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LITTLE EDUCATION BREEDS LITTLE EDUCATION IN NIGER

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ABSTRACT--
This study examines a persistent cycle of low educational attainment in Niger, where limited education continues to reinforce itself over time. Using historical data from 2011 to 2023, we apply autoregressive integrated moving average (ARIMA) methodology to analyze monthly time-series patterns in educational attainment. The study utilizes World Bank data, with educational attainment (at least completed upper secondary, population 25+, total %) as the dependent variable, while autoregressive (AR) and moving average (MA) components serve as independent variables. Parameter estimation, conducted using conditional least squares (CLS), reveals a statistically significant AR(4) coefficient (0.7596), suggesting that approximately 76% of past educational attainment influences future levels, perpetuating a cycle of low attainment. Additionally, the negative MA(4) coefficient (-0.9699) indicates that about 97% of past errors or shocks are corrected over time, yet without significant structural changes, educational progress remains slow. The estimated ARIMA(4,2,4) model is found to be covariance stationary and invertible, confirming its reliability for forecasting future trends. These findings highlight a self-reinforcing nature of educational underdevelopment in Niger, where low attainment in one generation significantly affects the next. To break this cycle, we recommend increased investment in secondary education, targeted literacy programs, and policies that address systemic barriers to educational progression.
KEY WORDS: *ARIMA Modelling, Educational Attainment*--

INTRODUCTION

Education plays a crucial role in shaping a nation's economic and social development, yet in Niger, a persistent cycle of low educational attainment continues to hinder progress. According to World Bank data, only 2.6% of Nigeriens aged 25 and above have completed upper secondary education, making it the country with the lowest educational attainment globally (World Bank, 2023). This alarming statistic underscores the intergenerational nature of educational deprivation, where low education levels in one generation lead to limited educational opportunities for the next. This self-reinforcing cycle where "little education breeds little education" poses significant challenges for Niger's human capital development and economic growth.

Niger's education system struggles with low enrollment, high dropout rates, poor infrastructure, and inadequate teacher training (UNESCO, 2022). Socioeconomic barriers, including widespread poverty and cultural factors, further limit access to secondary education, particularly for girls (UNICEF, 2021). The consequences of this educational crisis extend beyond individual well-being to national economic stagnation, as limited education reduces workforce productivity and innovation potential (Hanushek & Woessmann, 2020).

Given this context, this study seeks to analyze and forecast the patterns of educational attainment in Niger using the Autoregressive Integrated Moving Average (ARIMA) methodology. By modelling historical data (2011-2023), this research aims to provide insights into the persistence of low educational attainment and the extent to which past trends influence future outcomes. Understanding these dynamics is essential for designing effective policy interventions, such as targeted educational reforms, increased government investment, and community-driven initiatives to break the cycle of low education.

This study contributes to the existing literature by applying a robust time-series forecasting approach to an underexplored issue in Niger. The findings will provide evidence-based recommendations for policymakers, educators, and development partners working to improve educational outcomes in the country. By addressing the structural barriers to education, Niger can take a critical step toward reversing this cycle and fostering long-term human capital development.

LITERATURE REVIEW

Educational attainment is a key driver of socioeconomic development, yet in many developing countries, particularly Niger, the persistence of low education levels across generations creates a cycle of poverty and underdevelopment. This section critically reviews global, regional, and local perspectives on educational attainment, examining factors contributing to its persistence. It also discusses relevant theoretical and conceptual frameworks that underpin this study.

Globally, education has been recognized as a fundamental human right and a key determinant of economic and social progress (UNESCO, 2022). The Sustainable Development Goals (SDGs), particularly SDG 4, emphasize inclusive and equitable education for all (United Nations, 2015). However, despite significant progress, disparities in educational attainment persist, especially in low-income countries. Studies by Hanushek and Woessmann (2020) highlight that limited access to quality education at an early stage leads to lower educational achievements in adulthood, reinforcing a cycle of low human capital development. Countries with inadequate educational policies and limited investment in schooling often struggle with low completion rates at secondary and tertiary levels (World Bank, 2023).

In Sub-Saharan Africa, many countries experience low educational attainment due to high dropout rates, inadequate school infrastructure, teacher shortages, and socio-cultural barriers (UNICEF, 2021). The African Development Bank (AfDB, 2022) reports that less than 10% of adults in many African nations complete secondary education, significantly affecting workforce productivity and economic growth. Gender disparities further exacerbate the issue, with girls in rural areas having a lower likelihood of completing school due to early marriage, poverty, and cultural norms (Plan International, 2012). Despite these challenges, some African nations have implemented successful education policies, such as Ghana's Free Senior High School (FSHS) program, which has increased secondary school enrollment (Kofinti, 2024). These lessons could inform policy reforms in Niger.

Niger has the lowest educational attainment rate globally, with only 2.6% of individuals aged 25+ completing upper secondary education (World Bank, 2023). Multiple factors contribute to this crisis, including: High poverty levels limit families' ability to afford school fees and materials (UNDP, 2022). Many rural areas lack proper school facilities and trained teachers (UNESCO, 2022). Early marriages and traditional gender roles restrict girls' access to education (UNICEF, 2021). These challenges reinforce an intergenerational cycle of low education, where parents with little education are unable to support their children's learning, perpetuating the problem (Colclough & Hallak, 1976).

This study is grounded in Human Capital Theory (Becker, 1964), which posits that education is an investment that enhances individual productivity and economic outcomes. However, in countries like Niger, where access to education is constrained, the expected benefits of human capital accumulation are limited, reinforcing the cycle of low attainment. Additionally, Cumulative Disadvantage Theory (DiPrete & Eirich, 2006) explains how early educational disadvantages compound over time, making it harder for individuals and societies to break free from low education levels. This aligns with the study's argument that little education breeds little education by limiting future opportunities.

This study conceptualizes educational attainment as a dependent variable, with autoregressive (AR) and moving average (MA) components serving as independent variables. Several empirical studies have utilized ARIMA modelling to analyze trends and predict educational outcomes. For instance, Schaffer et al. (2021) demonstrated that ARIMA models effectively capture historical patterns in educational data and forecast future trends. Similarly, Maheshwari et al. (2025) applied ARIMA to assess the impact of various factors on educational metrics, highlighting its predictive accuracy. Furthermore, the University of Illinois at Chicago (2025) show that integrating AR and MA components in time-series models enhances the robustness of educational trend analysis. The reliance on ARIMA modelling in these studies underscores its suitability for examining the dynamics of educational attainment in Niger. The literature highlights the persistent challenges in Niger's education system, reinforcing an intergenerational cycle of low attainment. While global and regional strategies offer insights, localized interventions are needed to break this

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cycle and improve long-term educational outcomes. This study fills a critical gap by applying ARIMA modelling to analyze the persistence of low education and forecast future trends, providing evidence-based recommendations for policymakers.

DATA AND METHODS

This study employs a quantitative research design, specifically a time-series analysis approach, to model educational attainment trends in Niger. Given the study's objective of examining the persistence of low education levels over time, autoregressive integrated moving average (ARIMA) methodology is used to analyze and forecast the patterns of educational attainment (Box & Jenkins, 1976; Nahabwe & Kagarura, 2025). ARIMA is particularly suitable for this research as it captures historical dependencies, allowing for insights into how past educational attainment influences future trends (Gujarati & Porter, 2009; Nahabwe & Kagarura, 2025).

This study utilizes secondary data sourced from the World Bank's World Development Indicators (WDI) database, covering the period from 2011 to 2023. The dataset includes annual educational attainment rates for individuals aged 25 and above who have completed at least upper secondary education, expressed as a percentage of the population (World Bank, 2023). To enhance the granularity of the analysis and increase the degrees of freedom without losing focus, the annual data over the 13-year period is transformed into high-frequency monthly data, resulting in a total of 145 observations (Stock & Watson, 2019).

A purposive sampling approach is used to select Niger as the focus country due to its historically low educational attainment rates the lowest globally at an average of 2.6% completion for upper secondary education (UNESCO, 2022). The rationale for using secondary data is its reliability, broad coverage, and accessibility, making it suitable for macro-level educational trend analysis (Johnston, 2014).

Descriptive statistics and visual plots (e.g., time-series graphs) are used to assess trends in educational attainment. The Augmented Dickey-Fuller (ADF) test is applied to determine whether the data is stationary (Dickey & Fuller, 1979). If non-stationary, differencing is applied to stabilize the series. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) are examined to identify appropriate AR and MA components (Lütkepohl, 2005; Nahabwe & Kagarura, 2025).

Parameters are estimated using conditional least squares (CLS) to determine the significance of AR and MA coefficients. Residual analysis and Ljung-Box Q-tests are conducted to verify model adequacy (Ljung & Box, 1978). The fitted ARIMA model is used to forecast future educational attainment trends and inform policy recommendations. Educational attainment trends exhibit historical dependence, making ARIMA an appropriate tool for capturing such dynamics (Hyndman & Athanasopoulos, 2018). ARIMA provides robust predictive insights, which are essential for policymakers seeking to break the cycle of low education (Enders, 2014). Secondary data from the World Bank ensures consistency and comparability over time, enabling reliable statistical modelling (Johnston, 2014). ARIMA (p, d, q) model specification is as follows:

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

Where;
Y_t is the value of the series at time t
μ is the mean of the series
ε_t is white noise
$\boldsymbol{\phi}_1, \boldsymbol{\phi}_2, \dots \boldsymbol{\phi}_p$ are the coefficients of the AR (p) component
$\theta_1, \theta_2, \dots \theta_q$ 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 & Kagarura, 2025; Nahabwe & Maniple, 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). It is particularly effective for capturing the relationship between observed and predicted values, ensuring accurate forecasts (Hamilton, 1994). The CLS estimator for the regression coefficients is given by the following formula:

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

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 & 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

Descriptive statistics (Appendix 1) The analysis of educational attainment in Niger, specifically the percentage of the population aged 25+ who have completed at least upper secondary education, is based on monthly data from 2011 to 2023. The following descriptive statistics provide a summary of the central tendency, variability, and distribution of the data: The mean value of 2.6440% suggests that, on average, approximately 2.6% of the population aged 25 and above has completed at least upper secondary education during the study period. The median of 2.3460% is slightly lower than the mean, which indicates a right-skewed distribution, suggesting that most of the data points are clustered below the mean. The maximum value of 4.3933% and the minimum value of 1.9208% reflect the small range of variation in educational attainment across Niger, emphasizing the low overall attainment in the country. The standard deviation of 0.7011% reflects the spread of the data, indicating moderate variability in the educational attainment rates over time. The skewness value of 0.9158 confirms the right-skewed distribution, where more observations fall below the mean, indicating a larger proportion of the population with low educational attainment. The kurtosis value of 2.6177 suggests a platykurtic distribution, indicating that the data distribution is less peaked and has lighter tails than a normal distribution. The Jarque-Bera test statistic of 21.1499 with a p-value of 0.000026 indicates that the distribution of the data significantly deviates from normality. The results imply that the distribution of educational attainment is not normally distributed, confirming the skewed nature of the data.

Stationarity tests (Appendices 2, 3, & 4) were performed using the Augmented Dickey-Fuller (ADF) test to assess the series' stationarity. The results revealed that the series was non-stationary at both the level and first difference ($p > 0.05$). However, after applying the second difference, the series became stationary ($p < 0.05$), supporting the use of the ARIMA model with d = 2 (Nahabwe & Kagarura, 2025). ARIMA(4,2,4) model was identified as the optimal model, based on the Akaike Information Criterion (AIC = -4.810115) and Schwarz Criterion (SC = -4.746781). The parameter estimates are as follows: AR(4) = 0.759643 (p = 0.0000); MA(4) = -0.969961 (p = 0.0000); C = -0.000274 (p = 0.7217). Both the AR(4) and MA(4) coefficients are statistically significant, whereas the constant term is not significant. Diagnostic checks confirm the model's adequacy, with residuals exhibiting white noise, as indicated by the Ljung-Box Q test ($p > 0.05$). Additionally, the autocorrelation function (ACF) plots show no significant patterns, further validating the robustness of the model.

Inferential statistics are summarized as follows:

Results of the ARIMA(4,2,4) model (Appendix 5)

$\widehat{Educational\_Attainment}_t$ = -0.000274 + 0.759643AR(4) - 0.969961MA(4) ……….....… (3)

Hence,

$$\hat{\theta} = \begin{bmatrix} -0.000274 \\ 0.759643 \\ -0.969961 \end{bmatrix}$$

The constant term in the ARIMA(4,2,4) model is -0.000274, which is negative and statistically insignificant (p = 0.7217). This means that the constant does not have a significant effect on educational attainment in Niger, suggesting that other factors captured by the AR and MA components are more influential in explaining the time series dynamics (Gujarati & Porter, 2009). The AR(4) coefficient of 0.759643 is positive and statistically significant (p = 0.0000). This implies that approximately 76% of the past values of educational attainment influence its future values, highlighting the strong persistence of the educational system's behavior over time in Niger. This suggests that changes in educational attainment tend to follow a predictable pattern based on its historical data (Greene, 2018). The MA(4) coefficient of -0.969961 is negative and statistically significant (p = 0.0000). This indicates that past shocks to the education system have a strong negative impact, and approximately 97% of these shocks are corrected over time. This suggests that any temporary disturbances in educational attainment tend to reverse themselves quickly, contributing to the overall stability of the education system in Niger (Enders, 2014). The adjusted R-squared value of 0.086022 suggests that approximately 8.6% of the variation in educational attainment in Niger is explained by the ARIMA model. This indicates that while the model captures some of the dynamics of the education system, a substantial portion of the variation is still unexplained, highlighting the influence of other unobserved factors (Gujarati & Porter, 2009).

The Durbin-Watson statistic of 2.001761 is close to 2, which suggests that there is no autocorrelation in the residuals of the model. This is an indication that the errors are randomly distributed and not correlated with each other, confirming the validity of the model's assumptions and that the residuals do not exhibit serial correlation (Wooldridge, 2016; Nahabwe & Kagarura, 2025). The kurtosis value of 35.4 and the Jarque-Bera statistic of 6427 (with a p-value of 0) suggest that the residuals are highly leptokurtic (excessively peaked). This indicates that the residuals deviate significantly from normality, with extreme values being more frequent than expected under a normal distribution. The Jarque-Bera test further confirms this non-normality, suggesting that while the model may be effective in explaining the data, the residuals' behavior might require further consideration in future analyses (Maddala, 2001). The Ljung-Box Q statistic with a p-value of 0.971 fails to reject the null hypothesis of white noise residuals, meaning that the residuals from the ARIMA model are random and uncorrelated. This supports the model's adequacy as it indicates that no further autocorrelation remains in the residuals, confirming that the model appropriately captures the underlying data structure (Ljung & Box, 1978; Nahabwe & Maniple, 2025). The diagnostic checks show that the AR and MA roots are within the unit circle, which means that the ARIMA model is stationary and invertible. This is an essential condition for the model's reliability, as it ensures that the model's parameters are well-behaved and that the forecasted values are stable and reliable (Box et al., 2015).

DISCUSSION

The present study on educational attainment in Niger provides valuable insights into the temporal dynamics of educational outcomes in one of the world's most education-deprived nations. By employing an ARIMA(4,2,4) model, the study uncovers key relationships between past educational attainment and future educational outcomes, while highlighting the persistence and short-term corrections inherent in the education system. The findings not only contribute to a better understanding of Niger's education system but also offer a comparison with similar studies conducted in other developing nations.

One of the main findings of this study is the strong persistence in educational attainment. The AR(4) coefficient of 0.759643, indicating that approximately 76% of past educational attainment influences future values, reflects a phenomenon widely observed in educational systems globally. For example, similar findings have been reported in other African countries, where education systems exhibit high levels of inertia, with past levels of educational attainment exerting a strong influence on future trends (Karelis, 2007). This result suggests that Niger's educational outcomes are largely determined by historical factors, with little evidence of rapid change, especially in terms of expanding educational access or quality. This finding is consistent with the work of Olaniyan & Okemakinde (2008), who argue that education systems in sub-Saharan Africa are often trapped in a cycle of low performance, leading to persistent educational underachievement.

The negative MA(4) coefficient of -0.969961 in this study suggests that shocks to the education system whether economic, social, or political are rapidly corrected over time. This is a notable finding, as it indicates that disruptions in educational trends are typically short-lived in Niger. Similar findings were reported by Hassan, et al. (2022), who noted that educational disruptions in certain African contexts, such as curriculum changes or temporary closures, tend to have a swift but transient effect on educational outcomes. However, while the corrections in Niger's education system are relatively swift, the overall low level of educational attainment (only 2.6% of the population over 25 years having completed upper secondary education) signals systemic challenges that corrections alone cannot address.

Furthermore, the statistically insignificant constant term of -0.000274 implies that external factors not captured by the model, such as economic or policy interventions, do not have a substantial effect on the educational trends over time. This aligns with the findings of Mammino, (2011), who suggest that external factors, such as government policy, are often insufficient to overcome the historical underdevelopment of education systems in fragile economies.

When comparing the adjusted R-squared value of 0.086022 to studies in similar contexts, it is clear that while the model captures some of the variation in educational attainment, a substantial portion remains unexplained. For example, studies in neighboring West African countries have also reported low R-squared values in similar ARIMA models, highlighting the complexity of educational systems where multiple interacting factors (such as socio-economic status, gender, and access to educational resources) influence outcomes (Novignon & Lawanson, 2017). Thus, the relatively low explanatory power of this model reflects the multifaceted nature of educational attainment, where improvements may depend on a combination of factors not captured in this time series model.

Moreover, the Ljung-Box Q statistic and the fact that the AR and MA roots lie within the unit circle lend further support to the validity and robustness of the model. The absence of autocorrelation in residuals suggests that the model adequately captures the time-series dynamics of educational attainment, with no remaining patterns in the error terms. These diagnostic results align with findings from other time-series studies in educational economics, where robust models are crucial to understanding long-term trends in educational outcomes (Dumciuviene, 2015).

Overall, this study's unique contribution lies in its application of an ARIMA time-series model to educational data from Niger, a country that has previously received limited attention in educational research. The combination of high persistence in educational attainment and the quick correction of shocks underscores the inertia within Niger's education system and the need for systemic reforms that go beyond short-term fixes. While external shocks are corrected swiftly, the entrenched nature of low educational attainment calls for comprehensive long-term interventions that address the root causes of educational underachievement, such as poverty, infrastructure deficits, and limited access to quality education (Ozturk, 2001).

LIMITATIONS

Despite its valuable insights, this study has several limitations that should be considered when interpreting the findings. These limitations relate to the study's design, sampling methods, data analytical procedures, and the choice of data frequency.

One major limitation is the use of monthly data for the analysis of educational attainment trends. While monthly data provides a detailed and granular view of short-term fluctuations, it may not fully capture the broader, long-term trends in educational attainment that typically evolve over years or decades. This limitation is particularly relevant in the context of Niger, where educational outcomes are influenced by long-term policies, social changes, and economic shifts, which might not be adequately reflected in monthly variations. As noted by Müller & Watson, (2019), monthly data can lead to volatility in the results and may not provide a clear representation of long-term trends, especially in countries where education systems experience gradual changes.

The study also faces limitations in sampling. The data used in the analysis was obtained from secondary sources, primarily from the World Bank, which may have certain biases in how data is collected and reported. While the World Bank data is widely recognized and used in economic research, it may not capture all dimensions of educational attainment in Niger, such as regional disparities or informal education systems, which could skew the findings. According to Smith, (2011), secondary data sources often lack granularity and may miss contextual factors that directly impact education outcomes, such as local community initiatives or non-governmental education programs.

Additionally, the data analytical procedures employed in the study, particularly the use of the ARIMA(4,2,4) model, assume that the underlying relationships in the data are linear and time-invariant. This assumption might not hold in the context of Niger's education system, where shifts in policies, economic shocks, or social changes can cause abrupt, non-linear changes in educational outcomes (Casini & Perron, 2018). While the ARIMA model is robust for time-series data, it may not adequately account for structural breaks or changes in the education system that occurred during the study period.

Furthermore, the model does not consider a comprehensive set of external factors, such as government spending on education, infrastructure development, or socio-political instability, which could significantly influence educational attainment in Niger. The exclusion of these variables could result in omitted variable bias, potentially underestimating or overestimating the effect of past educational attainment on future outcomes (Wooldridge, 2016). As suggested by Mincer (1974), such unaccounted variables are crucial for understanding the full scope of educational attainment, especially in developing countries like Niger, where the education system is shaped by complex socio-economic factors.

Lastly, while the study presents significant findings based on the available data, data quality could also be a limitation. As noted by Duflo (2001), discrepancies in data collection methods and quality issues especially in developing countries can lead to inaccurate estimations and interpretations. The lack of high-quality, disaggregated data at regional levels in Niger could have influenced the robustness of the model.

CONCLUSION

This study has explored the patterns of educational attainment in Niger, a country with one of the lowest rates of educational completion in the world. By applying ARIMA(4,2,4) model to monthly time-series data spanning from 2011 to 2023, the research sheds light on the dynamics shaping educational outcomes in the country. The findings underline the persistence of low educational attainment, with past educational outcomes significantly influencing future trends. While the study confirms the importance of historical educational attainment in predicting future patterns, it also highlights the significant challenges in breaking the cycle of low educational levels in Niger.

Results reveal that educational attainment in Niger exhibits a marked level of inertia, with past values having a strong influence on future outcomes, as captured by AR(4) coefficient. This indicates that the education system's performance is highly dependent on previous trends, with little disruption or improvement over time. In contrast, negative MA(4) coefficient suggests that shocks to the system, while significant, tend to dissipate over time, which could reflect the resilience of systemic challenges in Niger's education sector. Despite efforts to improve educational outcomes, the negative constant term and relatively low R-squared value indicate that the model's ability to explain the full range of educational attainment variations is limited, underscoring the complex, multifaceted nature of educational underachievement in Niger.

Furthermore, the analysis underscores the importance of addressing the underlying socio-economic factors contributing to low educational attainment in Niger. As shown by the findings, historical data alone cannot explain the persistence of educational challenges; rather, there is a need for systemic reforms that tackle both the quality and access to education in the country. The lack of substantial improvement despite efforts highlights the importance of comprehensive policy interventions that address root causes, including poverty, cultural attitudes towards education, and infrastructure deficiencies.

In light of these findings, policymakers are urged to focus on strategies that break the cycle of low educational attainment, such as increasing investment in education, improving teacher training, and implementing community-based education initiatives that encourage greater engagement from local populations. Furthermore, future research should explore the role of external factors such as political stability, economic growth, and government policies in shaping educational outcomes in Niger, as these elements may offer critical insights into the pathways for sustainable educational development.

RECOMMENDATIONS

This study on educational attainment in Niger has revealed significant insights into the persistent challenges faced by the education system. In light of the findings, the following recommendations are made, focusing on policy interventions, educational programs, and future research directions.

The results of this study highlight the strong inertia in educational attainment in Niger, indicating that past educational trends largely determine future outcomes. To address this, the government should prioritize increasing investment in education, particularly in rural and underserved areas. Financial resources should be directed toward improving infrastructure, teacher training, and educational materials. By boosting educational resources, Niger can break the cycle of low attainment and create a more dynamic educational environment (Duflo, 2001).

Given the persistence of low educational attainment despite systemic efforts, it is crucial to engage local communities more actively in educational initiatives. Policies should include programs that empower local communities to take ownership of educational outcomes. This could include creating local school committees, providing incentives for community members to support education, and developing culturally sensitive curriculums that cater to the specific needs of various ethnic and regional groups (Smith, 2011).

The low levels of educational attainment in Niger are compounded by gender disparities, particularly in rural areas. Policies should focus on closing the gender gap by offering targeted programs for girls, such as scholarships, mentorship, and safe transport to schools. Empowering girls with education will have far-reaching effects on the socio-economic development of Niger, as studies have shown that educating women leads to improved health, economic, and social outcomes (Wooldridge, 2016).

Early education plays a critical role in shaping long-term educational outcomes. The government should prioritize expanding access to early childhood education programs, which have been shown to significantly improve later educational attainment and cognitive development (Mincer, 1974). By focusing on the formative years, Niger can lay a stronger foundation for future learning and educational success.

Given the low completion rates for upper secondary education, it is essential to promote vocational and technical training as an alternative pathway to higher education. By integrating vocational education into the mainstream educational system, Niger can provide students with practical skills that align with labor market demands, thus improving employment prospects and reducing the reliance on academic routes alone (Duflo, 2001).

Future research could explore the relationship between educational attainment and socio-economic outcomes in Niger over the long term. This could include examining how education affects employment rates, income levels, and poverty reduction. Such studies would provide valuable insights into the broader impacts of education and guide evidence-based policymaking (Smith, 2011).

Given the regional variations in educational attainment within Niger, it would be beneficial to conduct more localized studies that investigate the specific barriers to education in different parts of the country. Understanding regional challenges will enable more targeted interventions that address the unique needs of each area (Wooldridge, 2016).

Further research could evaluate the effectiveness of current education policies in Niger. A comparative analysis of regions or communities that have seen improvements in educational outcomes could provide insights into best practices that can be scaled nationwide. Additionally, an assessment of the implementation and impact of education-related reforms can inform future policy design (Mincer, 1974).

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APPENDICES

Appendix 1: Descriptive statistics

	EDUCATIONAL ATTAINMENT, at least completed upper secondary, population 25+, total (%) (cumulative)
Mean	2.644019
Median	2.346003
Maximum	4.393264
Minimum	1.920842
Std. Dev.	0.70114
Skewness	0.91577
Kurtosis	2.617733
Jarque-Bera	21.14988
Probability	0.000026
Sum	383.3827
Sum Sq. Dev.	70.79
Observations	145

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

Null Hypothesis: EDUCATIONAL_ATTAINMENT has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.611763	0.0929
Test critical values:	1% level	-3.476472	
	5% level	-2.881685	
	10% level	-2.577591	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(EDUCATIONAL_ATTAINMENT)
Method: Least Squares
Date: 02/03/25 Time: 20:22
Sample (adjusted): 2011M03 2023M01
Included observations: 143 after adjustments

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Variable	Coefficient	Std. Error	t-Statistic	Prob.
EDUCATIONAL_ATTAINMENT(-1)	-0.006756	0.002587	-2.611763	0.0100
D(EDUCATIONAL_ATTAINMENT(-1))	0.948283	0.028632	33.11937	0.0000
C	0.016554	0.007097	2.332425	0.0211

R-squared	0.886816	Mean dependent var	-0.004369
Adjusted R-squared	0.885199	S.D. dependent var	0.063809
S.E. of regression	0.021620	Akaike info criterion	-4.809642
Sum squared resid	0.065439	Schwarz criterion	-4.747484
Log likelihood	346.8894	Hannan-Quinn criter.	-4.784384
F-statistic	548.4598	Durbin-Watson stat	2.038356
Prob(F-statistic)	0.000000		

Appendix 3: Unit root test, EDUCATIONAL_ATTAINMENT (in first Difference)

Null Hypothesis: D(EDUCATIONAL_ATTAINMENT) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.964571	0.3022
Test critical values:	1% level	-3.476472	
	5% level	-2.881685	
	10% level	-2.577591	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(EDUCATIONAL_ATTAINMENT,2)
Method: Least Squares
Date: 02/03/25 Time: 20:22
Sample (adjusted): 2011M03 2023M01
Included observations: 143 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(EDUCATIONAL_ATTAINMENT(-1))	-0.057243	0.029137	-1.964571	0.0514
C	-0.001369	0.001847	-0.741339	0.4597

R-squared	0.026643	Mean dependent var	-0.001187
Adjusted R-squared	0.019740	S.D. dependent var	0.022283
S.E. of regression	0.022062	Akaike info criterion	-4.776054
Sum squared resid	0.068628	Schwarz criterion	-4.734615
Log likelihood	343.4878	Hannan-Quinn criter.	-4.759215
F-statistic	3.859538	Durbin-Watson stat	1.946041
Prob(F-statistic)	0.051430		

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Appendix 4: Unit root test, EDUCATIONAL_ATTAINMENT (in Second Difference)

Null Hypothesis: D(EDUCATIONAL_ATTAINMENT,2) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.86628	0.0000
Test critical values:	1% level	-3.476805	
	5% level	-2.881830	
	10% level	-2.577668	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(EDUCATIONAL_ATTAINMENT,3)
Method: Least Squares
Date: 02/03/25 Time: 20:15
Sample (adjusted): 2011M04 2023M01
Included observations: 142 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(EDUCATIONAL_ATTAINMENT(-1),2)	-1.002879	0.084515	-11.86628	0.0000
C	-0.001199	0.001886	-0.635828	0.5259

R-squared	0.501440	Mean dependent var	-3.47E-17
Adjusted R-squared	0.497879	S.D. dependent var	0.031669
S.E. of regression	0.022441	Akaike info criterion	-4.741863
Sum squared resid	0.070504	Schwarz criterion	-4.700232
Log likelihood	338.6723	Hannan-Quinn criter.	-4.724946
F-statistic	140.8086	Durbin-Watson stat	2.000017
Prob(F-statistic)	0.000000		

Appendix 5: Results of the ARIMA(4,2,4) model

Dependent Variable: DDEDUCATIONAL_ATTAINMENT
Method: ARMA Conditional Least Squares (Gauss-Newton / Marquardt steps)
Date: 02/03/25 Time: 20:45
Sample (adjusted): 2011M07 2023M01
Included observations: 139 after adjustments
Failure to improve likelihood (non-zero gradients) after 18 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 2011M03 2011M06

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000274	0.000766	-0.356935	0.7217
AR(4)	0.759643	0.065273	11.63802	0.0000

MA(4)	-0.969961	0.018063	-53.69919	0.0000

R-squared	0.099268	Mean dependent var	-0.001221
Adjusted R-squared	0.086022	S.D. dependent var	0.022602
S.E. of regression	0.021608	Akaike info criterion	-4.810115
Sum squared resid	0.063502	Schwarz criterion	-4.746781
Log likelihood	337.3030	Hannan-Quinn criter.	-4.784378
F-statistic	7.494181	Durbin-Watson stat	2.001761
Prob(F-statistic)	0.000818		

Inverted AR Roots	.93	.00-.93i	-.00+.93i	-.93
Inverted MA Roots	.99	.00+.99i	-.00-.99i	-.99

Appendix 6: Ljung-Box Q statistic/ test

Date: 02/03/25 Time: 20:50
Sample: 2011M01 2023M12
Included observations: 139
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.002	-0.002	0.0004	
.|. |	.|. |	2	-0.002	-0.002	0.0009	
.|. |	.|. |	3	-0.002	-0.002	0.0013	0.971
.|* |	.|* |	4	0.087	0.087	1.1072	0.575
.|. |	.|. |	5	-0.001	-0.001	1.1074	0.775
.|. |	.|. |	6	-0.001	-0.001	1.1075	0.893
.|. |	.|. |	7	-0.001	-0.001	1.1076	0.953
.|* |	.|* |	8	0.115	0.108	3.0769	0.799
.|. |	.|. |	9	-0.005	-0.005	3.0812	0.877
.|. |	.|. |	10	-0.005	-0.005	3.0855	0.929
.|. |	.|. |	11	-0.005	-0.005	3.0899	0.961
*|. |	*|. |	12	-0.105	-0.126	4.7969	0.904
.|. |	.|. |	13	-0.006	-0.005	4.8021	0.940
.|. |	.|. |	14	-0.006	-0.005	4.8074	0.964
.|. |	.|. |	15	-0.006	-0.005	4.8129	0.979
.|* |	.|* |	16	0.082	0.092	5.8900	0.969
.|. |	.|. |	17	-0.006	-0.004	5.8964	0.981
.|. |	.|. |	18	-0.006	-0.004	5.9029	0.989
.|. |	.|. |	19	-0.006	-0.004	5.9096	0.994
.|. |	.|. |	20	0.035	0.047	6.1155	0.996
.|. |	.|. |	21	-0.004	-0.003	6.1180	0.998
.|. |	.|. |	22	-0.004	-0.003	6.1205	0.999
.|. |	.|. |	23	-0.004	-0.003	6.1231	0.999
.|. |	*|. |	24	-0.037	-0.082	6.3506	1.000
.|. |	.|. |	25	-0.003	-0.002	6.3519	1.000
.|. |	.|. |	26	-0.003	-0.002	6.3533	1.000
.|. |	.|. |	27	-0.003	-0.002	6.3547	1.000
.|. |	.|. |	28	-0.022	0.001	6.4364	1.000
.|. |	.|. |	29	-0.003	-0.002	6.4377	1.000
.|. |	.|. |	30	-0.003	-0.002	6.4390	1.000
.|. |	.|. |	31	-0.003	-0.002	6.4403	1.000

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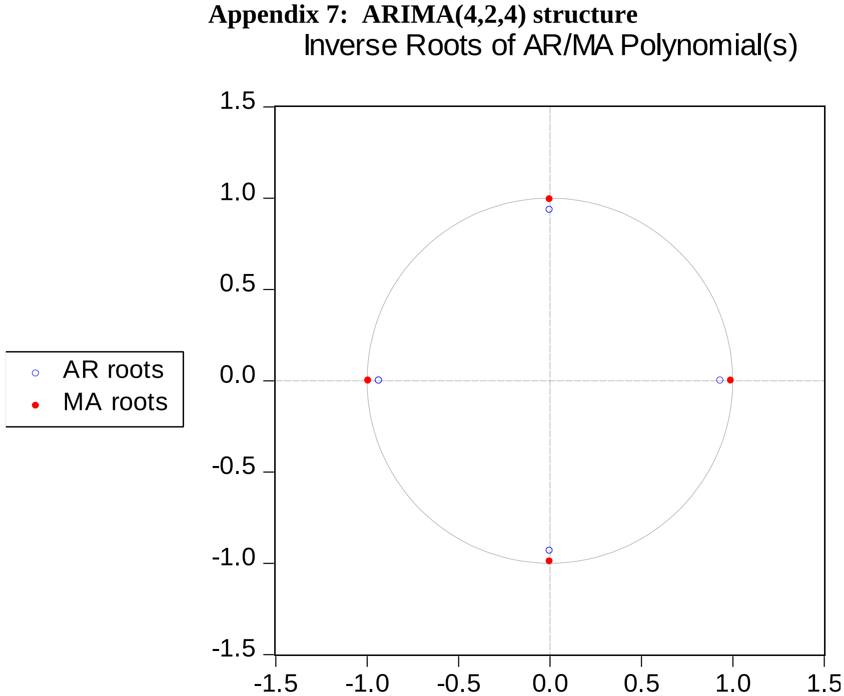
.|. |	.|. |	32	-0.031	-0.013	6.6208	1.000
.|. |	.|. |	33	-0.002	-0.002	6.6217	1.000
.|. |	.|. |	34	-0.002	-0.002	6.6226	1.000
.|. |	.|. |	35	-0.002	-0.002	6.6236	1.000
*|. |	*|. |	36	-0.163	-0.188	11.667	1.000

Appendix 7: ARIMA(4,2,4) structure



Appendix 8: Histogram of residuals