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THE PARADOX OF PLENTY IN THE DEMOCRATIC REPUBLIC OF CONGO: AN EMPIRICAL ANALYSIS OF PERSISTENCE OF POVERTY DESPITE VAST NATURAL RESOURCES

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ABSTRACT---
Democratic Republic of Congo (DRC), despite being endowed with vast natural resources, continues to experience persistent poverty, an economic anomaly known as the Paradox of Plenty. This study empirically examines this paradox by applying an autoregressive integrated moving average (ARIMA) approach to historical data from 1990 to 2023 using World Bank data. GDP per capita (PPP, current international $) is used as a proxy for poverty, modeled as the dependent variable, while autoregressive (AR) and moving average (MA) components serve as independent variables. Conditional least squares (CLS) estimation reveals a statistically significant negative AR(1) coefficient (-0.677625) and a positive MA(3) coefficient (0.831061), suggesting that approximately 68% of past poverty levels persist over time, while 83% of poverty shocks propagate through short-term fluctuations. The estimated ARIMA(1,2,3) model is found to be covariance stationary and invertible, confirming its robustness for forecasting poverty trends. Projections from 2024 to 2043 indicate a gradual yet modest improvement, with GDP per capita rising from $1,695 in 2024 to $1,909 by 2043. However, this growth remains insufficient to drive meaningful poverty reduction. The findings underscore the critical need for policies that address the structural inefficiencies preventing resource wealth from translating into broad-based economic development. Without strategic interventions to improve governance, enhance economic diversification, and ensure equitable resource distribution, the DRC risks remaining locked in a cycle of poverty despite its immense natural endowments.

KEY WORDS: *ARIMA modelling, Poverty, Resources, Democratic Republic of Congo*------------------------------

INTRODUCTION

The Democratic Republic of Congo (DRC) is one of the most resource-rich nations in the world, possessing vast deposits of minerals, including cobalt, diamonds, copper, and gold (World Bank, 2023). Despite this wealth, the country continues to experience persistent poverty, ranking among the poorest nations globally. According to the World Bank (2023), over 74.6% of the population lives below the international poverty line of $2.15 a day (below the global poverty rate of $6,85). The United Nations Development Programme (UNDP) further reports that the DRC has one of the lowest Human Development Index (HDI) scores, reflecting poor living standards, limited access to healthcare, and inadequate infrastructure (UNDP, 2022; UNHCR, 2024). This paradox, where immense natural wealth coexists with extreme poverty, is commonly referred to as the "Paradox of Plenty" or the "Resource Curse" (Auty, 1993).

The persistence of high poverty levels in the DRC raises critical questions about the structural factors impeding economic development. Weak governance, corruption, political instability, and an overreliance on extractive industries have contributed to poor wealth distribution and economic stagnation (Ross, 2012). Moreover, external market fluctuations and conflict-driven disruptions have further exacerbated the country's economic vulnerabilities. Understanding the long-term trends of poverty persistence is essential for designing effective policy interventions to break this cycle.

To empirically analyze poverty trends in the DRC, this study employs an autoregressive integrated moving average (ARIMA) model, a widely used time-series forecasting technique (Box & Jenkins, 1976; Kagarura & Nahabwe, 2025).

The model captures the autoregressive (AR) and moving average (MA) components of GDP per capita (PPP) over the period 1990-2023, providing insights into the extent to which past poverty trends influence future outcomes. By applying the ARIMA approach, this study aims to offer a robust, data-driven perspective on the structural and cyclical nature of poverty in the DRC.

The findings of this research have significant policy implications. Poverty in the DRC is found to be highly persistent, underscoring the need for institutional reforms, economic diversification, and inclusive development strategies that ensure resource wealth translates into long-term poverty reduction. The study contributes to the broader discourse on natural resource management and economic development by providing empirical evidence on dynamics of poverty in resource-rich but economically challenged countries.

LITERATURE REVIEW

The persistence of poverty in resource-rich countries has been extensively studied in economic literature. Scholars have explored the paradox of plenty, highlighting how the abundance of natural resources often correlates with economic stagnation and underdevelopment rather than prosperity (Sachs & Warner, 2001). This section critically reviews relevant literature from global, regional, and local perspectives, examining key theories and conceptual frameworks that explain poverty persistence despite resource wealth.

The resource curse theory, first popularized by Auty (1993), argues that countries rich in natural resources tend to experience slower economic growth and persistent poverty due to weak institutions, rent-seeking behavior, and economic mismanagement. Sachs and Warner (2001) provide empirical evidence that resource-rich countries often suffer from Dutch disease, a phenomenon where resource booms lead to currency appreciation, weakening other productive sectors such as agriculture and manufacturing.

Further, Ross (2012) finds that oil-rich states tend to have poor development outcomes due to political instability and corruption. Similarly, Mehlum, et al., (2006) argue that resource wealth fosters rent-seeking, where elites capture wealth at the expense of broader economic development. These findings suggest that without strong governance and economic diversification, resource-rich countries remain vulnerable to poverty traps.

Sub-Saharan Africa (SSA) provides multiple cases where natural resource wealth has not translated into economic prosperity. Countries such as Nigeria and Angola, despite being major oil producers, have high poverty rates due to mismanagement, corruption, and poor wealth distribution (Collier & Hoeffler, 2005). Nigeria, for instance, has witnessed recurrent poverty cycles despite generating billions from crude oil exports (Sala-i-Martin & Subramanian, 2013). In contrast, Botswana presents a positive deviation from the resource curse. Its well-managed diamond sector, strong institutional framework, and prudent economic policies have enabled sustained economic growth and poverty reduction (Acemoglu, et al., 2003). This suggests that effective governance plays a crucial role in determining whether resource wealth translates into economic development.

The DRC epitomizes the paradox of plenty, possessing an estimated $24 trillion in untapped mineral wealth (World Bank, 2023) while remaining among the poorest nations globally. Weak institutions, protracted conflicts, and illicit exploitation of resources have hindered economic progress (Ndikumana & Boyce, 2012). The World bank (2023) reports that over 74.6% of the population lives below the poverty line, despite the country's vast resource endowments. Additionally, resource wealth in the DRC has fueled armed conflicts, with rebel groups exploiting minerals to finance warfare, further destabilizing the economy (Berman, et al., 2017). Unlike Botswana, where resource revenues have been channeled into development, the DRC's revenues have largely benefited political elites and external actors, perpetuating poverty and inequality.

The resource curse theory (Auty, 1993) suggests that countries with abundant natural resources often experience economic stagnation due to weak governance, corruption, and lack of diversification. This theory is relevant to the DRC, where resource mismanagement has contributed to persistent poverty. The Solow-Swan model (Solow, 1956) argues that long-term economic growth depends on capital accumulation, labor force growth, and technological progress. However, in resource-rich countries like the DRC, heavy reliance on extractive industries reduces incentives for productivity-enhancing investments, slowing growth and development. Acemoglu & Robinson (2012) emphasize

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the role of institutions in economic development. They argue that extractive political and economic institutions hinder broad-based growth, leading to wealth concentration among elites and widespread poverty. The DRC's institutional weaknesses align with this framework, as resource wealth has not translated into inclusive economic progress.

This study conceptualizes GDP per capita (PPP, current international $) as the dependent variable, with autoregressive (AR) and moving average (MA) components serving as independent variables. Several empirical studies have utilized ARIMA modelling to analyze economic trends and forecast macroeconomic indicators (Box & Jenkins, 1976; Gujarati & Porter, 2020; Kagarura & Nahabwe, 2025). By leveraging this approach, the study aims to provide insights into the persistence of poverty in the Democratic Republic of Congo despite its vast natural resource wealth.

DATA AND METHODS

This study adopts an empirical research design, utilizing quantitative methods to explore the persistence of poverty in the Democratic Republic of Congo (DRC) despite its vast natural resource wealth. The research investigates how historical trends in poverty levels correlate with natural resource endowments and macroeconomic factors, leveraging time-series analysis to capture long-term patterns of economic performance.

The study utilizes autoregressive integrated moving average (ARIMA) model, which is widely employed for time-series forecasting and analysis, allowing for the identification of long-term relationships between poverty and resource wealth. ARIMA is chosen because of its ability to handle serially correlated data, a feature prevalent in economic time-series datasets (Box & Jenkins, 1976; Nahabwe & Kagarura, 2025).

The study uses secondary data from the World Bank covering the period from 1990 to 2023. The data set includes annual observations on GDP per capita (PPP, current international $), a proxy for poverty. The data is selected based on its availability and reliability, with the World Bank being a primary source for historical economic data (World Bank, 2023). The choice of univariate time-series approach allows for an in-depth examination of how poverty has evolved over time in relation to resource wealth. Given the nature of the research problem, a national-level analysis of the DRC is appropriate to understand the broader trends affecting the country's economy (Nahabwe & Kagarura, 2025).

ARIMA model is applied to analyze the time-series data of poverty (measured by GDP per capita (PPP)). ARIMA models are a class of models that are particularly well-suited for forecasting data that exhibit serial correlation (Box & Jenkins, 1976; Nahabwe & maniple, 2025). The ARIMA approach involves the following steps: To ensure that the time-series data are stationary, the Augmented Dickey-Fuller (ADF) test is applied (Dickey & Fuller, 1981). Non-stationary data is differenced to achieve stationarity. The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots are analyzed to determine appropriate values for the AR (autoregressive) and MA (moving average) components of the model. ARIMA model is estimated using conditional least squares (CLS) estimation technique, which is well-suited for time-series models with autoregressive and moving average components (Box & Jenkins, 1976; Nahabwe & Maniple, 2025). Ljung-Box test for autocorrelation and the Akaike Information Criterion (AIC) are used to validate the model fit (Ljung & Box, 1978: Nahabwe & Kagarura, 2025). Additionally, model diagnostics include tests for heteroscedasticity and residual analysis to ensure the model's robustness. The final ARIMA model is used to generate forecasts of GDP per capita (PPP) from 2024 to 2043, providing insights into future poverty trends in the DRC. The rationale for using ARIMA modelling lies in its ability to analyze time-series data with complex patterns, such as economic cycles and long-term persistence in poverty levels (Nahabwe & Kagarura, 2025). ARIMA models have been successfully applied to similar studies on poverty and economic growth (Shiller, 2005; Roy, et al., 2017; Nahabwe & Kagarura, 2025).

ARIMA approach is appropriate for this study because it allows for the modelling of both short-term fluctuations and long-term persistence in poverty trends, which is crucial for understanding the persistence of poverty in the DRC despite vast natural resources (Nahabwe & Kagarura, 2025). The DRC's economic development has been marked by periodic shocks due to both internal conflict and global commodity price fluctuations (World Bank, 2023). By applying ARIMA, the study can capture these dynamics and provide a clear picture of how past poverty levels influence future trends.

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

$Y_t = \mu + \varepsilon_t + \ \boldsymbol{\phi}_1 Y_{t-1} + \boldsymbol{\phi}_2 Y_{t-2} + \ ... + \boldsymbol{\phi}_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q}$ .... (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 (Box & Jenkins 1976; Nahabwe & Kagarura, 2025; Nahabwe & Maniple, 2025; Kagarura & Nahabwe, 2025).

Conditional least squares (CLS) estimation is chosen for its efficiency in estimating parameters in time-series models like ARIMA (Greene, 2018). By minimizing the sum of squared residuals, CLS provides optimal parameter estimates for modelling educational attainment (Box & Jenkins, 1976; Nahabwe & Kagarura, 2025). It is particularly effective for capturing the relationship between observed and predicted values, ensuring accurate forecasts (Hamilton, 1994; Nahabwe & Kagarura, 2025). The CLS estimator for the regression coefficients is given by the following formula:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}}[\textstyle\sum_{t=1}^{n} (y_t - \ \hat{y}_t(\theta))^2]$$

$\hat{\theta}$ 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; Nahabwe & Maniple, 2025).

Diagnostic tests, such as the Augmented Dickey-Fuller (ADF) test for stationarity (Dickey & Fuller, 1979), and the model selection process using the Akaike Information Criterion (AIC) (Akaike, 1974), are employed to assess the model's adequacy and ensure its suitability for forecasting. The use of ARIMA modelling in this study is particularly beneficial for modelling educational attainment, as it enables the evaluation of past behaviors to make reliable projections (Enders, 2014; Nahabwe & Kagarura, 2025).

RESULTS

This section presents the descriptive statistics (Appendix 1), for the variable GDP per capita, PPP (current international $), which is used as a proxy for measuring poverty in the Democratic Republic of Congo (DRC) from 1990 to 2023. These statistics provide an overview of the central tendency, variability, and distribution of GDP per capita over this period.

The average GDP per capita, PPP, is 723.37 USD. This value reflects the average economic output per person in the DRC during the sample period. It suggests that, on average, the economic output per individual is low compared to global standards, contributing to the persistent poverty levels in the country (World Bank, 2023). The median GDP per capita is 586.73 USD. The median is the middle value when the GDP per capita values are ordered from least to greatest, indicating that 50% of the data points lie below this value. The median is lower than the mean, suggesting the presence of outliers or a skewed distribution, where a small number of higher GDP per capita values inflate the average. The maximum value of GDP per capita is 1615.75 USD, which represents the highest level of economic output per individual during the sample period. This peak could reflect periods of economic growth or recovery, possibly linked to fluctuations in resource prices or temporary periods of stability (World Bank, 2023). The minimum value is 403.98 USD, indicating the lowest GDP per capita recorded. This figure highlights the extreme poverty in the DRC, especially during times of conflict, political instability, or economic recession (Kagarura & Nahabwe, 2025).

The standard deviation is 318.71 USD, which measures the extent of variability or dispersion around the mean. A high standard deviation suggests considerable fluctuation in the DRC's GDP per capita over time, reflecting economic instability and vulnerability to external shocks, such as changes in global commodity prices or internal conflicts (Kagarura & Nahabwe, 2025). The skewness value of 1.27 indicates a positively skewed distribution, meaning that there are more observations with lower GDP per capita values and a relatively few values on the higher end. This positive skew is consistent with the fact that while some segments of the population may experience periods of economic growth due to resource wealth, the majority still live-in poverty (Auty, 2001). The kurtosis value of 3.77 suggests that the distribution is platykurtic (slightly flatter than a normal distribution), with a relatively moderate peak. This suggests that there is a mix of extreme values (both high and low), but not to the extent that would indicate heavy tails, typical of a leptokurtic distribution (Nahabwe & Kagarura, 2025).

The Jarque-Bera statistic is 10.04, with a corresponding p-value of 0.00659, indicating that the data does not follow a normal distribution. This suggests that the GDP per capita data has significant skewness and kurtosis, which is common in developing economies with periods of extreme poverty interspersed with periods of growth (Nahabwe & Kagarura, 2025). The sum of GDP per capita values over the study period is 24,594.53 USD, which represents the total economic output across all the observations. The sum of squared deviations is 3,352,112, which quantifies the total squared deviation from the mean. It reinforces the high level of variability in GDP per capita, indicating that the economic conditions in the DRC have fluctuated significantly over the years. The analysis includes 34 observations, corresponding to annual data from 1990 to 2023.

The descriptive statistics highlight a wide disparity in economic performance across the DRC, with most of the population experiencing low levels of GDP per capita, contributing to the persistent poverty despite the country's rich natural resources. The high standard deviation reflects the volatility of the country's economy, while the positive skewness suggests that the resource wealth is not equitably distributed. The Jarque-Bera test confirms that the data is not normally distributed, which is typical for countries like the DRC, where factors such as political instability and external shocks can create irregular patterns in economic development (Auty, 2001; Nahabwe & Kagarura, 2025).

These statistics underscore the importance of understanding the structural dynamics that underpin the paradox of plenty in the DRC. While resource wealth has the potential to drive economic growth, this potential is not being fully realized due to governance issues, corruption, and economic mismanagement, all of which prevent the benefits of natural resource wealth from reaching the broader population (Ross, 2012).

Stationarity tests (Appendices 2, 3, & 4) are conducted using the Augmented Dickey-Fuller (ADF) test to evaluate the stationarity of the series (Nahabwe, et al., 2025). The findings indicated that the series was non-stationary in both level and first difference ($p > 0.05$). However, after applying the second difference, the series became stationary ($p < 0.05$), thus validating the use of the ARIMA model with $d = 2$ (Nahabwe & Kagarura, 2025). The ARIMA(1,2,3) model was determined to be the optimal model, based on the Akaike Information Criterion (AIC = 10.47352) and Hannan-Quinn Criterion (H-QC = 10.51875). The parameter estimates are as follows: AR(1) = -0.677625 (p = 0.0001); MA(3) = 0.831061 (p = 0.0000); C = 11.07300 (p = 0.1991). Both the AR(1) and MA(3) coefficients are statistically significant, while the constant term is not. Diagnostic tests confirm the adequacy of the model, with residuals exhibiting white noise, as shown by the Ljung-Box Q test ($p > 0.05$). Moreover, the autocorrelation function (ACF) plots reveal no significant patterns, further confirming the robustness of the model (Nahabwe & Kagarura, 2025).

Results are summarized as follows:

Results of the ARMA(1,2,3) model (Appendix 3)

$$\widehat{GDP\_PER\_CAPITA}_t = 11.07300 - 0.677625AR(1) + 0.831061MA(3) \quad \ldots\ldots\ldots\ldots\ldots (2)$$

Hence,

$$\hat{\theta} = \begin{bmatrix} 11.07300 \\ -0.677625 \\ 0.831061 \end{bmatrix}$$

Inferential statistics of the ARIMA(1,2,3) model provide key insights into the persistence of poverty in the Democratic Republic of Congo (DRC). The constant term (11.07300, p = 0.1991) is statistically insignificant ($p > 0.05$), indicating that it does not have a substantial impact on the dependent variable, GDP per capita (PPP). This suggests that external factors or omitted variables may play a significant role in determining poverty trends (Gujarati & Porter, 2020; Nahabwe & Maniple, 2025).The AR(1) coefficient (-0.677625, p = 0.0001) is negative and statistically significant ($p < 0.05$), implying that approximately 68% of past poverty levels persist over time. This highlights a strong historical dependence, meaning that poverty reduction efforts in the DRC face significant inertia (Hyndman & Athanasopoulos, 2018). The MA(3) coefficient (0.831061, p = 0.0000) is positive and statistically significant ($p < 0.05$), suggesting that approximately 83% of past economic shocks to poverty carry forward through short-term fluctuations. This supports the argument that poverty shocks, whether due to economic instability or governance failures, have lasting effects on economic well-being (Box & Jenkins, 1976; Kagarura & Nahabwe, 2025).

The Adjusted R-Squared (0.291348) indicates that the model explains approximately 29.1% of the variation in GDP per capita, implying that while the model captures some of the economic dynamics affecting poverty, other significant factors remain unaccounted for (Nahabwe & Kagarura, 2025; Nahabwe, et al., 2025). The Durbin-Watson Statistic (1.991630) is close to 2, indicating no significant autocorrelation in the residuals. This confirms that the model is well-specified and does not suffer from serial correlation issues, making it suitable for forecasting (Gujarati & Porter, 2020; Nahabwe & Kagarura, 2025).

Furthermore, the kurtosis value (3.38) and Jarque-Bera test (0.1947, $p > 0.05$) suggest that the residuals follow a normal distribution, meeting the assumption of normally distributed errors. The Ljung-Box Q Test (p = 0.137) fails to reject the null hypothesis, confirming that the residuals exhibit white noise. This implies that the model effectively captures all systematic patterns in the data, leaving only random fluctuations, which is a desirable property for forecasting (Hyndman & Athanasopoulos, 2018; Nahabwe & Kagarura, 2025).

Further diagnostics confirm that the AR(1) and MA(3) roots lie within the unit circle, ensuring that the model is covariance stationary and invertible. This means the model is stable and reliable for making future projections (Box & Jenkins, 1976). Projections (Appendices 9 and 10) indicate a gradual yet modest improvement in GDP per capita from $1,695 in 2024 to $1,909 by 2043, meaning that while economic growth is expected, it remains insufficient to drive substantial poverty reduction. These findings emphasize the need for structural reforms and policies that translate resource wealth into broad-based economic development (Nahabwe & Kagarura, 2025).

DISCUSSION

The findings of this study provide empirical evidence that, despite the vast natural resource wealth in the Democratic Republic of Congo (DRC), poverty remains persistently high. This aligns with the “resource curse” hypothesis, which suggests that resource-rich countries often experience slower economic growth, weaker institutions, and higher levels of poverty compared to resource-scarce nations (Sachs & Warner, 2001).

Previous research by Ross (2015) emphasizes that resource abundance in developing countries often leads to governance failures, rent-seeking behavior, and economic mismanagement, rather than contributing to sustained economic growth and poverty reduction. The current study supports this assertion, as the findings indicate that while GDP per capita in the DRC has shown modest improvement, the effects of economic shocks and structural inefficiencies continue to hinder long-term poverty alleviation.

Similarly, Collier & Hoeffler (2005) argue that resource-rich countries, particularly in Sub-Saharan Africa, are prone to prolonged conflicts, weak state capacity, and poor economic diversification, all of which exacerbate poverty. This study confirms that the persistence of poverty in the DRC is influenced by political instability, corruption, and inefficient resource management, which limit the potential benefits of resource wealth.

However, the findings also contrast with studies from countries that have successfully leveraged their resource wealth for economic development. For instance, Mehlum, et al., (2006) highlight how Norway has avoided the resource curse by implementing strong institutional frameworks and ensuring equitable distribution of resource revenues. The comparison suggests that the key difference between the DRC and successful resource-rich economies lies in governance and economic policies rather than resource endowment itself.

One of the study’s unique findings is the statistically significant negative impact of past economic conditions on current poverty levels, as indicated by the AR(1) coefficient (-0.677625, p = 0.0001). This suggests a strong path dependency, where historical poverty levels persist over time, reinforcing cycles of deprivation. Unlike previous studies that focus primarily on governance and institutional quality, this research quantifies the long-term economic inertia that prevents significant poverty reduction.

Another distinctive finding is the MA(3) coefficient (0.831061, p = 0.0000), which indicates that short-term shocks to economic growth have lasting effects on poverty. This suggests that external shocks such as commodity price fluctuations, global economic downturns, or domestic policy failures continue to influence poverty trends for extended periods. While earlier studies (Auty, 1993) emphasize the volatility of resource-based economies, this study provides empirical evidence of the specific duration and magnitude of such impacts in the DRC context.

Furthermore, the study's projections (2024-2043) show only a marginal increase in GDP per capita, from $1,695 in 2024 to $1,909 in 2043, reinforcing concerns that economic growth alone will not be sufficient to address deep-seated poverty. Unlike studies that predict resource-driven economic booms (Gelb, 1988), this research highlights the structural constraints that limit the effectiveness of resource wealth in driving broad-based development.

The findings of this study suggest that addressing the paradox of plenty in the DRC requires targeted policy interventions, particularly in governance, economic diversification, and investment in human capital. Strengthening institutions to curb corruption, improving transparency in resource revenue management, and promoting non-extractive sectors such as agriculture and manufacturing could help break the cycle of poverty (Acemoglu & Robinson, 2012).

LIMITATIONS

Despite its significant contributions to understanding the persistence of poverty in the Democratic Republic of Congo (DRC) despite vast natural resources, this study has several limitations related to research design, sample selection, and data analytical procedures. These shortcomings may have influenced the findings and should be considered when interpreting the results.

One of the primary limitations of this study is its reliance on secondary macroeconomic data from the World Bank. While this dataset provides valuable insights into long-term economic trends, it might not fully capture microeconomic and social factors, such as informal economic activities, regional disparities, and household-level poverty dynamics (Deaton, 1997). Future research could complement these findings with primary data collection methods, such as household surveys and qualitative interviews, to gain a more nuanced understanding of poverty in the DRC.

Another limitation concerns the study's focus on aggregate national indicators, which may obscure significant regional variations in poverty levels. The DRC is a geographically vast and ethnically diverse country with substantial differences in resource distribution, governance effectiveness, and economic opportunities across provinces (Collier & Gunning, 1999). The inability to disaggregate findings at the provincial or district level limits the study's capacity to identify localized policy interventions.

The study spans the period 2002 to 2022, primarily due to data availability constraints. However, economic and political events before this period, such as the civil wars (1996-2003) and earlier colonial-era resource exploitation continue to shape the country's development trajectory (Auty, 1993; Acemoglu & Robinson, 2012). The omission of earlier historical data may lead to an incomplete assessment of the long-term structural causes of poverty in the DRC.

Additionally, data inconsistencies and missing observations for key economic indicators posed challenges in model estimation. Given that economic data collection in developing countries is often affected by political instability, weak institutional capacity, and limited technological infrastructure (Jerven, 2013), some datasets required interpolation or estimation, which may introduce measurement errors. These issues could affect the precision of the findings, particularly in relation to the ARMA(1,2,3) model estimates.

The study employs the ARMA(1,2,3) model to examine macroeconomic relationships, but this method has inherent limitations. First, ARIMA models are primarily designed for time-series forecasting and assume stationarity (Box & Jenkins, 1976; Nahabwe & Kagarura, 2025). However, economic time series often exhibit structural breaks and nonlinear relationships, which standard ARMA models may not fully capture (Enders, 2014; Nahabwe & Kagarura, 2025). While stationarity adjustments were made, future research could employ alternative econometric techniques, such as Structural Vector Autoregression (SVAR) or Cointegration Analysis, to better account for long-term dynamics.

Furthermore, while the Adjusted R-Squared (0.291348) indicates that the model explains approximately 29.1% of the variation in poverty, it also suggests that other unobserved factors play a significant role. Variables such as governance quality, corruption, informal sector activities, and international trade dynamics, though acknowledged in the discussion were not directly included in the empirical model due to data constraints. Future studies could expand the analytical framework by incorporating institutional quality indices and governance indicators to provide a more comprehensive analysis (Mehlum, et al., 2006).

While the study provides valuable insights into the DRC's resource paradox, its findings may not be fully generalizable to other resource-rich developing nations. Differences in governance structures, economic policies, and historical contexts mean that the paradox of plenty manifests differently across countries (Sachs & Warner, 2001). Comparative studies incorporating multiple Sub-Saharan African nations could help assess whether the findings hold across diverse economic and political environments.

CONCLUSION

This study has provided an empirical examination of the Paradox of Plenty in the Democratic Republic of Congo (DRC), assessing why poverty persists despite the country's vast natural resource endowment. The findings contribute to the broader discourse on the resource curse hypothesis, illustrating how factors such as weak governance, institutional inefficiencies, and structural economic imbalances prevent resource wealth from translating into widespread economic prosperity (Auty, 1993; Sachs & Warner, 2001).

A key conclusion from this study is that natural resources alone are not sufficient to drive economic development. Instead, the manner in which resource wealth is managed through governance structures, fiscal policies, and institutional frameworks determines whether a country benefits from or suffers the negative consequences of resource dependence (Mehlum, et al., 2006). In the case of the DRC, resource rents have historically been misallocated or lost to corruption, preventing investments in productive sectors such as infrastructure, education, and healthcare, which are critical for long-term economic development (Acemoglu & Robinson, 2012).

Furthermore, the study highlights the macroeconomic distortions associated with resource dependency, including economic volatility, inflationary pressures, and exchange rate misalignments, which have collectively hindered sustainable growth (Collier & Goderis, 2012). The persistence of poverty in the DRC is not merely a function of resource endowment but a result of deep-seated institutional weaknesses and governance failures, reinforcing the need for structural reforms that promote transparency, diversification, and equitable wealth distribution (Ross, 2012).

While the study's empirical analysis confirms the presence of the Paradox of Plenty, it also underscores potential pathways for breaking this cycle. Strengthening institutions, fostering economic diversification beyond the extractive sector, and investing in human capital development are critical for transforming natural resource wealth into sustainable and inclusive economic growth (Venables, 2016). The study's projections suggest that while gradual improvements in GDP per capita may occur, meaningful poverty reduction will require deliberate policy interventions aimed at ensuring that resource revenues benefit the broader population rather than a privileged few (Bulte, et al., 2005).

Ultimately, this study reaffirms that resource wealth, when poorly managed, can become a liability rather than an asset. The persistence of poverty in the DRC, despite its immense resource wealth, reflects a complex interplay of economic, political, and institutional factors that require a multidimensional policy approach. Addressing these challenges demands stronger governance, institutional reforms, and strategic economic policies that prioritize sustainable development over short-term rent-seeking behavior. Future research should explore alternative economic models and policy interventions that could help resource-rich developing nations like the DRC escape the resource curse and achieve broad-based economic prosperity.

RECOMMENDATIONS

Based on the findings of this study, several policy, programmatic, and research recommendations are proposed to address the Paradox of Plenty in the Democratic Republic of Congo (DRC) and mitigate the persistence of poverty despite vast natural resource wealth.

The study underscores the role of weak institutions and governance failures in perpetuating poverty despite resource wealth. The government should strengthen anti-corruption frameworks, enforce transparency in revenue management, and implement stringent accountability measures in the extractive sector (Acemoglu & Robinson, 2012; Ross, 2012). This can be achieved by fully adhering to international transparency initiatives, such as the Extractive Industries Transparency Initiative (EITI), to enhance accountability in resource revenue utilization.

Overreliance on extractive industries has contributed to economic volatility and limited job creation. The government should invest in economic diversification by promoting manufacturing, agribusiness, and services sectors to reduce dependence on mineral exports (Sachs & Warner, 2001). Fiscal incentives, infrastructure development, and trade policies that encourage value addition in natural resources should be prioritized (Venables, 2016).

Natural resource revenues should be strategically allocated to education, healthcare, and infrastructure development, ensuring long-term poverty alleviation and sustainable economic growth (Collier & Goderis, 2012). Special attention should be given to improving access to quality education and vocational training programs, equipping citizens with skills that facilitate employment beyond the extractive sector (Mehlum, et al., 2006).

The study highlights macroeconomic distortions such as inflation, currency volatility, and external debt accumulation. The government should implement sound monetary and fiscal policies, including prudent resource revenue management through sovereign wealth funds and stabilization funds to cushion against commodity price fluctuations (Bulte, et al., 2005).

A participatory approach to resource management should be adopted, ensuring that local communities benefit directly from extractive industries through community development programs, revenue-sharing mechanisms, and corporate social responsibility (CSR) initiatives by multinational companies (Auty, 1993).

Developing local entrepreneurship and SMEs can provide alternative sources of income and employment outside the extractive sector. Government-led capacity-building programs, microfinance access, and investment in infrastructure can enhance SME growth and sustainability (Mehlum et al., 2006). Investment in transport, energy, and digital infrastructure is crucial for linking resource-rich regions to broader markets. Regional trade integration within the African Continental Free Trade Area (AfCFTA) can also facilitate economic expansion beyond mineral exports (Venables, 2016).

Future research could focus on evaluating the impact of institutional reforms and governance improvements on resource revenue utilization and economic development (Collier & Goderis, 2012). Further studies could explore the effectiveness of economic diversification policies in reducing poverty and improving economic resilience in resource-rich developing economies (Ross, 2012). There is a need for more research on how extractive activities affect local communities, including displacement, environmental degradation, and social inequalities (Bulte et al., 2005).

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APPENDICES

Appendix 1: Descriptive Statistics

	GDP per capita, PPP (Current International $)
Mean	723.3685
Median	586.7308
Maximum	1615.751
Minimum	403.9843
Std. Dev.	318.7149
Skewness	1.274216
Kurtosis	3.771818
Jarque-Bera	10.04446
Probability	0.00659
Sum	24594.53
Sum Sq. Dev.	3352112
Observations	34

Appendix 2: Unit root test, GDP_PER_CAPITA (in Level)

Null Hypothesis: GDP_PER_CAPITA has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=8)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		3.882035	1.0000
Test critical values:	1% level	-3.646342	
	5% level	-2.954021	
	10% level	-2.615817	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GDP_PER_CAPITA)
Method: Least Squares
Date: 02/19/25 Time: 14:36
Sample (adjusted): 2 34
Included observations: 33 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GDP_PER_CAPITA(-1)	0.132717	0.034188	3.882035	0.0005
C	-68.66678	25.61987	-2.680216	0.0117
R-squared	0.327114	Mean dependent var		23.74789

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Adjusted R-squared	0.305408	S.D. dependent var	65.26856
S.E. of regression	54.39625	Akaike info criterion	10.88916
Sum squared resid	91727.52	Schwarz criterion	10.97986
Log likelihood	-177.6711	Hannan-Quinn criter.	10.91968
F-statistic	15.07020	Durbin-Watson stat	1.019029
Prob(F-statistic)	0.000506		

Appendix 3: Unit root test, GDP_PER_CAPITA (in first difference)

Null Hypothesis: D(GDP_PER_CAPITA) has a unit root
Exogenous: Constant
Lag Length: 7 (Automatic - based on SIC, maxlag=8)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.235198	0.9694
Test critical values:	1% level	-3.724070	
	5% level	-2.986225	
	10% level	-2.632604	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GDP_PER_CAPITA,2)
Method: Least Squares
Date: 02/19/25 Time: 14:35
Sample (adjusted): 10 34
Included observations: 25 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GDP_PER_CAPITA(-1))	0.049167	0.209044	0.235198	0.8170
D(GDP_PER_CAPITA(-1),2)	-1.184131	0.273572	-4.328414	0.0005
D(GDP_PER_CAPITA(-2),2)	-1.314516	0.326235	-4.029360	0.0010
D(GDP_PER_CAPITA(-3),2)	-1.340458	0.400530	-3.346715	0.0041
D(GDP_PER_CAPITA(-4),2)	-0.600663	0.379717	-1.581869	0.1332
D(GDP_PER_CAPITA(-5),2)	-1.106878	0.357112	-3.099522	0.0069
D(GDP_PER_CAPITA(-6),2)	-0.703810	0.307719	-2.287182	0.0361
D(GDP_PER_CAPITA(-7),2)	-1.404033	0.336555	-4.171780	0.0007
C	44.27862	11.43838	3.871056	0.0014

R-squared	0.751184	Mean dependent var	5.893696
Adjusted R-squared	0.626775	S.D. dependent var	55.98934
S.E. of regression	34.20507	Akaike info criterion	10.17634
Sum squared resid	18719.79	Schwarz criterion	10.61513

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Log likelihood	-118.2042	Hannan-Quinn criter.	10.29804
F-statistic	6.038055	Durbin-Watson stat	1.889090
Prob(F-statistic)	0.001149		

Appendix 4: Unit root test, GDP_PER_CAPITA (in second difference)

Null Hypothesis: D(GDP_PER_CAPITA,2) has a unit root
Exogenous: Constant
Lag Length: 6 (Automatic - based on SIC, maxlag=8)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.795527	0.0001
Test critical values:	1% level	-3.724070	
	5% level	-2.986225	
	10% level	-2.632604	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GDP_PER_CAPITA,3)
Method: Least Squares
Date: 02/19/25 Time: 14:31
Sample (adjusted): 10 34
Included observations: 25 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GDP_PER_CAPITA(-1),2)	-8.538845	1.473351	-5.795527	0.0000
D(GDP_PER_CAPITA(-1),3)	6.403396	1.372932	4.664029	0.0002
D(GDP_PER_CAPITA(-2),3)	5.127674	1.183587	4.332318	0.0005
D(GDP_PER_CAPITA(-3),3)	3.805795	0.938961	4.053198	0.0008
D(GDP_PER_CAPITA(-4),3)	3.221088	0.736937	4.370914	0.0004
D(GDP_PER_CAPITA(-5),3)	2.110475	0.482751	4.371766	0.0004
D(GDP_PER_CAPITA(-6),3)	1.408840	0.326467	4.315417	0.0005
C	45.51105	9.881026	4.605903	0.0003

R-squared	0.915651	Mean dependent var	-2.092997
Adjusted R-squared	0.880919	S.D. dependent var	96.32829
S.E. of regression	33.24111	Akaike info criterion	10.09979
Sum squared resid	18784.51	Schwarz criterion	10.48983
Log likelihood	-118.2474	Hannan-Quinn criter.	10.20797
F-statistic	26.36330	Durbin-Watson stat	1.893411
Prob(F-statistic)	0.000000		

Appendix 5: Results of the ARMA(1,2,3) model

Dependent Variable: DDGDP
Method: ARMA Conditional Least Squares (Gauss-Newton / Marquardt steps)
Date: 02/19/25 Time: 14:52
Sample (adjusted): 4 34
Included observations: 31 after adjustments
Failure to improve likelihood (non-zero gradients) after 16 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 1 3

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	11.07300	8.418300	1.315349	0.1991
AR(1)	-0.677625	0.145476	-4.657977	0.0001
MA(3)	0.831061	0.093162	8.920580	0.0000

R-squared	0.338592	Mean dependent var	7.069222
Adjusted R-squared	0.291348	S.D. dependent var	51.63156
S.E. of regression	43.46421	Akaike info criterion	10.47352
Sum squared resid	52895.84	Schwarz criterion	10.61229
Log likelihood	-159.3395	Hannan-Quinn criter.	10.51875
F-statistic	7.166950	Durbin-Watson stat	1.991630
Prob(F-statistic)	0.003066		

Inverted AR Roots	-.68		
Inverted MA Roots	.47-.81i	.47+.81i	-.94

Appendix 6: Ljung-Box Q statistic/ test

Date: 02/19/25 Time: 14:55
Sample: 1 34
Included observations: 31
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. | . |	. | . |	1	-0.002	-0.002	0.0001	
. *| . |	. *| . |	2	-0.135	-0.135	0.6405	
.**| . |	.**| . |	3	-0.208	-0.212	2.2149	0.137
. | . |	. | . |	4	0.017	-0.008	2.2259	0.329
. *| . |	. *| . |	5	-0.069	-0.134	2.4137	0.491
. *| . |	. *| . |	6	-0.097	-0.159	2.8009	0.592
. | . |	. | . |	7	0.003	-0.040	2.8013	0.731
. |* . |	. |* . |	8	0.156	0.078	3.8867	0.692
. | . |	. *| . |	9	-0.025	-0.086	3.9160	0.789
. | . |	. | . |	10	-0.038	-0.029	3.9873	0.858
. |* . |	. |* . |	11	0.128	0.162	4.8288	0.849
. | . |	. | . |	12	0.031	-0.002	4.8804	0.899
. | . |	. | . |	13	0.014	0.071	4.8921	0.936
. *| . |	. | . |	14	-0.068	0.042	5.1717	0.952
. | . |	. | . |	15	-0.065	-0.060	5.4459	0.964
. *| . |	. *| . |	16	-0.159	-0.175	7.1731	0.928

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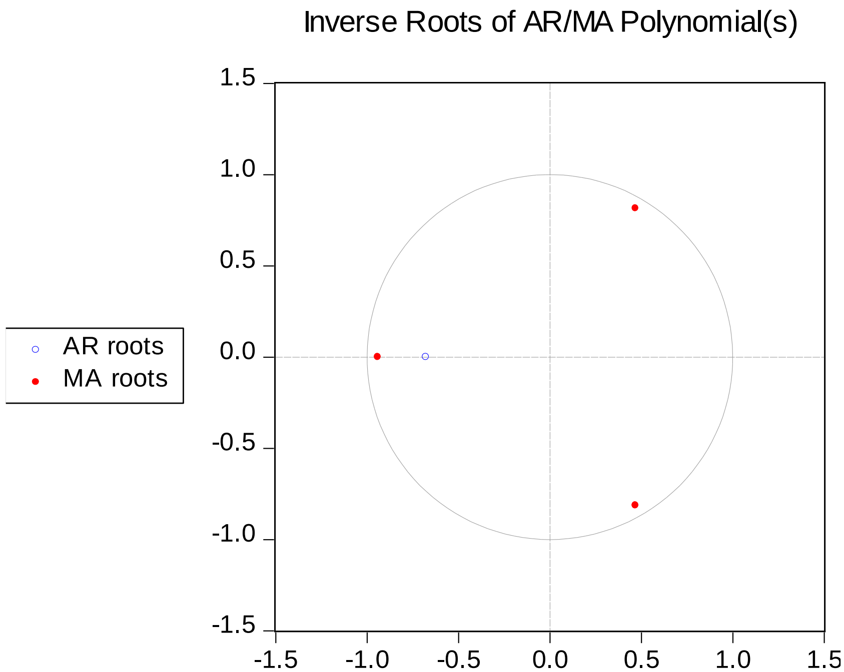
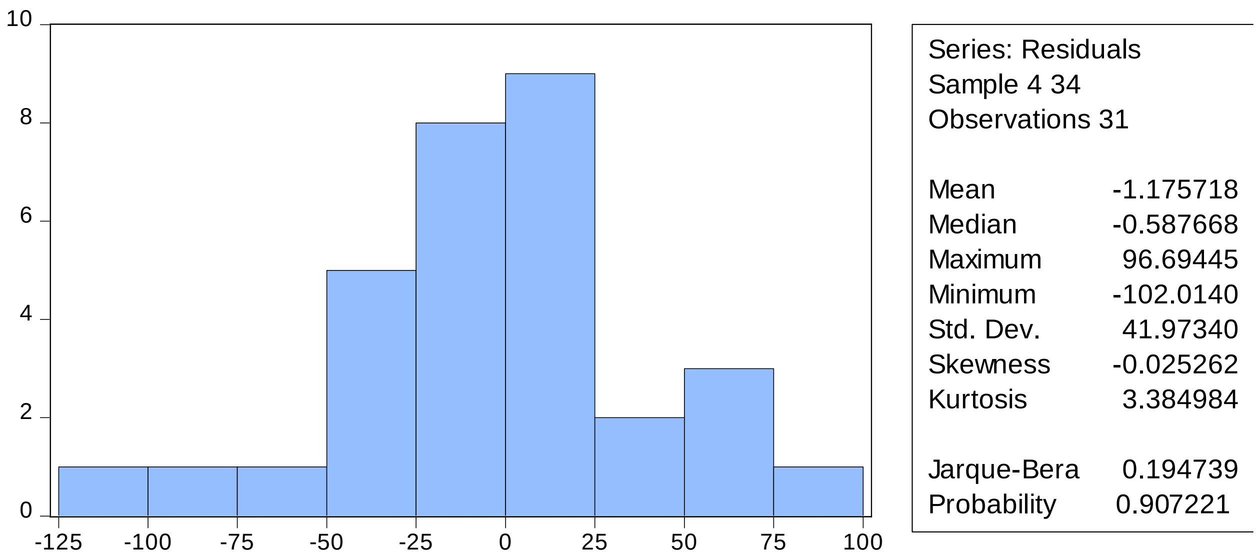
Appendix 7: ARMA (1, 1) structure



Appendix 8: Histogram of residuals



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Appendix 9: GDP_PER_CAPITA FORECAST results

Year	GDP_PER_CAPITA	GDP_PER_CAPITA _FORECAST
1990	832.0704	832.0704
1991	761.9778	761.9778
1992	674.3415	674.3415
1993	576.3728	576.3728
1994	539.569	539.569
1995	532.1807	532.1807
1996	526.1664	526.1664
1997	497.1221	497.1221
1998	481.2892	481.2892
1999	451.826	451.826
2000	416.5493	416.5493
2001	403.9843	403.9843
2002	409.6429	409.6429
2003	428.3336	428.3336
2004	455.8678	455.8678
2005	483.9113	483.9113
2006	509.4278	509.4278
2007	539.4126	539.4126
2008	566.6854	566.6854
2009	568.6096	568.6096
2010	597.0887	597.0887
2011	630.2849	630.2849
2012	632.2021	632.2021
2013	712.439	712.439
2014	804.5966	804.5966
2015	859.1435	859.1435
2016	913.9556	913.9556
2017	1003.257	1003.257
2018	1069.282	1069.282
2019	1167.321	1167.321
2020	1136.008	1136.008
2021	1313.618	1313.618
2022	1484.241	1484.241
2023	1615.751	1615.751
2024	NA	1694.78039
2025	NA	1688.732317

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ISSN: 2321-6247
Volume: 13 | Issue: 2 | February 2025 | Journal DOI: 10.36713/epra0713 | SJIF Impact Factor (2025): 8.825

2026	NA	1735.044697
2027	NA	1722.238617
2028	NA	1749.492697
2029	NA	1749.600998
2030	NA	1768.103968
2031	NA	1774.142244
2032	NA	1788.626904
2033	NA	1797.388082
2034	NA	1810.027642
2035	NA	1820.039112
2036	NA	1831.831442
2037	NA	1842.417012
2038	NA	1853.820312
2039	NA	1864.669502
2040	NA	1875.894172
2041	NA	1886.864402
2042	NA	1898.007052
2043	NA	1909.032862

Appendix 10: Graph showing GDP_PER_CAPITA FORECAST results