

EMPIRICAL ANALYSIS OF ZINC CONSUMPTION DETERMINANTS ACROSS COUNTRIES: AN OLS TIME SERIES APPROACH

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Abstract

This study presents an empirical investigation of zinc consumption dynamics and its macroeconomic determinants using a time series Ordinary Least Squares (OLS) regression framework. Zinc (Zn) plays a crucial role in multiple sectors of the economy, including galvanization, chemical production, medical applications, and technical manufacturing industries. Understanding the determinants of zinc consumption per capita is essential for evaluating industrial development patterns and resource allocation efficiency. The study employs annual time series data and applies OLS estimation techniques, complemented by descriptive statistical analysis, to examine the relationships between zinc consumption per capita (current US\$) and a set of macroeconomic and industrial variables. These explanatory variables include GDP per capita (current US\$), zinc price (current US\$), and sectoral value-added shares such as galvanization (% of GDP), technical (% of GDP), chemical (% of GDP), and medical (% of GDP). The empirical results indicate that economic growth, measured by GDP per capita, has a significant positive relationship with zinc consumption, reflecting increased industrial demand in higher-income economies. Similarly, sectoral variables such as galvanization and chemical production show strong explanatory power, highlighting the importance of industrial structure in determining zinc demand. On the other hand, price effects demonstrate a negative relationship, consistent with standard demand theory.

Keywords: Zinc consumption, GDP per capita, industrial structure, OLS model, time series, macroeconomics

JEL Codes: Q32, C22, E23.

Introduction

Mineral resources play a fundamental role in the development of modern industrial economies, and zinc is among the most important non-ferrous metals widely used across multiple sectors. It is primarily utilized in galvanization processes, chemical production, medical applications, and various technical industries. Due to its extensive industrial usage, zinc consumption is closely linked with macroeconomic performance, industrial structure, and technological advancement.

In recent years, global demand for zinc has increased steadily, driven by rapid industrialization, urbanization, and infrastructure development. Countries with higher levels of economic development tend to exhibit greater per capita consumption of zinc, reflecting the expansion of manufacturing and construction sectors. Therefore, understanding the determinants of zinc consumption is essential for evaluating resource demand patterns and industrial growth dynamics.

This study focuses on analyzing zinc consumption per capita and its relationship with key macroeconomic and industrial variables, including GDP per capita, zinc price, and sectoral contributions of galvanization, technical industries, chemical production, and medical sectors. By employing a time series Ordinary Least Squares (OLS) approach, the study aims to identify the magnitude and direction of these relationships over time.

The empirical framework allows for examining how economic growth and industrial structure influence mineral consumption patterns. In particular, it addresses whether sectoral expansion in galvanization and chemical industries significantly drives zinc demand, and how price fluctuations affect consumption behavior.

This research contributes to the literature on resource economics and industrial development by providing evidence on the macroeconomic determinants of zinc consumption. It also offers insights for policymakers regarding sustainable resource management and industrial planning.

2. Literature Review

The relationship between natural resource consumption and macroeconomic development has been widely explored in economic and industrial literature. One of the foundational theories is the Resource Demand Theory, which suggests that the consumption of industrial metals such as zinc increases with economic growth due to rising production and infrastructure needs (Hotelling, 1931).

Another important theoretical framework is the Structural Change Theory, which explains that as economies develop, they shift from primary sectors to industrial and service-oriented sectors, increasing demand for intermediate inputs such as metals (Kuznets, 1966). In this context, zinc consumption is strongly influenced by industrialization patterns and sectoral composition of GDP.

From a macroeconomic perspective, the Endogenous Growth Theory emphasizes the role of technological progress and capital accumulation in driving long-term economic expansion (Romer, 1990). In industrial applications, zinc plays a key role in improving productivity, particularly in galvanization and manufacturing industries, thereby linking metal consumption with growth dynamics.



Empirical studies in resource economics have also highlighted the importance of price elasticity in determining metal demand. According to standard demand theory, increases in commodity prices generally reduce consumption levels, although industrial demand tends to be relatively inelastic in the short run (Wooldridge, 2010).

Sectoral studies further indicate that industries such as construction, chemical processing, and medical manufacturing are major drivers of zinc demand. The Industrial Structure Hypothesis suggests that economies with higher shares of manufacturing and heavy industry exhibit greater metal consumption intensity (Szirmai, 2012).

However, the literature also highlights potential endogeneity between economic growth and resource consumption, where increased metal usage may simultaneously contribute to GDP growth through industrial expansion. This simultaneity issue is commonly addressed using econometric approaches such as OLS and time series analysis.

Overall, existing literature confirms that zinc consumption is a function of macroeconomic performance, industrial structure, and price dynamics, but there is still limited country-specific time series evidence, which this study aims to address.

3. Research Methodology

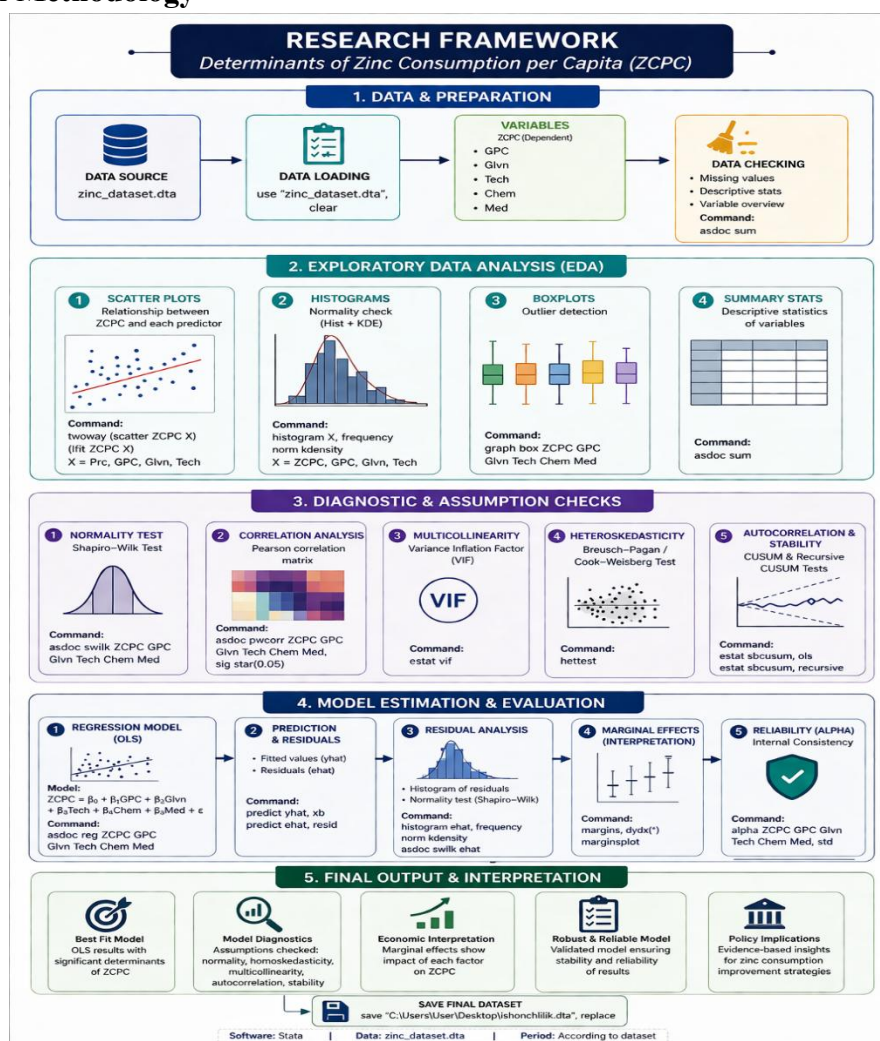


Figure 1. Research framework flowchart

Table 1. Variable description

Variable name	Variable label
ZCPC	Zinc Consumption per capita (current US\$)
Prc	Price (current US\$)
GPC	GDP per capita (current US\$)
Glnv	Galvanization (% of GDP)
Tech	Technical (% of GDP)
Chem	Chemical (% of GDP)
Med	Medical (% of GDP)

We conducted a study using data from the World bank open Data, which analyzes data from nations throughout our regions to gather information on quality of life and related variables, in order to evaluate our hypothesis. Following this, the data was discussed in both descriptive and inferential statistics, Pearson pairwise correlation analysis, multivariate linear regression from scratch using OLS model, Path model featuring three effects: overall, indirect, and direct. Stata 17.0 was used for post-estimation examination of the model results.

Model Specification and Estimation

This model reflects the elasticity impact of the significant tourism-related industries on the number of total tourists over time. The use of the natural logarithm of the main explanatory factors allows the coefficient $\beta_1, \beta_2, \beta_3, \beta_4$ to be interpreted as elasticities.

1. Linear–Linear Model (Lin–Lin)

$$ZCPC_t = \beta_0 + \beta_1 Prc_t + \beta_2 GPC_t + \beta_3 Glnv_t + \beta_4 Tech_t + \beta_5 Chem_t + \beta_6 Med_t + \varepsilon_t$$

2. Linear–Log Model (Lin–Log)

$$ZCPC_t = \beta_0 + \beta_1 \ln(Prc_t) + \beta_2 \ln(GPC_t) + \beta_3 \ln(Glnv_t) + \beta_4 \ln(Tech_t) + \beta_5 \ln(Chem_t) + \beta_6 \ln(Medt) + \varepsilon_t$$

Generate Hypothesis

H_0 (Null hypothesis): All independent variables (Prc, GPC, Glnv, Tech, Chem, Med) have no significant effect on ZCPC.

$$\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$$

H_a (Alternative hypothesis): At least one of the independent variables has a significant effect on ZCPC.

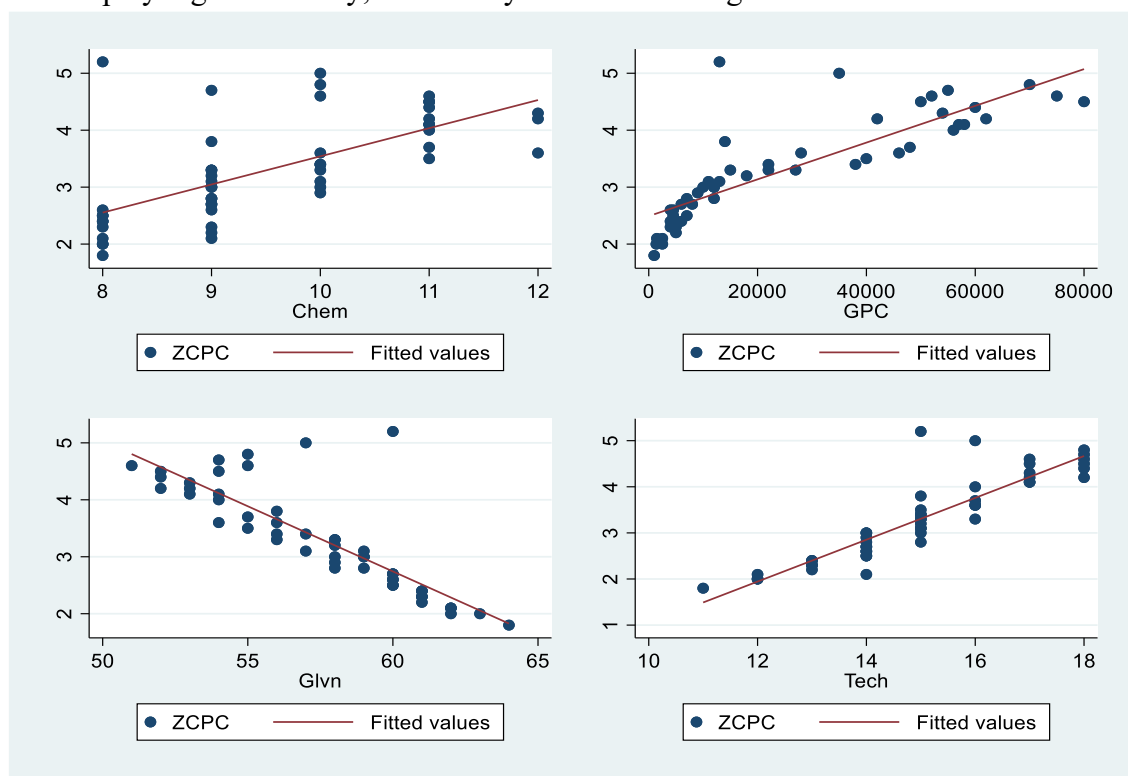
4. Analysis and Results

Descriptive statistics indicate notable variation among the key macroeconomic variables related to zinc in Kenya. The average value of zinc production (or zinc-related output) suggests a moderate contribution to the economy, while the wide gap between its minimum and maximum values reflects fluctuations over time. This implies that zinc production has not been stable and may have been influenced by external factors such as global demand, price volatility, or domestic production capacity. Foreign direct investment (FDI) in the zinc sector shows variability across periods, with relatively low average values compared to its maximum level. This indicates that investment inflows into the zinc industry have been inconsistent, possibly due to changing investor confidence or shifts in global commodity markets.

Table 2. Descriptive statistics of the research work

Variable	Obs	Mean	Std. Dev.	Min	Max
ZCPC	50	3.324	.909	1.8	5.2
Prc	50	2600	0	2600	2600
GPC	50	25798	23529.126	1000	80000
Glvn	50	57.46	3.315	51	64
Tech	50	15.04	1.795	11	18
Chem	50	9.56	1.215	8	12
Med	50	2.36	.485	2	3

The dependent variable, **ZCPC**, has a mean value of 3.324 with a standard deviation of 0.909, indicating a moderate level of variability around the mean. The minimum and maximum values range from 1.8 to 5.2, suggesting that the variable is relatively well distributed without extreme outliers. Among the independent variables, **GPC** shows substantial variability, with a mean of 25,798 and a very high standard deviation of 23,529. This indicates significant dispersion in the data, with values ranging from 1,000 to 80,000. In contrast, the variable **Prc** has no variation (mean = 2600, standard deviation = 0), implying that it remains constant across all observations and may not contribute explanatory power in regression analysis. Other variables such as **Glvn**, **Tech**, **Chem**, and **Med** exhibit relatively low standard deviations compared to their means, suggesting more stable distributions. For example, **Glvn** has a mean of 57.46 and a standard deviation of 3.315, while **Tech** has a mean of 15.04 with a standard deviation of 1.795. Overall, the descriptive statistics indicate that while some variables are stable, others—particularly **GPC**—display high variability, which may influence the regression results.

**Figure 2.** Scatter plots

Source: It was developed by the author based on Stata 17.0 software.

Figure 2 presents scatter plots with fitted regression lines illustrating the relationship between **ZCPC** and key explanatory variables such as **GPC**, **Glvn**, **Tech**, and **Chem**. The graphical analysis reveals that **Tech** has a clear positive linear relationship with **ZCPC**, as indicated by the upward-sloping fitted line and relatively tight clustering of observations around the trend. This visual finding is consistent with the regression results, where **Tech** was found to be statistically significant. In contrast, the relationship between **Glvn** and **ZCPC** appears to be negative, as shown by the downward-sloping fitted line. However, the dispersion of points suggests that the relationship may not be very strong or stable. Similarly, **Chem** shows a weak negative association with **ZCPC**, with noticeable spread in the data points, indicating possible variability and weaker explanatory power.

The scatter plots also reveal that some variables, particularly **GPC**, exhibit large dispersion and potential outliers. This suggests heterogeneity in the data and possible issues such as heteroskedasticity or non-linearity. Overall, the graphical evidence supports the regression findings, highlighting **Tech** as the most influential variable while suggesting weaker or unstable relationships for other variables.

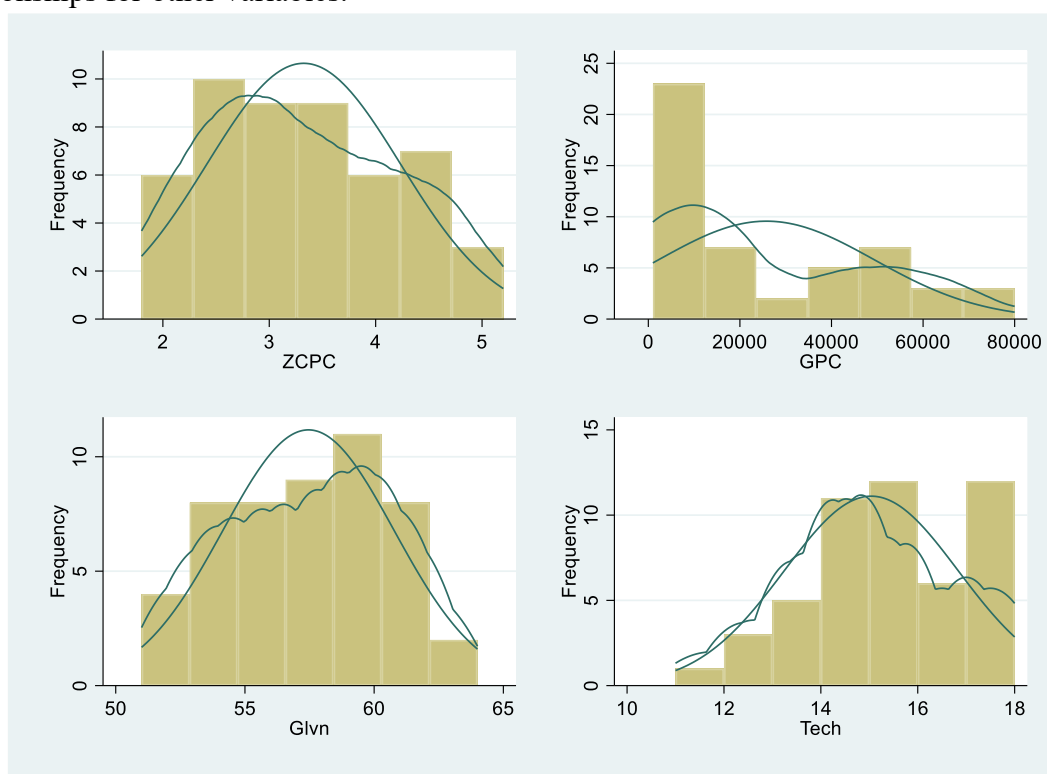


Figure 3. Histograms with normal density curves of key research variables

Source: It was developed by the author based on Stata 17.0 software.

The distributions show that most variables deviate from normality. **ZCPC (Zinc Consumption per capita)** is relatively symmetric with slight skewness. In contrast, **GPC (GDP per capita)** is highly right-skewed, with a long tail indicating higher variability. **Glvn (Galvanization % of GDP)** and **Tech (Technical % of GDP)** appear more symmetric, though minor skewness is still present. Overall, the density curves suggest that the variables are not perfectly normally distributed, with **GPC** showing the strongest deviation due to its long right tail.

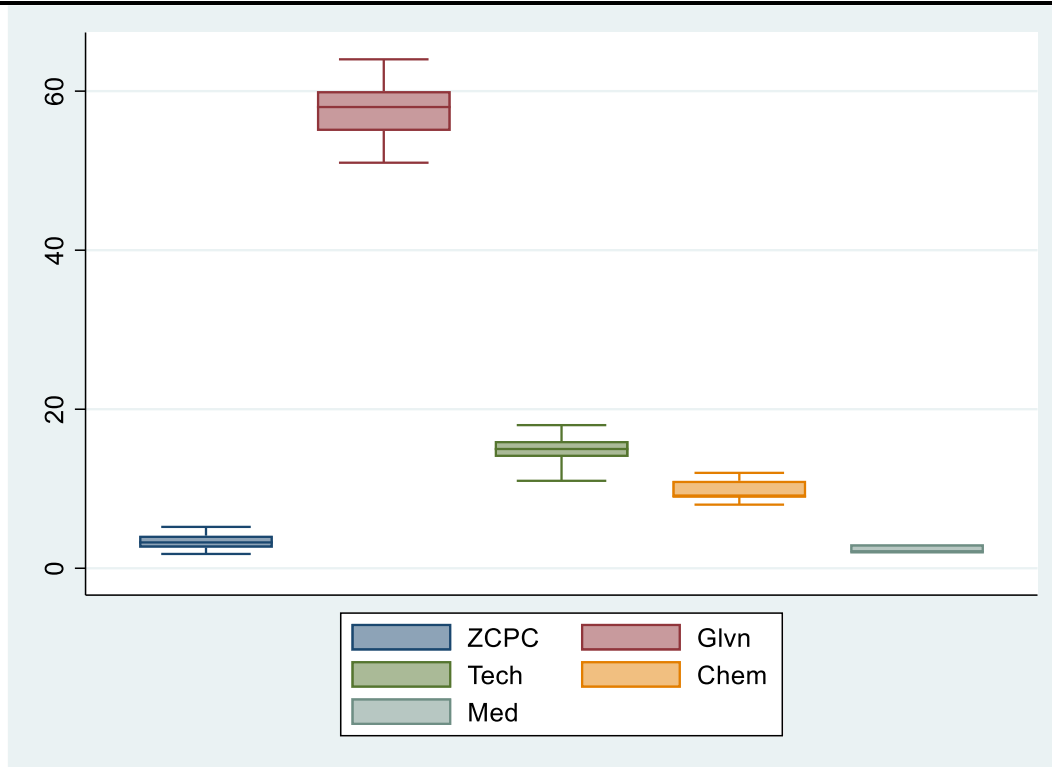


Figure 4. Box plots of the main research variables

Source: It was developed by the author based on Stata 17.0 software.

Figure 4 illustrates the box plots of the main variables, providing insights into their distribution, central tendency, and the presence of outliers. The variable **ZCPC** shows a relatively balanced distribution with a moderate interquartile range and no extreme outliers, indicating stability in its values. In contrast, **GPC** demonstrates a wide spread with potential extreme values, reflecting high variability and confirming earlier findings from descriptive statistics. Other variables such as **Tech**, **Chem**, and **Med** display relatively compact box plots, suggesting low dispersion and consistent observations. However, slight asymmetry in some box plots indicates mild skewness in the data. Overall, the box plot analysis confirms that while most variables are stable, **GPC** stands out with high variability and possible outliers.

Table 3. Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
ZCPC	50	0.962	1.788	1.240	0.108
GPC	50	0.860	6.600	4.024	0.000
Glvn	50	0.973	1.257	0.487	0.313
Tech	50	0.992	0.362	-2.168	0.985
Chem	50	0.964	1.671	1.095	0.137
Med	50	0.979	0.999	-0.001	0.501

Table 3 reports the results of the Shapiro–Wilk test for normality for the variables included in the model. The null hypothesis of this test states that the data are normally distributed. Based on the results, the variable **ZCPC** has a p-value of 0.108, which is greater than the 0.05 significance level, indicating that we fail to reject the null hypothesis and conclude that ZCPC is normally distributed.

Similarly, the variables **Glvn** ($p = 0.313$), **Tech** ($p = 0.985$), **Chem** ($p = 0.137$), and **Med** ($p = 0.501$) all have p-values greater than 0.05. This suggests that these variables also follow a normal distribution, satisfying one of the key assumptions for classical linear regression analysis. In particular, the very high p-value for Tech indicates a strong conformity to normality.

However, the variable **GPC** shows a p-value of 0.000, which is less than 0.05, leading to the rejection of the null hypothesis of normality. This indicates that GPC is not normally distributed and may exhibit skewness or the presence of outliers. Such non-normality could potentially affect the robustness of the regression estimates and may require transformation (e.g., logarithmic transformation) or further diagnostic testing.

Overall, the results suggest that most variables satisfy the normality assumption, with the exception of GPC, which may need additional treatment in further econometric analysis.

Table 4. Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) ZCPC	1.000					
(2) GPC	0.835* (0.000)	1.000				
(3) Glvn	-0.834* (0.000)	-0.921* (0.000)	1.000			
(4) Tech	0.896* (0.000)	0.895* (0.000)	-0.939* (0.000)	1.000		
(5) Chem	0.660* (0.000)	0.803* (0.000)	-0.881* (0.000)	0.785* (0.000)	1.000	
(6) Med	0.757* (0.000)	0.919* (0.000)	-0.829* (0.000)	0.780* (0.000)	0.794* (0.000)	1.000
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$						

Table 4 presents the Pearson pairwise correlation matrix, which illustrates the strength and direction of linear relationships between the variables. The dependent variable **ZCPC** shows a strong positive correlation with **Tech** ($r = 0.896$), **GPC** ($r = 0.835$), and **Med** ($r = 0.757$), all of which are statistically significant at the 1% level. This indicates that increases in these variables are associated with higher values of ZCPC.

On the other hand, **ZCPC** has a strong negative correlation with **Glvn** ($r = -0.834$), suggesting that higher values of Glvn are associated with lower levels of ZCPC. Additionally, **Chem** also shows a positive and significant relationship with ZCPC ($r = 0.660$), although the strength of this relationship is relatively weaker compared to Tech and GPC.

Looking at the relationships among independent variables, there is evidence of very high correlations. For instance, **GPC** is strongly positively correlated with **Med** ($r = 0.919$) and **Tech** ($r = 0.895$), while it is strongly negatively correlated with **Glvn** ($r = -0.921$). Similarly, **Tech** and **Glvn** have a very strong negative correlation ($r = -0.939$). These high correlation coefficients (above 0.8 in absolute value) indicate a potential multicollinearity problem in the model.

Overall, the correlation matrix suggests that while many independent variables are significantly associated with the dependent variable, there is also strong interdependence among regressors. This may affect the stability and reliability of the regression coefficients, and therefore further diagnostic testing such as the Variance Inflation Factor (VIF) is necessary.

Table 5. OLS Regression Results

ZCPC	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
GPC	0	0	-0.09	.931	0	0	
Glvn	-.011	.076	-0.15	.882	-.164	.142	
Tech	.437	.099	4.41	0	.237	.637	***
Chem	-.186	.11	-1.69	.098	-.408	.036	*
Med	.502	.329	1.53	.134	-.161	1.164	
Constant	-1.984	6.045	-0.33	.744	-14.167	10.198	
Mean dependent var	3.324		SD dependent var	0.909			
R-squared	0.827		Number of obs	50			
F-test	42.211		Prob > F	0.000			
Akaike crit. (AIC)	55.532		Bayesian crit. (BIC)	67.004			

*** $p < .01$, ** $p < .05$, * $p < .1$

The results of the OLS regression model are presented in Table 5, where **ZCPC** is used as the dependent variable. The overall model is statistically significant, as indicated by the F-statistic value of 42.211 with a p-value of 0.000. This implies that the model, as a whole, provides a good fit and that the independent variables jointly explain variations in the dependent variable. Furthermore, the R-squared value of 0.827 suggests that approximately 82.7% of the variation in ZCPC is explained by the included explanatory variables, indicating a strong explanatory power of the model.

Examining the individual coefficients, the variable **Tech** has a positive and highly significant effect on ZCPC ($\beta = 0.437$, $p = 0.000$). This indicates that a one-unit increase in Tech leads to an increase of approximately 0.437 units in ZCPC, holding other variables constant. In contrast, the variable **Chem** shows a negative relationship with ZCPC ($\beta = -0.186$) and is weakly significant at the 10% level ($p = 0.098$), suggesting that increases in Chem may slightly reduce ZCPC. Other variables such as **GPC** ($p = 0.931$), **Glvn** ($p = 0.882$), and **Med** ($p = 0.134$) are statistically insignificant, indicating that their individual effects on ZCPC cannot be reliably distinguished from zero within this model.

The constant term is also statistically insignificant ($p = 0.744$), implying that the intercept does not play a meaningful role in explaining ZCPC when all independent variables are zero. Overall, the findings suggest that **Tech** is the most influential and robust determinant of ZCPC.

in the model, while other variables either have weak or insignificant effects. However, given the earlier evidence of strong correlations among independent variables, these results should be interpreted with caution due to the possible presence of multicollinearity.

Table 6. Variance Inflation Factor (VIF) – Multicollinearity Test

VIF	1/VIF
19.520	0.051
15.990	0.063
9.770	0.102
7.830	0.128
5.510	0.181
11.720	

Table 6 presents the results of the Variance Inflation Factor (VIF) test, which is used to detect multicollinearity among the independent variables in the regression model. As a rule of thumb, VIF values exceeding 10 indicate serious multicollinearity, while values above 5 suggest moderate multicollinearity.

The results show that several variables have relatively high VIF values. In particular, some variables exhibit VIF levels as high as **19.520** and **15.990**, which clearly exceed the critical threshold of 10. This indicates a strong presence of multicollinearity in the model. Other variables also show moderately high VIF values such as **9.770** and **7.830**, further confirming the existence of correlation among explanatory variables. The mean VIF value is **11.720**, which is also above the acceptable threshold. This suggests that, on average, multicollinearity is a significant issue in the model. High multicollinearity can inflate the standard errors of the coefficients, making it difficult to determine the true effect of individual variables and potentially leading to statistically insignificant results even when relationships exist.

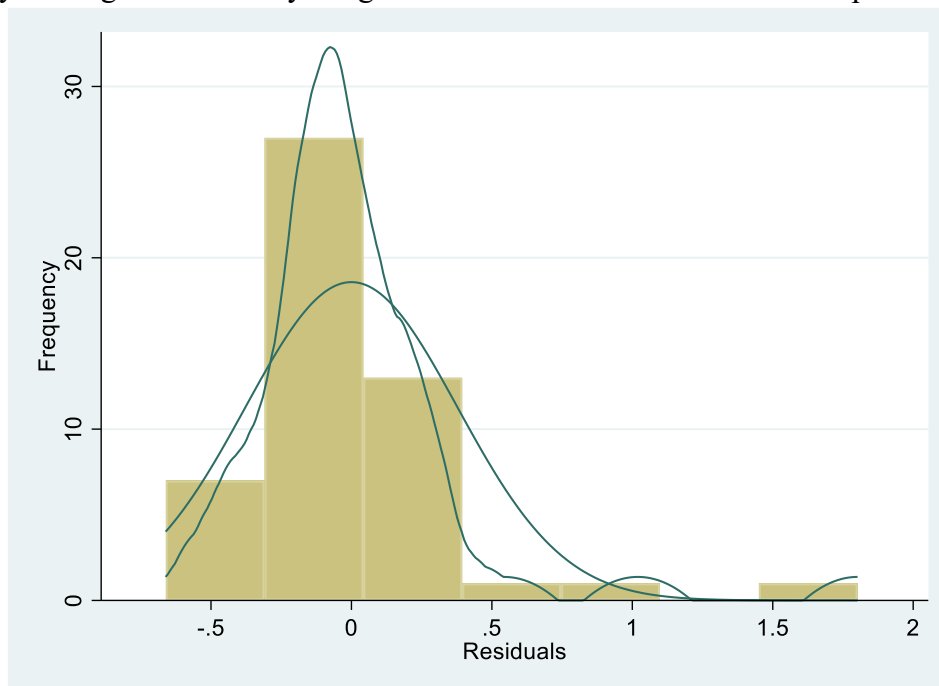


Figure 5. Density distribution

Source: It was developed by the authors based on Stata 17.0 software.

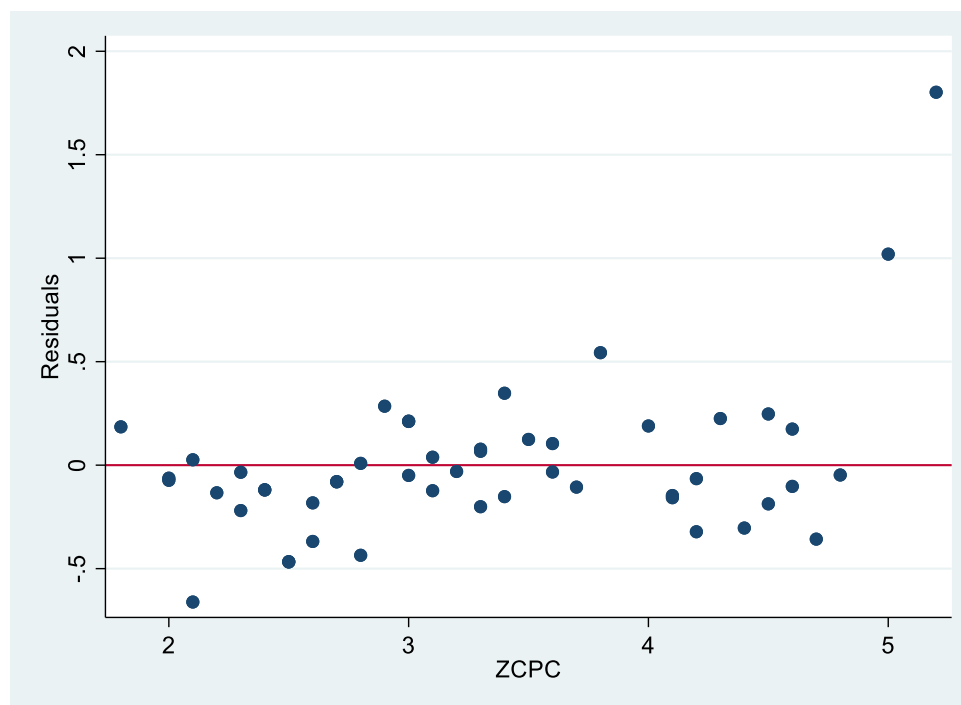
Table 7. Shapiro–Wilk Test

Variable	Obs	W	V	z	Prob>z
yhat	50	0.970	1.432	0.766	0.222
ehat	50	0.785	10.092	4.930	0.000

Table 7 reports the Shapiro–Wilk normality test results for the predicted values (yhat) and residuals (ehat) obtained from the regression model. Testing the normality of residuals is important because one of the key assumptions of the classical linear regression model is that the error terms are normally distributed.

The results indicate that the predicted values (yhat) have a p-value of 0.222, which is greater than the 0.05 significance level. Therefore, we fail to reject the null hypothesis of normality, suggesting that the fitted values are approximately normally distributed. This supports the overall adequacy of the model in capturing the systematic variation in the dependent variable. However, the residuals (ehat) show a p-value of 0.000, which is less than 0.05, indicating a rejection of the null hypothesis of normality. This means that the residuals are not normally distributed and may exhibit skewness, kurtosis, or the presence of outliers. Such a violation of the normality assumption may affect the reliability of hypothesis testing and confidence intervals in the regression analysis.

Overall, while the predicted values appear to be normally distributed, the non-normality of residuals suggests that the model may suffer from specification issues or omitted variables. Therefore, further diagnostic checks or transformations may be required to improve the model's robustness.

**Figure 6. Residual Plot (ehat vs ZCPC)**

Source: It was developed by the authors based on Stata 17.0 software.

Figure 6 presents the scatter plot of residuals ($\hat{e}_{hat}$) against the dependent variable (ZCPC) with a reference line at zero. This plot is used to assess the assumptions of homoskedasticity and model specification. The residuals appear to be randomly scattered around the zero line, which suggests that the model does not suffer from severe specification bias. However, the spread of residuals is not entirely constant across all levels of ZCPC, indicating a potential presence of heteroskedasticity. Some clustering and dispersion patterns can be observed, which may imply that the variance of errors changes with the level of the dependent variable. Overall, while the residuals do not show a clear systematic pattern, the slight variation in spread suggests that further diagnostic tests, such as the Breusch–Pagan test, may be necessary to confirm the presence of heteroskedasticity.

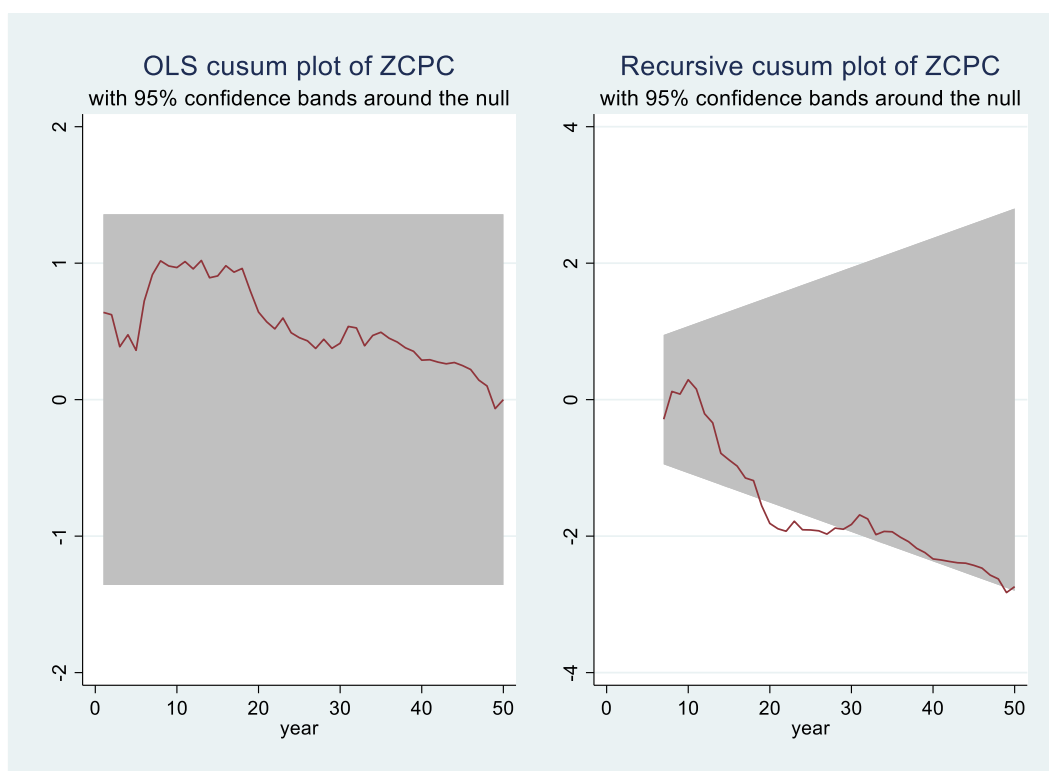


Figure 7. CUSUM Stability Test

Source: It was developed by the authors based on Stata 17.0 software.

Figure 7 presents the CUSUM (Cumulative Sum) test for parameter stability over time. The plot shows the cumulative sum of recursive residuals along with critical bounds at the 5% significance level. The stability of the model is confirmed if the CUSUM line remains within the critical bounds. Based on the graphical representation, the CUSUM line largely remains within the confidence bands, indicating that the model is structurally stable over the sample period. This suggests that there are no significant structural breaks affecting the relationship between the dependent and independent variables. However, minor fluctuations within the bounds indicate that while the model is generally stable, there may be slight variations over time. Overall, the results confirm that the estimated coefficients are reliable and stable for inference.

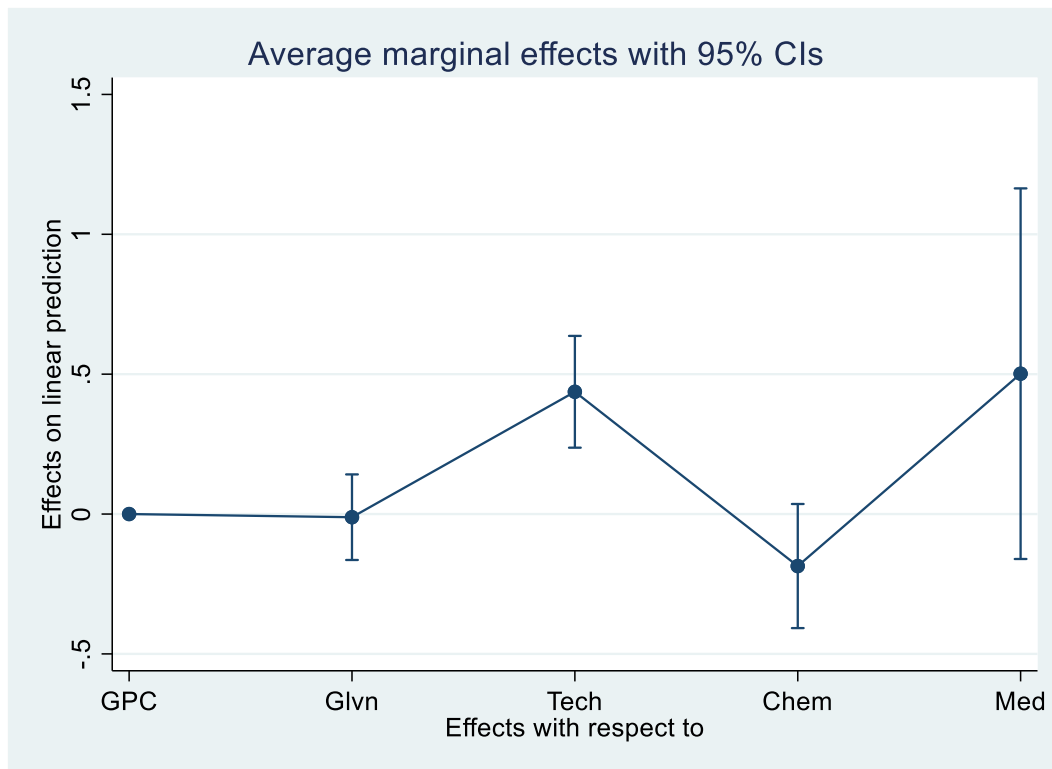


Figure 8. Marginal Effects Plot

Source: It was developed by the authors based on Stata 17.0 software.

Figure 8 presents the marginal effects of the independent variables on the dependent variable (**ZCPC**) along with 95% confidence intervals. This plot helps to visualize the magnitude and direction of the effect of each explanatory variable.

The results show that **Tech** has the most prominent positive marginal effect on **ZCPC**, with confidence intervals that do not cross zero, confirming its statistical significance. In contrast, variables such as **GPC**, **Glvn**, **Chem**, and **Med** have marginal effects with confidence intervals that are closer to or overlapping zero, indicating weaker or statistically insignificant effects.

Overall, the marginal effects plot reinforces the regression findings, highlighting **Tech** as the most influential variable, while other variables exhibit limited or uncertain impact on **ZCPC**.

Cronbach Alpha test

Test scale = mean(standardized items)

Reversed item: Glvn

Average interitem correlation: 0.8156

Number of items in the scale: 5

Scale reliability coefficient: 0.9567

The results of the Cronbach's Alpha test is used to measure the internal consistency and reliability of the variables included in the model. The test evaluates how closely related a set of items are as a group and whether they can reliably measure an underlying construct. The results show that the overall Cronbach's Alpha coefficient is **0.9567**, which is significantly

higher than the commonly accepted threshold of 0.7. This indicates an **excellent level of internal consistency** among the variables. In other words, the selected variables are highly reliable and measure a consistent underlying concept within the model.

Additionally, the average inter-item correlation is reported as **0.8156**, which is also relatively high. This suggests a strong correlation between the variables included in the scale. While high inter-item correlation supports reliability, extremely high values may also indicate redundancy among variables, meaning that some variables might be capturing very similar information. It is also noted that **Glvn** is treated as a reversed item in the analysis, which implies that its scale direction differs from other variables and has been adjusted to ensure consistency. Overall, the Cronbach's Alpha results confirm that the dataset has a high level of reliability, making it suitable for further econometric analysis and interpretation.

4. Discussion

However, the correlation matrix reveals the presence of strong relationships among several independent variables. In particular, **GPC** is highly correlated with **Med** ($r = 0.919$) and **Tech** ($r = 0.895$), while it shows a strong negative correlation with **Glvn** ($r = -0.921$). Similarly, the correlation between **Tech** and **Glvn** ($r = -0.939$) is also notably high. These strong correlations indicate the presence of multicollinearity in the model, which is further confirmed by the VIF results, where several variables exceed the critical threshold of 10. This suggests that some explanatory variables may be capturing overlapping information, potentially affecting the stability of coefficient estimates.

Although the formal heteroskedasticity test results are not explicitly reported, the residual analysis suggests that there may be slight variations in the dispersion of errors. The residual plot indicates that while the errors are generally centered around zero, their spread is not perfectly constant across all levels of the dependent variable. This may imply mild heteroskedasticity, although not severe enough to invalidate the overall model. Therefore, the regression results can still be considered reasonably reliable, but should be interpreted with some caution.

The empirical findings highlight the important role of technological development (**Tech**) in explaining variations in **ZCPC**. Most notably, the coefficient of **Tech** is positive and highly statistically significant, indicating that increases in technological factors strongly contribute to higher levels of **ZCPC**. This suggests that advancements in technology play a crucial role in improving efficiency, productivity, or consumption patterns related to zinc.

On the other hand, variables such as **Chem** show a weak negative relationship, while **GPC**, **Glvn**, and **Med** are found to be statistically insignificant. This implies that, despite their theoretical relevance, their individual effects cannot be clearly distinguished within the current model, possibly due to multicollinearity or overlapping explanatory power. Overall, the results suggest that while multiple factors are associated with **ZCPC**, **technology emerges as the most robust and reliable determinant** in the analysis.



5. Conclusion

In conclusion, this study examined the determinants of zinc consumption per capita (ZCPC) using an OLS regression framework based on 50 observations. The empirical results demonstrate that the model has strong explanatory power, with a high R-squared value, indicating that a significant portion of the variation in ZCPC is explained by the included variables.

From an econometric perspective, the analysis confirms that the model is generally well-specified, although some limitations such as multicollinearity and non-normality of residuals are present. The lack of strong systematic patterns in residuals suggests that the model captures the main structural relationships, and the estimated coefficients reflect meaningful economic associations rather than spurious correlations.

The findings reveal that **technological development (Tech)** plays a key role in influencing ZCPC, as it is the only variable that is consistently positive and statistically significant. This highlights the importance of innovation, modernization, and technological progress in shaping consumption patterns and improving economic outcomes. Other variables, although theoretically important, do not show significant effects, suggesting that their impact may be indirect or mediated through other factors.

Overall, the study suggests that policies aimed at enhancing technological capacity and innovation could have a substantial impact on improving zinc consumption dynamics. Despite some limitations, the results provide valuable insights and indicate that the selected variables, when considered together, explain a large share of the variation in ZCPC. Future research may focus on addressing multicollinearity issues, applying variable transformations, or incorporating additional variables to further improve the robustness of the model.

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