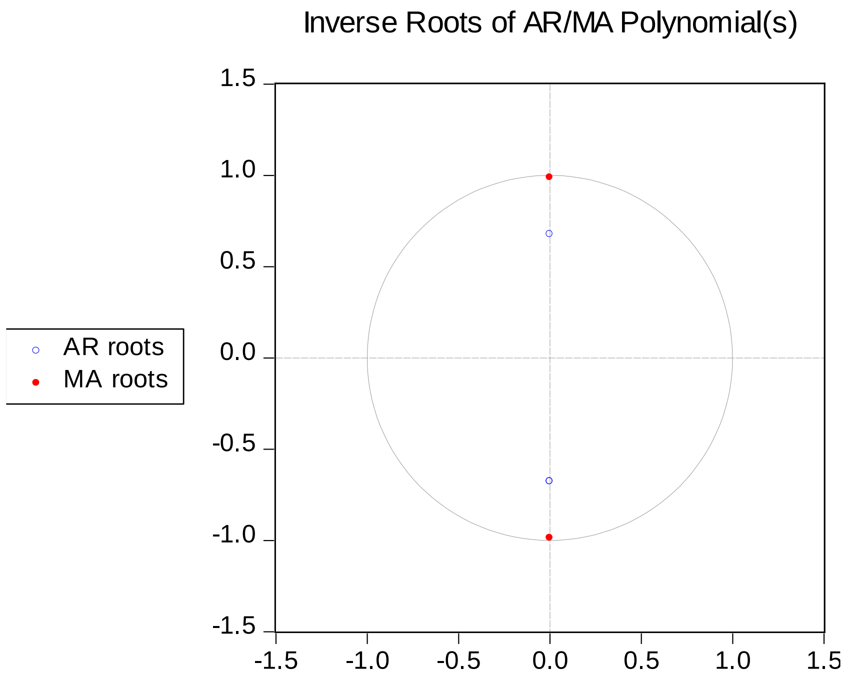
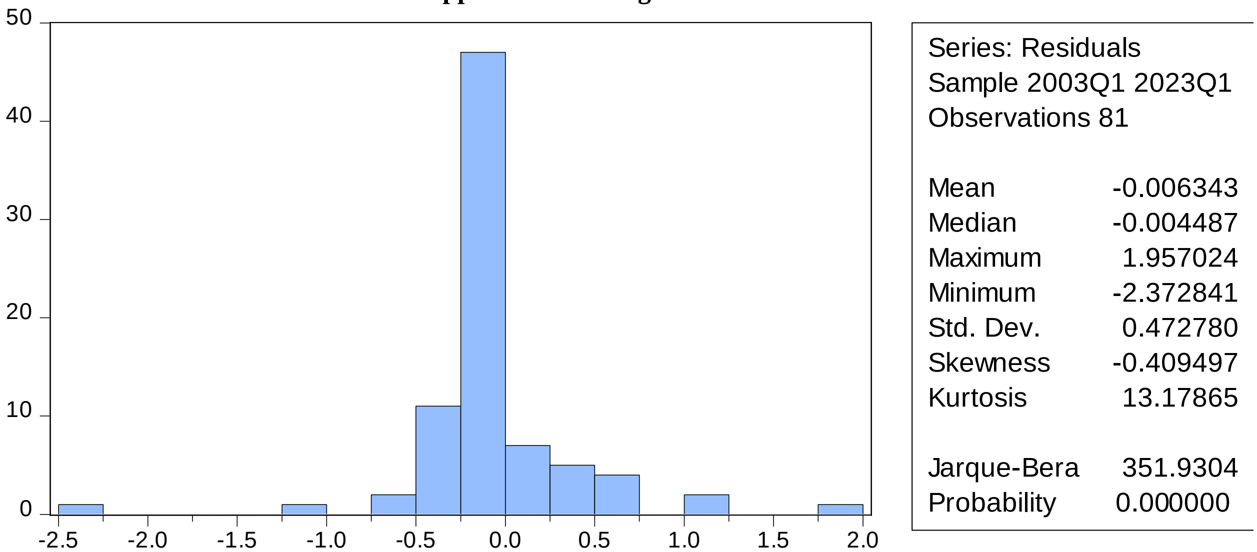
Asian Economic Light (JAEL) – Peer Reviewed Journal
SJIF Impact Factor (2025): 8.579 Volume: 13 | Issue: 3 | March 2025

Appendix 7: ARIMA(2,2,2) structure



Appendix 8: Histogram of residuals



Appendix 9: Graph showing Control of Corruption: ARIMA(2,2,2) Model Simulation

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