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Income Tax, Household Consumption in South Africa: A QARDL Approach

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ABSTRACT

This study empirically investigates the effect of Pay As You Earn (PAYE) tax on household consumption in South Africa by employing the Quantile Autoregressive Distributed Lag (QARDL) model, using annual time series data from 1994 to 2023 obtained from the South African Reserve Bank (SARB). The QARDL analysis reveals that, in the long run, the PAYE tax is statistically insignificant across the lower, middle, and upper quantiles. However, household disposable income is statistically significant and positively associated with household consumption in all quantiles over the long run. In terms of unemployment, the results show that it is statistically insignificant in the lower quantiles (0.10 and 0.25), while it becomes statistically significant in the middle quantiles (0.40, 0.50, and 0.60), as well as in the 0.75 upper quantile, with a negative coefficient. However, in the 0.90 upper quantile, unemployment is statistically insignificant. In the short run, PAYE tax is statistically significant in the lower quantiles (0.10 and 0.25), middle quantiles (0.40, 0.50, and 0.60), and the 0.75 upper quantile. This implies that an increase in PAYE tax leads to a decrease in household consumption. In contrast, at the 0.90 upper quantile, PAYE tax is statistically insignificant. Based on these findings, the study recommends that the government should consider reducing PAYE tax for low- and middle-household consumers to boost short-run household consumption. Additionally, enhancing disposable income and reducing unemployment through targeted policies can support long-term consumption growth.

Keywords: Pay As You Earn Tax, Household Consumption, QARDL, South Africa
JEL Classifications: H24, D12, C22

1. INTRODUCTION

The relationship between income tax and household consumption is particularly relevant in the context of South Africa's post-pandemic recovery and ongoing fiscal policy debates. As the government seeks to rebuild the economy and address widening fiscal deficits, decisions around tax policy have direct implications for consumer spending and overall economic growth (IMF, 2021; World Bank, 2022). Income tax, in particular, plays a crucial role in shaping disposable income levels, which in turn influence household consumption patterns (Modigliani and Brumberg, 1954; Aron and Muellbauer, 2006; Hindls et al., 2022). Understanding this relationship is essential for designing policies that strike a balance between revenue generation and economic stimulation (OECD, 2021). In a country where inequality and unemployment remain pressing challenges, evaluating the impact of income tax on consumption can help inform more inclusive and effective fiscal strategies (Statistics South Africa, 2023; Bhorat et al., 2021).

This study focuses on the Pay As You Earn (PAYE) tax, which serves as a proxy for income tax. In South Africa, during the 1996/97 financial year, salaries were expected to rise across the economy. However, PAYE tax collections were projected to fall R335 million short of the budgeted amount (SARB, 2022). This shortfall was attributed to declining employment levels, which led to lower PAYE collections. In addition, efficient assessment processing by SARS resulted in increased refund payments.

Meanwhile, PAYE tax rates continued to rise. In 2014/15, the second income tax bracket was set at 25%, increasing to 26% in

2015/16 (SARS, 2022). The rate in the third bracket rose from 30% in 2014/15 to 31% in 2015/16 (SARS, 2022). In the fourth bracket, the rate increased from 35% in 2014/15 to 36% in 2015/16 (SARS, 2022). The fifth bracket rose from 38% in 2014/15 to 39% in 2016/17 (SARS, 2022). The sixth bracket increased from 40% in 2014/15 to 41% in 2016/17 (SARS, 2022). In 2017/18, the South African government introduced a seventh bracket with a high tax rate of 45% (SARS, 2022). This continuous rise in the rates of PAYE tax resulted to a decline in household consumption.

In 2011, household consumption decreased from 4.1% to 2.2% in 2015 (SARB, 2024). Household consumption declined from 2.2% in 2015 to 1.7% in 2017 (SARB, 2024). In 2017, it was 1.7%, and it went down to 1.3% in 2019, followed by a decline of 0.6% between 2019 and 2023 (SARB, 2024). This continued decline in household consumption is a major concern for the South African economy. Hence, this study aims to examine the potential differential effects of PAYE tax across different levels of household consumption.

This study makes several key contributions to the existing literature. First, it is among the pioneering efforts to employ the Quantile Autoregressive Distributed Lag (QARDL) model to examine the relationship between PAYE tax and household consumption in South Africa. By doing so, it captures the heterogeneous effects of PAYE tax across the consumption distribution providing a more nuanced understanding of how low, middle, and high consuming households respond to changes in tax policy. Second, the study offers timely empirical evidence in the context of South Africa's post-pandemic recovery and ongoing structural challenges such as inequality and unemployment. The findings contribute to policy debates by highlighting the need for more inclusive and equitable fiscal strategies that do not disproportionately impact vulnerable households. Finally, by focusing on a period of significant shifts in PAYE tax rates and consumption trends, the study deepens our understanding of the long-term implications of tax policy on household behaviour. This enhances its relevance for current and future efforts to design tax systems that balance revenue generation with social equity.

2. THEORETICAL LITERATURE AND EMPIRICAL REVIEW

The literature review explores three key theories regarding the relationship between taxation and household consumption. The literature review examines three key theories concerning the relationship between taxation and household consumption. The first is the Permanent Income Hypothesis (PIH): proposed by Milton Friedman, the PIH suggests that individuals base their consumption decisions on expected long-term income rather than current income levels. As a result, only permanent changes in taxation such as sustained adjustments in PAYE tax are likely to significantly influence consumption behaviour (Friedman, 1957; Attanasio and Pavoni, 2021). The second is the Life-Cycle Hypothesis (LCH): developed by Modigliani and Brumberg, the LCH posits that individuals plan their consumption and savings over their entire lifetime, aiming to smooth consumption across different periods. PAYE tax policies can affect this intertemporal allocation by altering disposable income during prime working years, thereby influencing long-term consumption planning (Modigliani and Brumberg, 1954; Kaplan and Violante, 2022). Lastly, the Keynesian Consumption Theory: rooted in the work of John Maynard Keynes, this theory argues that current consumption is primarily driven by current disposable income. Consequently, increases in PAYE tax reduce disposable income, leading to a decline in household consumption particularly among lower-income households with higher marginal propensities to consume (Keynes, 1936; Ganong and Noel, 2019).

A number of scholars have reviewed the context of the relationship between income tax and household consumption. Zhang (2021) found that in China, income tax reform can significantly boost consumption. Zhang (2021) examined the effect of individual income tax reform on residents' consumption. Based on the review of the literature the focus was income tax reform to improve the threshold level in 2018. Furthermore, Chen and Ni (2023) employed heterogeneity analysis to capture the link between tax structure, tax salience, and consumption gap, between urban and rural residents in China, from 2002 to 2020. According to the study's findings, income tax can better reduce the consumption gap between urban and rural residents. Shiqiang and Yujia (2023) suggested that taxes on income have a positive effect on consumption. Shiqiang and Yujia (2023) used the individual consumption model and provincial-level panel data to empirically investigate the influence of tax regulation on private consumption in China with reference to Zhang (2017), who studied the impact of personal income tax on the structure of residents' consumption expenditure. To conduct the corresponding analysis Engel's coefficient was used to test this prediction over the period 1999-2012. The findings of the study provided evidence that income tax harms household consumption.

Čok et al. (2012) studied the distribution of personal income tax changes in Slovenia using an exclusive taxpayer database and a general-equilibrium modelling technique over the period from 2004, including the most recent adjustments because of the late-2000s financial crisis. This study's empirical evidence suggests that a decrease in personal income tax burden substantially boosts household consumption in Slovenia. Souleles (1999) used ordinary least squares (OLS) and two-stage least squares (2SLS) to examine the empirical link between household consumption and income tax refunds from 1980 to 1991 in the US. Souleles (1999) found a sensitive response of household consumption to income tax refunds. This concurs with Cloyne and Surico (2017), who revealed that, from a statistical point of view, tax cuts tend to affect consumption. Cloyne and Surico (2017) examined household debt and the dynamic effects of income tax changes during the period 1978-2009 through a vector autoregression (VAR) in the UK and the US.

On the other hand, Johnson et al. (2006) used ordinary least squares (OLS) and two-stage least squares (2SLS) to analyse the relationship between household expenditure and income tax rebates in the US between July and September 2001. The findings affirmed that the 2001 income tax rebates encouraged household consumption. On the other hand, Bonga-Bonga et al. (2016) used the computable general equilibrium framework to analyse the effect of an expansion in property taxes on the economy in South Africa. The outcomes found by Bonga-Bonga et al. (2016) indicate that a rise in property taxes negatively affects the demand for the factor of production and low-income households' consumption.

In South Africa, literature on the relationship between income tax and household consumption is under-represented. Numerous studies have focused on the income tax and government spending, while others have tried to examine the effect of income tax on economic growth. Works of several scholars have been reviewed in the context of the income tax-government expenditure link, such as Van Rensburg et al. (2022), who conducted a study on the size of fiscal expenditure multipliers in South Africa over the period 2009-2019. Van Rensburg et al. (2022) used an econometric model to evaluate the fiscal multipliers and found a positive connection between income tax and government spending. On the other hand, Ndahiriwe and Gupta (2007) found bi-directional causality between taxes and expenditure. The study used Granger causality tests in a Vector Error Correction framework to explore the effect of the causal relationship between taxes and expenditure in South Africa. This study used annual data from 1960:1 to 2006:2. Tendengu et al. (2022) assessed the effect of public sector expenditure, public consumption spending, and taxation, on economic growth in South Africa. This study used the ARDL method to examine the annual data from 1988 to 2018. Tendengu et al. (2022) suggested that there is a positive relationship between taxation and economic growth in South Africa.

The above results were confirmed by Pamba (2022), who found a positive link between income tax and economic growth in South Africa. Pamba (2022) used time series data from 1994 to 2015 to assess the relationship between tax revenue components and economic growth using the ARDL technique, in line with Khobai and Dladla (2018), who used the ARDL framework to investigate the effect of taxation on economic growth from 1981 to 2016. Khobai and Dladla (2018) found a negative relationship between taxes and economic growth in South Africa. This is contrary to the findings of Kavese and Phiri (2020), who found a positive relationship between income tax and growth in South Africa. Kavese and Phiri (2020) employed the ARDL method to analyse quarterly data from 2002Q1 to 2017Q4.

The empirical literature reviewed above makes it clear that most studies examining the relationship between income tax and household consumption have not employed the QARDL method. In the South African context, this study finds that the link between income tax and household consumption is not well documented. The existing empirical evidence primarily focuses on the relationship between income tax and other economic factors, such as economic growth. None of the reviewed studies investigated the impact of income tax on household consumption in South Africa. Furthermore, the findings of the reviewed literature on the income tax–consumption relationship are inconsistent. Therefore, this study applies the QARDL model to analyse the effect of income tax on household consumption in South Africa.

3. METHODOLOGY AND DATA

3.1. The Normality Test

The normality test in the QARDL model is used primarily as a diagnostic tool to check the distribution of the variables. The assumption of the QARDL model does not strictly require a normally distributed series (Shahzad et al., 2021). This study used the multivariate normality test to assess if the variables are normally distributed.

3.2. The Multivariate Normality Test

The multivariate normality test has been developed by various statisticians with different methods. These several tests of the multivariate normality method include; Shapiro-Wilk, Henze-Zirkler, Mardia's Skewness, Mardia's Kurtosis, and Doornik-Hansen.

The Shapiro-Wilk test was developed by Patrick Royston in the early 1980s, and operates well in detecting departures from normality, especially in small sample sizes (Kres, 1983). The combined test statistic W is computed from individual Shapiro-Wilk statistics W_i as:

$$W^* = \sum_{i-1}^{p} \frac{W_i - \bar{W}}{s_w} \tag{1}$$

Where $\bar{W}$ is the mean of the individual Shapiro-Wilk statistics, s_w is the standard deviation of the individual Shapiro-Wilk statistics, W^* can then be compared to a normal distribution to determine significance. The Mardia's tests, which are based on multivariate skewness and kurtosis, were constructed by Kanti V. Mardia in 1970, and are the most widely used tests for assessing deviations from normality in multivariate skewness (Farrell et al., 2007). In addition, Mardia's Skewness and Mardia' Kurtosis tests remain a standard in statistical analysis for identifying non-normality. The Mardia's Multivariate Skewness equation is specified as follows:

$$b_1 = \sum_{i=1}^{n} \sum_{j=1}^{n} [(X_i - \bar{X})' S^{-1} (X_j - \bar{X})]^3 \tag{2}$$

Where: $(X_i - \bar{X})$ represents the deviation of the i-th observation from the mean, S^{-1} is the inverse of the sample covariance matrix, and $(X_i - \bar{X})'$ indicate the transpose of the deviation vector. The multivariate kurtosis statistic is calculated as follows:

$$b_2 = \frac{1}{n} \sum_{i=1}^{n} [(X_i - \bar{X})' \ S^{-1} \ (X_i - \bar{X} \ )]^2 \tag{3}$$

On the other hand, the Henze-Zirkler test was introduced by Norbert Henze and Bernhard Zirkler in 1990. This test is based on the characteristic function and is known for its good performance under a wide range of alternatives (Ebner and Henze, 2020). The test statistic Henze-Zirkler is specified as:

$$HZ = \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{n} exp\left(-\frac{1}{2} d_{ij}\right) - 2\left(1 + \frac{1}{2}\right)^{-p/2}$$

$$\sum_{i=1}^{n} exp\left(-\frac{1}{4} d_{ii}\right) + n\left(1+1\right)^{-p/2} \tag{4}$$

Where: d_{ij} stands for the Mahalanobis distance between the i-th and j-th observations:

$$d_{ij} = (X_i - X_j)' S^{-1} (X_i - X_j) \quad (5)$$

p is the number of variables. The Doornik-Hansen test was formed by Doornik and Hansen in 1994; this test is an extension of the Shapiro-Wilk test and is used for testing multivariate normality in the context of regression models. The Doornik-Hansen test combines skewness and kurtosis measures and is used in econometric analyses (A-Mandah et al., 2016). The test statistic Doornik-Hansen (DH) test is given by:

$$DH = -2\sum_{i=1}^{p} \log(W_i) \quad (6)$$

Where W_i are the individual p-values for skewness and kurtosis tests, and p is the number of variables. The DH statistic follows a chi-square distribution with $2p$ degrees of freedom.

The decision rule for the multivariate normality tests is that if the P-value ≤ α (1%, 5%, or 10%), this suggests that the data does not have a multivariate normal distribution. This study is of the view that if at least one of the multivariate normal distribution tests suggests that the data deviates from normality, it is crucial to conclude that the normality assumption might not hold.

3.3. Data Sources

The data for the variables that were examined in this study were extracted from the SARB database. Due to the limited number of quarterly data available in South Africa, this study used annual data starting from 1994 up to 2023 with 30 observations. This study period was chosen to check the impact of PAYE tax on household consumption after the first South African democratic election and after the economic devastation caused by the Covid-19 pandemic, hence, using the estimation of the QARDL regression model to check the effect of PAYE tax on household consumption during the specified study period.

3.4. Quantile Unit Root Test

The quantile Augmented Dickey-Fuller (QADF) and quantile Phillips-Perron test (QPP) tests for unit root analyses were estimated in this study, instead of standard unit root tests such as ADF and PP, since the data is not normally distributed. The quantile unit root methods provide more robust inference and avoid biased results (Koenker and Xiao, 2004; Anwar et al., 2021).

3.4.1. Quantile augmented Dickey-Fuller test

The QADF test is an extension of the traditional ADF test. The quantile unit root test is designed to improve unit root detection by dealing with outliers in time series (Kuo, 2016; Koenker and Xiao, 2004; Galvao, 2009; Bahmani-Oskooee and Ranjbar, 2016). In other words, the QADF test generalizes the ADF test to different quantiles τ of the conditional distribution of the time series. Thus, this study followed the unit root test based on quantile regression proposed by Koenker and Xiao (2004). The basic form of the QADF test equation estimated in this study for a given quantile τ is:

$$\Delta y_t^{(\tau)} = \alpha^{(\tau)} + \beta^{(\tau)} t + \gamma^{(\tau)} y_{t-1}^{(\tau)} + \sum_{i=1}^{p} \delta_i^{(\tau)} \Delta y_{t-i}^{(\tau)} + \varepsilon_t^{(\tau)} \quad (7)$$

Where $y_t^{(\tau)}$ represents the τ-th quantile of the time series at time t. $\Delta y_t^{(\tau)}$ is the first difference of the τ-th quantile, $\alpha^{(\tau)}$, $\beta^{(\tau)}$, $\gamma^{(\tau)}$, $\delta_i^{(\tau)}$ are the parameters associated with the τ-th quantile, $\varepsilon_t^{(\tau)}$ is the error term for the τ-th quantile.

The rule of thumb is if the P-value is less than the significance level (1%, 5%, 10%), reject the null hypothesis, and the series is stationary. When the P-value is greater or equal to the level of significance the series is non-stationary.

3.4.2. Quantile Phillips-Perron test

The QPP test is the extension of the standard PP unit root test. The quantile unit root test provides a significant improvement in time series analysis by allowing for adjustments that account for distribution-specific effects, making it a powerful tool for assessing unit root in the series (Ling and McAleer; 2004; Liu et al., 2021). This study estimated the following QPP equation, which is based on the quantile unit root test regression proposed by Li and Zheng (2017).

$$t_\alpha(\tau) = \frac{\hat{\alpha}(\tau) - 1}{S(\hat{\alpha}(\tau))} \quad (8)$$

Where $\hat{\alpha}(\tau)$ is the autoregressive coefficient estimated for the τ-th quantile, $S(\hat{\alpha}(\tau))$ is its robust standard error. The decision rule, as discussed in the above section if the P-value is less than the significance level (1%, 5%, 10%), reject the null hypothesis, and the series is stationary. When the P-value is greater than or equal to the level of significance, the series is non-stationary.

3.5. Quantile Cointegration

This study adopted the cointegrating relation quantile processes which involve analysing cointegration relationships at various quantiles of the conditional distribution of the dependent variable. This methodology extends traditional cointegration analysis, to examine the cointegrating relationship that might vary across the distribution (Xiao, 2009; Cho et al. 2015). By employing quantile regression techniques, this method allows for the investigation of potential heterogeneity and asymmetry in the long-run relationships between variables at different points of the distribution, such as the median or extreme tails (Schweikert, 2018). This type of analysis is particularly useful in econometrics for assessing non-linear dynamics in cointegrating relationships (Cho et al., 2015).

In this study, the estimation of quantile cointegrating relationships is performed using the visual plot which has multiple quantile levels that show the cointegrating relation, and each line represents the behaviour of the cointegrating relation for different parts of the distribution, with the 0.5 quantile (median) being highlighted in red and labelled as "Estimated." The decision rule is that if the cointegrating relationship holds at certain quantiles but not others, this suggests that the relationship between the variables may be heterogeneous or asymmetric across the distribution (Schweikert, 2018). In other terms, if the different quantile lines generally move together but show some divergence in certain periods, this suggests that the relationship between the variables might vary across quantiles, which implies heterogeneity.

3.6. QARDL Long and Short Run Model Specification

In analysing the potential differential effects of PAYE tax across different levels of South African consumption of households, this study modified the model previously used by Gohar et al. (2022). That study examined the short-run and long-run effects of income and price changes across various quantiles of the consumption expenditures in 7 emerging countries over the period 1991-2020, the mathematical formula takes the following form:

$$Q_{CP} = b_0(\tau) + \sum_{i=1}^{n1} b_1(\tau)\Delta InCP_{t-i} + \sum_{i=0}^{n2} b_2(\tau)\Delta InNI_{t-i} + \sum_{i=0}^{n3} b_3(\tau)\Delta InPR_{t-i} + \sum_{i=0}^{n3} b_4(\tau)\Delta InIR_{t-i} + \alpha_1(\tau) InCP_{t-i} + \alpha_2(\tau) InNI_{t-i} + \alpha_3(\tau) InPR_{t-i} + \alpha_4(\tau) InIR_{t-i} + e_t(\tau) \tag{9}$$

Where *CP* stands for household consumption, *NI* represents income, *PR* is prices, *IR* is interest rate. This study modified equation (9) by excluding variables that were not reviewed by the current study, such as *IR* the interest rate, *NI*: income, and *PR*: prices. This study replaced these variables by PAYE tax, household disposable income, and unemployment to fulfil the aim of the research. Another variable was used as-is, household consumption which takes the following abbreviation (HC). Therefore, the following equation is in line with equation (9), which represents the long run QARDL technique for this thesis is formulated as follows:

$$Q_{HC} = \alpha_0(\tau) + \alpha_1(\tau) InHC_{t-i} + \alpha_2(\tau) InLPAYE_{t-i} + \alpha_3(\tau) InLUER_{t-i} + e_t(\tau) \tag{10}$$

Where (τ): signifies the quantile distribution, α_1, α_2, and α_3 represent the long-run coefficients which capture the long-term equilibrium relationship between the dependent variable and independent variables. After the QARDL long run model, this study also conducted the short run model, since the long-run model focuses on the equilibrium relationship, while the short-run model deals with the dynamics of how the system adjusts to changes. Therefore, the short run QARDL model for this study can be presented in its functional form below:

$$Q_{HC} = b_0(\tau) + \sum_{i=1}^{n1} b_1(\tau)\Delta InHC_{t-i} + \sum_{i=1}^{n2} b_2(\tau)\Delta InLPAYE_{t-i} + \sum_{i=0}^{n3} b_3(\tau)\Delta InLUER_{t-i} + e_t(\tau) \tag{11}$$

Where: Δ indicates the difference operator, (τ) signifies the quantile distribution, b_0 mean the drift coefficient, n_1, n_2 and n_3 denote lag orders, b_1, b_2, and b_3 indicate the short-run coefficients. The short-run dynamics are captured by the error correction mechanism, which adjusts for deviations from the long-run equilibrium.

3.7. Quantile Process Estimates

This study estimated and visualized quantile process estimates to significantly enhance the depth of statistical analysis by providing a more comprehensive understanding of the relationships between variables. In essence, quantile process estimates are a valuable tool for conveying the complexity of the relationships being studied (Kim, 2007). In the quantile process estimates used in this study, the horizontal axis represents quantiles ranging from lower to upper quantiles. The vertical axis represents the estimated coefficients for each variable. The blue line represents the coefficient estimates at each quantile, while the orange lines represent the confidence intervals. In this study, for each subplot, the variation of the coefficients across quantiles reveals the impact of the explanatory variable on the response variable changes across the conditional distribution of the dependent variable.

Furthermore, the curve of the blue line shows the relationship between the independent variable and the dependent variable varies across the distribution. If the blue line slopes upward for higher quantiles, the variable has a stronger effect in the upper part of the distribution. On the other hand, the width of the confidence intervals provides insight into the precision of the estimates. Chernozhukov (2005) believes that the wider intervals suggest greater uncertainty in the coefficient estimates at specific quantiles.

3.8. Tests for Equality of Parameters across Quantiles and Stability of the Model

This section represents the estimation of the quantile slope equality test and the Wald test estimation.

3.8.1. Quantile slope equality

This study used a quantile slope equality test to determine whether the coefficients (slopes) of the explanatory variables are statistically equal across different quantiles of the conditional distribution of the dependent variable. The quantile slope equality test helps assess if a single regression coefficient can adequately describe the impact of explanatory variables on the explained variable for the entire distribution, or if the effects vary significantly across quantiles (Maiti, 2021). In this study, the quantile slope equality was employed for understanding whether the relationship between independent and dependent variables is consistent across the distribution. According to Bera et al. (2013), the standard method to test quantile slope equality involves conducting a Wald test; the test statistics are calculated as follows:

$$W = (\hat{\beta}_{\tau_1} - \hat{\beta}_{\tau_2})'(V(\hat{\beta}_{\tau_1}) + V(\hat{\beta}_{\tau_2}))^{-1}(\hat{\beta}_{\tau_1} - \hat{\beta}_{\tau_2}) \tag{12}$$

Where $\hat{\beta}_{\tau_1}$ and $\hat{\beta}_{\tau_2}$ are the estimated quantile coefficients at τ_1 and τ_2, $V(\hat{\beta}_{\tau})$ is the variance-covariance matrix of the quantile regression estimate $\hat{\beta}$ at quantile τ. The decision rule is that if the P-value is less than a 5% level of significance, this suggests the rejection of the null hypothesis that the slope coefficients are equal across quantiles.

3.8.2. Wald test estimation

The Wald test in this study is estimated to allow testing of specific hypotheses about the quantile regression coefficients (Xiao, 2009). That might be tested if the effect of a particular variable is zero at a given quantile, or if a set of coefficients is jointly zero. This study conducted a Wald test to understand the significance and impact of variables on different parts of the outcome distribution (Choi et al., 2005). To perform a Wald test on a quantile regression, where the null hypothesis is that certain coefficients are equal to zero, the Wald test statistics takes the following formulation:

$$W = (C\hat{\beta})^{'}(C\hat{V}C^{'})^{-1}(C\hat{\beta}) \quad (15)$$

Where $\hat{\beta}$ is the vector of estimated coefficients, $\hat{V}$ is the covariance matrix of the estimated coefficients, C is the matrix specifying the constraints. The null hypothesis is that the coefficients are jointly zero. The decision rule is that if the P-value is <1% or 5% significant level, this suggests that the coefficients are significant in explaining the dependent variable in the model.

3.8.3. Stability diagnostic test

Stability diagnostic tests are performed to confirm that the model maintains the assumptions of classical regression analysis and does not violate any fundamental conditions, which is a misspecification of error. To test whether an independent variable is stable at a 5% significance level or not, this study employed the cumulative sum (CUSUM) test and cumulative sum of squares (CUSUMQ) test (Brown et al., 1975). These tests checked the null hypothesis which posits that the model parameters have characteristics of stability, while the alternative hypothesis suggests that the parameters exhibit instability. The test is shown by means of a graph, where a CUSUM line is tested against two lines of 5% significance level. If the CUSUM curve crosses either of the two 5% critical thresholds, the null hypothesis is not accepted, indicating that the model exhibits instability (Dao, 2021). Hence, the model represents features of stability where the CUSUM line lies in between the two lines of a 5% significance level.

4. EMPIRICAL RESULTS

4.1. Multivariate Normality Test

This study finds it critical to estimate the normality test to determine the nature of the variables under review in this study, such as household consumption, pay as you earn tax, household disposable income, and unemployment, before engaging in the QARDL model. The multivariate normality test is used in this study, since it has different normality tests as discussed in the previous chapter. The results are presented in Table 1.

The Shapiro-Wilk multivariate normality test found that the series is not normally distributed, since the P-value is 0%, less than the 1% level of significance, as demonstrated in Table 1. These results concur with those of the Henze-Zirkler normality test in Table 1, with a P-value of 9.26%, which is less than the 10% significance level. It is clear in Table 1 that Mardia's Skewness normality test revealed that the variables are not normally distributed, since the P-value is equal to 0.44% and less than the 1% level of significance, in line with the adjusted Mardia's Skewness with a P-value of 0.03%, less than the 1% significance level.

Table 1: Multivariate normality test results

Test	T-statistics	P-value
Shapiro-Wilk	0.7753	0.0000
Henze-Zirkler	0.9335	0.0928
Mardia's Skewness	17.5158	0.0044
Adjusted Mardia's Skewness	17.5158	0.0003
Mardia's Kurtosis	53.5069	0.1237
Doornik-Hansen	18.9575	0.0896

Source: Author's computation using Eviews 14

The Mardia's Kurtosis normal test has a P-value of 12.37%, which is greater than the 10% significance level, which indicates that the series is normally distribution. Table 1 also demonstrates that the Doornik-Hansen normality test has a P-value of 8.96%, less than the 10% significance level, which signifies that the variables are not normally distributed.

In summary, the series is not normally distributed, and these findings support the estimation of the QARDL model, since the normal distribution of the variables is not a prerequisite of the QARDL method (Shahzad et al., 2021).

4.2. Quantile Unit Root Test

This econometric study applies the Quantile Augmented Dickey-Fuller and Quantile Phillips-Perron unit root tests, as discussed in the previous chapter. The quantile ADF unit root test was estimated in this study, followed by the quantile PP unit root test. Table 2 below presents the results for the QADF unit root test at level, of each quantile.

Table 2 indicates that in the lower quantiles, household consumption has a P-value of 99.7% at quantile 0.10 and a P-value of 76.1% at quantile 0.25; pay as you earn tax has a P-value of 77.5% at quantile 0.10. Additionally, household disposable income has a P-value of 99.3% and 91%, and unemployment has a P-value of 69.2% and 50.9% in quantiles 0.10 and 0.25, respectively. All the p-values of the variables of interest are greater than the 10% level of significance, which signifies that the series is not stationary at the specified lower quantiles. In the middle quantiles, the P-value of household consumption is 55.1% at quantile 0.40, household disposable income has the following P-values of 13.9% at quantile 0.40, and unemployment is sitting with a P-value of 23.2%. It means that all the mentioned variables are not stationary at the 0.40 middle quantiles, since the P-values are greater than the 10% level of significance.

On the other hand, in Table 2, pay as you earn tax has a P-value of 0.1% at quantile 0.25, which is less than the 1% significance level. This means that the variables are stationary at specified lower quantiles. Furthermore, pay as you earn tax is stationary at quantile 0.40, which less than the 1% significance level. At quantile 0.50 and 0.60, household consumption, pay as you earn tax, and household disposable income are stationary, as presented in Table 2.

Table 2: Quantile augmented Dickey-Fuller test at level

Quantiles	HC	PAYE	HDI	UER
	Probability	Probability	Probability	Probability
0.10	0.997	0.775	0.993	0.692
0.25	0.761	0.001***	0.910	0.509
0.40	0.551	0.000***	0.139	0.232
0.50	0.015**	0.000***	0.001***	0.369
0.60	0.000***	0.004***	0.000***	0.357
0.75	0.001***	0.013**	0.000***	0.783
0.90	0.001***	0.013**	0.000***	0.783

*Statistically significant at 10% level, **Statistically significant at 5% level, ***Statistically significant at 1% level. Source: Author's computation using STATA 17

Table 2 indicates that in the upper quantiles, household consumption, pay as you earn tax, and household disposable income are stationary at quantile 0.75 and 0.90.

However, Table 2 indicates that unemployment is not stationary at quantiles 0.50 and 0.60. Table 2 indicates that unemployment is not stationary in both quantiles 0.75 and 0.90.

In conclusion, in Table 2, some of the variables of interest in this study are not stationary across some of the quantiles, while other variables are stationary in some quantiles. This study continued to check the stationarity of the non-stationary variables at specific quantiles at level. The QADF unit root test at first difference results are reported in Table 3.

At quantiles 0.10 and 0.25, household consumption is not stationary, while pay as you earn tax, household disposable income and unemployment are only non-stationary at quantile 0.10 but stationary at quantile 0.25, as indicated in Table 3. In the middle quantiles (0.40, 0.50 and 0.60), household consumption, pay as you earn tax, household disposable income, and unemployment are stationary, since their respective P-values are less than the 1% level of significance.

In the upper quantiles, it is noted that household consumption, pay as you earn tax, household disposable income, and unemployment have a P-value of 0%, which is less than the 1% significance level. This means that the variables are all stationary at the upper quantiles, as demonstrated in Table 3. The results of quantile Phillips-Perron test at level are presented in Table 4.

Table 4 indicates that in the lower quantiles, household consumption has a P-value of 99.6% at quantile 0.10, and a P-value of 49.8% at quantile 0.25, and pay as you earn tax has a P-value of 77.4% at quantile 0.10. Additionally, household disposable income has a P-value of 99.2% and 90.9%, and unemployment has a P-value of 69.2% and 50.8% in quantiles 0.10 and 0.25, respectively.

All the P-values of the variables of interest are greater than the 10% level of significance, which signifies that the series is not stationary at the specified lower quantiles. On the other hand, in Table 4, pay as you earn tax has a P-value of 0% at quantile 0.25. In the middle quantiles, the P-value of household consumption is 55% at quantile 0.40, household disposable income has a P-values of 13.8% at quantile 0.40, and unemployment is sitting with a P-value of 23.2%. It means that all the mentioned variables are not stationary at the 0.40 middle quantile, since the P-values are greater than the 10% level of significance. On the other hand, pay as you earn tax is stationary at quantile 0.40, with a P-value of 0%, which is less than the 1% significance level.

At quantiles 0.50, and 0.60, household consumption, pay as you earn tax, and household disposable income are stationary, as presented in Table 4. However, Table 4 indicates that unemployment is not stationary at quantiles 0.50 and 0.60. Lastly, Table 4 indicates that in the upper quantiles, household consumption, pay as you earn tax, and household disposable income, are stationary at quantiles 0.75 and 0.90, while unemployment is not stationary in both quantiles 0.75 and 0.90. In summary, in Table 4 some of the variables of interest in this study are not stationary across some of the quantiles, while other variables are stationary in some quantiles. As presented in Table 4 below, this study estimated the QPP unit root test at first difference to check the stationarity of the non-stationary quantiles in Table 4.

At quantiles 0.10 and 0.25, household consumption is stationary, while pay as you earn tax, household disposable income and unemployment are only non-stationary at quantile 0.10 but stationary at quantile 0.25, as indicated in Table 5. In the middle quantiles, household consumption, pay as you earn tax, household disposable income, and unemployment are stationary, since their respective P-values are less than the 1% level of significance. In the upper quantiles it is noted that household consumption, pay as you earn tax, household disposable income, and unemployment have a P-value of 0%, which is less than the 1% significance level. This means that the variables are all stationary at the middle and upper quantiles.

Table 3: Quantile augmented Dickey-Fuller test at first difference

Quantiles	HC	PAYE	HDI	UER
	Probability	Probability	Probability	Probability
0.10	0.626	1.000	0.368	1.000
0.25	0.432	-	0.091*	0.000***
0.40	0.000***	-	0.000***	0.000***
0.50	-	-	-	0.000***
0.60	-	-	-	0.000***
0.75	-	-	-	0.000***
0.90	-	-	-	0.000***

*Statistically significant at 10% level, **Statistically significant at 5% level, ***Statistically significant at 1% level. Source: Author's computation using STATA 17

Table 4: Quantile Phillips-Perron test at level

Quantiles	HC	PAYE	HDI	UER
	Probability	Probability	Probability	Probability
0.10	0.996	0.774	0.992	0.692
0.25	0.498	0.000***	0.909	0.508
0.40	0.550	0.000***	0.138	0.232
0.50	0.015**	0.000***	0.001***	0.369
0.60	0.000***	0.003***	0.000***	0.357
0.75	0.000***	0.012**	0.000***	0.783
0.90	0.000***	0.012**	0.000***	0.783

*Statistically significant at 10% level, **Statistically significant at 5% level, ***Statistically significant at 1% level. Source: Author's computation using STATA 17

Table 5: Quantile Phillips-Perron test at first difference

Quantiles	HC	PAYE	HDI	UER
	Probability	Probability	Probability	Probability
0.10	0.626	1.000	0.367	1.000
0.25	0.431	-	0.099*	0.000***
0.40	0.000***	-	0.000***	0.000***
0.50	-	-	-	0.000***
0.60	-	-	-	0.000***
0.75	-	-	-	0.000***
0.90	-	-	-	0.000***

*Statistically significant at 10% level, **Statistically significant at 5% level, ***Statistically significant at 1% level. Source: Author's computation using STATA 17

Based on the results of QADF and QPP at level and first difference, household consumption, pay as you earn tax, household disposable income, and unemployment are stationary in most of the quantiles.

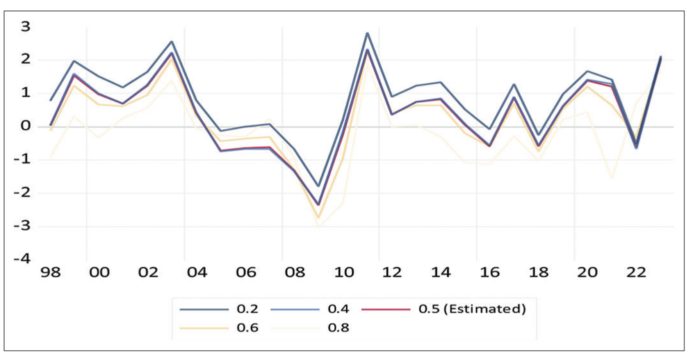
4.3. Quantile Cointegration

This study estimated quantile cointegration processes to investigate how cointegration varies across different parts of the distribution, which can help in understanding if the relationship between pay as you earn tax on household consumption changes, depending on whether they are at extreme values (upper or lower quantiles), or closer to the median. Figure 1 shows multiple quantile levels of the cointegrating relation, and each line represents the behaviour of the cointegrating relation for different parts of the distribution, with the 0.5 quantile (median) being highlighted in red and labelled as "Estimated."

Figure 1 shows fluctuations in the cointegrating relation over time. There are periods of peaks, such as in 2010 and 2022, and troughs in years 2008 and 2014. These changes imply varying degrees of cointegration across different quantiles, meaning that the relationship between the underlying variables is not constant and exhibits varying strength across different parts of their distribution.

The different quantile lines generally move together but show some divergence in certain periods, suggesting that the relationship between the variables might vary across quantiles; this implies heterogeneity. The lower quantiles tend to deviate more during certain periods, indicating that the impact on the lower part of the distribution is different compared to the upper part, as demonstrated in Figure 1.

Figure 1: Cointegrating relations quantile processes test results



Source: Author's computation using Eviews 14

4.4. Long-run QARDL Estimates Results

This study estimated the long-run QARDL model to check the effect of pay as you earn tax on household consumption the results are presented in Table 6 below.

Table 6 shows pay as you earn tax is not significant in the lower, middle, and upper quantiles in the long run. These results are supported by Li and Li (2020), who found that taxes on income are not statistically significantly related to consumption.

The lower quantiles in Table 6 signify that household disposable income is statistically significant at the 5% level. It means that household disposable income has a positive impact on household consumption in the long run. Moving to the middle quantiles, 0.40 and 0.50, the household disposable income is statistically significant at the 1% level, since both quantiles have a P-value of 0.5%. In the 0.60 middle quantile, the household disposable income has a P-value of 1.09% which is less than the 5% level of significance, as presented in Table 6.

This also implies a positive relationship between household disposable income and household consumption in the middle quantiles, in the long run. Table 6 further demonstrates that disposable income is statistically significant at the 5% level in the upper quantiles and has a positive coefficient, which indicates household disposable income and household consumption are positively related in the long run. The results are in line with Ruan and Yan (2022) and Sulistyowati et al. (2017), who discovered that household disposable income and consumption of household are positively related, and this concurs with the results presented in Table 6.

It is clearly demonstrated in Table 6 that unemployment is statistically insignificant in the lower quantiles and the 0.90 upper quantile. These findings are supported by Yıldırım and Yıldırım (2017), who revealed an insignificant effect of unemployment on consumption.

Whereas in the middle quantiles (0.40 and 0.50), unemployment is statistically significant at 10%, while at the 0.60 middle quantiles, unemployment is statistically significant at the 5% level, with a negative coefficient. This means that unemployment has a harmful effect on household consumption in the long run. In the 0.75 upper quantile, unemployment is statistically significant at the 1% level with a P-value of 0.94%, which indicates that a 1% increase in unemployment causes a 5.8554 units decrease in consumption of households in the long run.

Table 6: Long-run QARDL estimates

Quantile	LPAYE		HDI		LUER	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
0.10	14.2955	0.5081	1.3861	0.0420**	−3.0517	0.4874
0.25	13.0320	0.3325	1.2635	0.0142**	−2.7819	0.2936
0.40	11.5565	0.3182	1.2856	0.0053***	−4.1116	0.0626*
0.50	11.7485	0.3093	1.2736	0.0054***	−4.1565	0.0587*
0.60	15.3297	0.2301	1.1968	0.0109**	−4.5642	0.0486**
0.75	8.9333	0.4496	0.9426	0.0258**	−5.8554	0.0094***
0.90	10.7829	0.5610	1.2059	0.0818*	−6.9684	0.1535

*Statistically significant at 10% level, **Statistically significant at 5% level, ***Statistically significant at 1% level. Source: Authors own computation using E-views 14

This is in line with Gupta and Kishore (2022), Alegre and Pou (2016), Christelis et al. (2015) Fagereng et al. (2024), Dickens et al. (2017) and Habanabakize et al. (2017), who found that unemployment harms the consumption of households. However, the 0.90 upper quantile is statistically insignificant. The following empirical evidence (Kroft and Notowidigdo, 2016; Bentolila and Ichino, 2008) is of the view that unemployment has an insignificant impact on household consumption.

4.5. Short Run QARDL Estimates Results

The results of the estimation of the QARDL short-run model between pay as you earn tax and household consumption are reported in Table 7.

Table 7 indicates that all the error correction terms from the lower to the upper quantiles have a negative coefficient and significant P-values. This implies that the model will return to equilibrium in the long run, after the short run shock.

In the short run, the pay as you earn tax is statistically significant at the 5% level in the lower quantiles, with negative coefficients, as reported in Table 7. This signifies that pay as you earn tax harms the consumption of households in the short run. In the middle quantiles, pay as you earn tax is also statistically significant with negative coefficients, as shown in Table 7. This implies that the increase in pay as you earn tax leads to a decrease in household consumption. Table 7 indicates that at the 0.75 upper quantile, the pay as you earn tax has a p-value of 3.8%, less than the 5% significance level. This means a 1% increase in pay as you earn tax results in a 14.700 units decrease in consumption of households. This concurs with the findings of those of Agheli et al. (2009), who obtained a negative and significant relationship between taxes on income and household consumption. Zhang (2017) concurs with this notion, and asserts that there is a negative connection between income tax and the consumption of households.

On the other hand, in the 0.90 upper quantile, pay as you earn tax is statistically insignificant. Şen and Kaya (2016) and Wang (2022) believe that the connection between taxes on income and consumption differs, depending on time.

According to Table 7, household disposable income is statistically significant in the lower quantiles with positive coefficients, which means a rise in disposable income leads to an increase in household consumption, in the short run. In the middle quantiles, household disposable income has a positive statistically significant coefficient, as reported in Table 7. This signifies that an increase in household disposable income causes a rise in consumption of households in the short run. Table 7 indicates that in the upper quantiles, household disposable income has positive statistically significant coefficients, which means household disposable income is positively related to household consumption in the short run. In this view, Hone and Marisennayya (2019) argue that a rise in disposable income boosts the consumption of households. Muzindutsi and Mjeso (2018) also found a positive effect of disposable income on household consumption.

In Table 7, unemployment at the lower and middle quantiles is statistically significant with a positive coefficient. This implies that an increase in unemployment results in a rise in household consumption, which is in line with the 0.75 upper quantile. These findings concur with the findings of Popovici and French (2013), who found that unemployment encourages consumption. This is following Janlert and Hammarström (1992), who found that unemployment has a positive significant relationship with household consumption. These results are supported by Campos and Reggio (2015), who argued that unemployment does not cause a decline in household consumption.

On the other hand, at the 0.90 upper quantile, unemployment is statistically insignificant. In the same manner, Alegre and Pou (2016) established that the relationship between unemployment and consumption is insignificant.

4.6. Quantile Process Estimates Results

This set of quantile process estimates demonstrated in Figure 2 gives insight into how each independent variable influences changes across the distribution of household consumption.

Figure 2 indicates that some variables, such as pay as you earn tax, have an increasing effect at higher quantiles, while unemployment has a downward-sloping blue line, which suggests that its impact is stronger at lower quantiles and weakens toward higher quantiles. The confidence bands are relatively narrow, indicating precision in the estimates. The household disposable income has a downward-sloping blue line, implying that the effect diminishes as we move toward higher quantiles.

4.7. Equality of Parameters across Quantiles and Stability of the Model

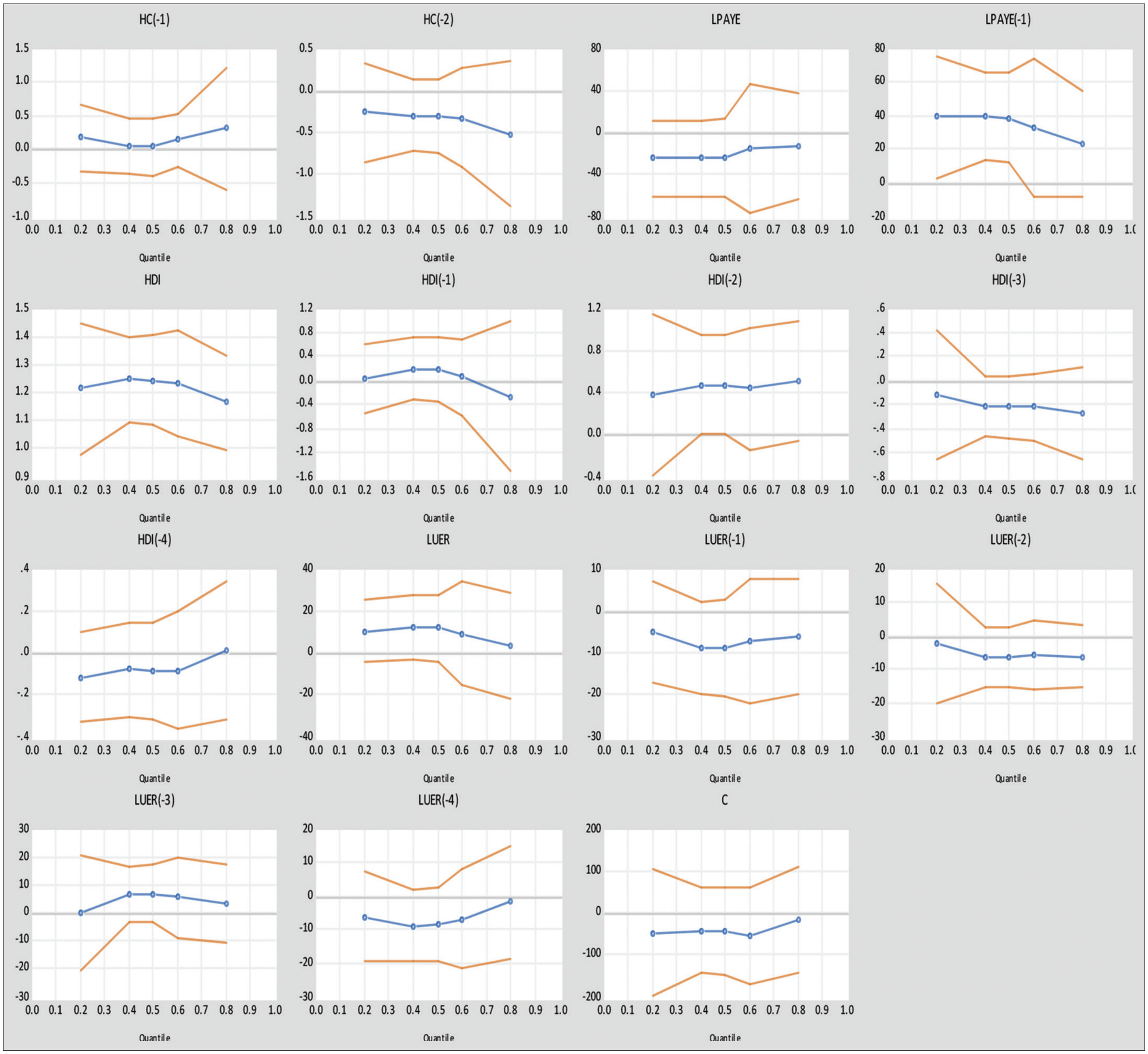
This section discusses the results of the tests for equality of parameters across quantiles, Table 8 represents the slope of the equality test findings.

Table 7: Short-run QARDL estimates

Quantile	ECM		LPAYE		HDI		LUER	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	p-value
0.10	−0.860	0.000***	−23.802	0.036**	1.2181	0.000***	10.213	0.054*
0.25	−0.965	0.000***	−24.761	0.013**	1.213	0.000***	10.274	0.024**
0.40	−0.982	0.000***	−25.228	0.010**	1.215	0.000***	10.616	0.018**
0.50	−0.9199	0.008***	−24.600	0.001***	1.245	0.000***	12.112	0.000***
0.60	−0.9220	0.0112**	−24.026	0.002***	1.245	0.000***	11.880	0.001***
0.75	−0.6838	0.0681*	−14.700	0.038**	1.233	0.000***	9.099	0.007***
0.90	−0.7339	0.058*	−3.673	0.641	1.207	0.000***	3.184	0.376

*Statistically significant at 10% level, **Statistically significant at 5% level, ***Statistically significant at 1% level. Source: Authors own computation using E-views 14

Figure 2: Quantile process estimates results



Source: Author's computation using Eviews 14

It is clear from Table 8, that the slope equality is the same across the quantile levels, since the P-value is 99.34%, greater than the 5% level of significance. The following Table 9 represents the Wald test results of the model.

Table 9 indicates that there is strong evidence against the null hypothesis that the coefficients C(1), C(3), C(5), and C(10) are jointly zero. This implies that these coefficients are significant in explaining the dependent variable in the model. In other terms household consumption, pay as you earn tax, household disposable income, and unemployment are significant contributors to the model, since the p-values are both statistically significant at the 1% level. Figure 3 below shows the CUSUM and CUSUMQ test results.

Table 8: Quantile slope equality test

Test	Chi-square statistic	Probability
Wald test	8.2416	0.9934

Source: Authors own computation using E-views 14

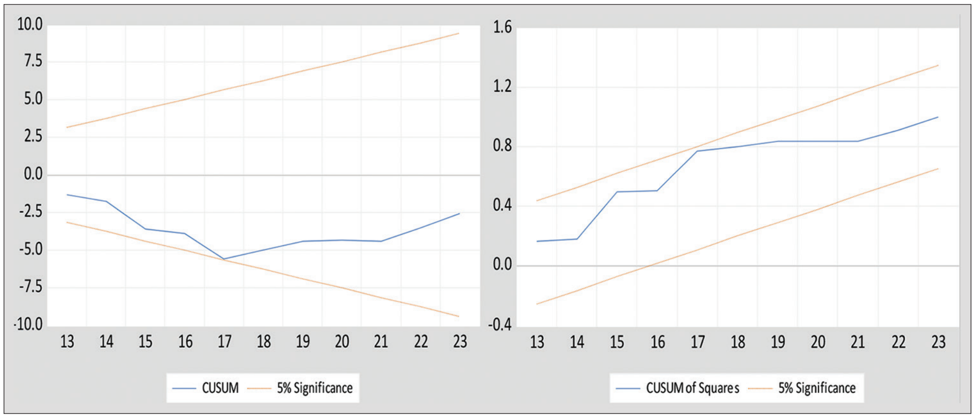
Table 9: Wald test results

Null hypothesis	Test statistics	Probability
C(1)=0, C(3)=0, C(5)=0, C(10)=0	F statistics	0.0000
	Chi-square	0.0000

Source: Authors own computation using E-views 14

The findings presented in Figure 3 indicate that the QARDL model exhibits stability, as both the CUSUM and CUSUMQ curves

Figure 3: QARDL dynamic stability test results



Source: Author's computation using Eviews 14

remain within the 5% level of significance. Therefore, the null hypothesis of model instability is rejected.

5. CONCLUSIONS, SUMMARY, AND POLICY IMPLICATIONS

This study empirically examined the effect of Pay As You Earn (PAYE) tax on household consumption in South Africa using the Quantile Autoregressive Distributed Lag (QARDL) model and annual data from 1994 to 2023. The key findings reveal that, in the long run, PAYE tax has no statistically significant impact on household consumption across all quantiles. In contrast, household disposable income consistently shows a statistically significant and positive relationship with consumption, underscoring its central role in influencing household spending behaviour. Additionally, unemployment is found to be statistically significant in the middle and upper-middle quantiles, with a negative coefficient, indicating its dampening effect on consumption in those segments. In the short run, PAYE tax negatively affects household consumption across most quantiles, except the highest (0.90), where it is statistically insignificant. The study contributes to the literature by employing the QARDL approach, which allows for a nuanced understanding of the asymmetric and heterogeneous effects of fiscal variables across different levels of household consumption. This methodological contribution enhances the understanding of the dynamics between taxation and consumption behaviour in an emerging economy context.

The findings support theories emphasizing the importance of disposable income in determining household consumption. They also highlight the limitations of linear models in capturing the complex, quantile-specific effects of fiscal policy instruments. For practitioners involved in economic planning and tax administration, the results emphasise the need to consider the short-run behavioural responses of households to changes in direct taxation, particularly among low- and middle-household consumers.

The evidence suggests that increases in PAYE tax can suppress household consumption in the short run, especially for lower and middle-household consumers. Therefore, tax policy should be carefully calibrated to avoid unintended consumption slowdowns. Enhancing household disposable income and reducing unemployment can yield more sustainable improvements in consumption patterns. Policymakers are encouraged to introduce targeted PAYE tax relief measures, particularly for lower- and middle-household consumers, to support consumption and stimulate economic activity. Additionally, broader reforms aimed at increasing household disposable income such as raising the tax-free threshold or providing income-based rebates should be considered. Active labour market policies are also vital to address the negative effects of unemployment on consumption.

6. DECLARATION OF FUNDING

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