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Income Patterns by Gender, Race and Marital Status in South Africa

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ABSTRACT

Income remains a fundamental determinant of individual and household well-being, shaping access to essential resources such as education, healthcare, housing, and social mobility. While philosophical debates may question the direct link between income and happiness, there is little dispute that a lack of income often results in heightened vulnerability, social exclusion, and limited agency. In this regard, income poverty not only affects material living standards but also undermines human dignity and increases susceptibility to exploitation and deprivation. Within the global development discourse, particularly as outlined in the United Nations Sustainable Development Goals (SDGs), poverty eradication is centrally linked to the promotion of inclusive economic growth and equitable access to income and wealth. Addressing poverty, however, requires an appreciation of its multidimensional nature and the structural inequalities that underpin it. This study investigates the determinants of household head labour salary in South Africa, utilizing cross-sectional data from the 2023 General Household Survey (GHS). Employing an Ordinary Least Squares (OLS) regression model on a sample of 10,883 households, the research aims to identify how demographic characteristics, marital status, and employment status influence individual earnings. The model explained 21.4% of the variance in labour salary, demonstrating a statistically significant overall fit. Key findings reveal that the age of the household head is a significant positive predictor of labour salary, consistent with human capital theory. Crucially, the analysis highlights persistent and substantial racial income disparities, with White and Indian/Asian household heads earning significantly more than their African and Coloured counterparts. For instance, White household heads earned 2.4 times more per month than African household heads, after controlling for other factors. A significant "marriage premium" was also identified, where legally married household heads earned more than those in other marital statuses. Interestingly, gender (being a female household head) did not show a statistically significant direct effect on labour salary in this model. These findings underscore the enduring impact of historical inequalities on South Africa's labour market, particularly along racial lines. The study recommends intensified policy interventions to address racial wage gaps, continued investment in human capital, and further research into the nuanced dynamics of gender and marital status on income to foster greater equity and economic well-being across the country.

Keywords: Labour Salary; Income Inequality; Household Head; South Africa; OLS Regression

INTRODUCTION

The pursuit for a better life remains a struggle for many people across the globe especially post Covid-19 (World Bank Group, 2024). Speed of upward mobility has slowed down form many societies as global attention has shifted to other pressing issues like wars and changes in global politics (Li, 2021). Multiple crises have divided the global attention that hitherto was focused on achieving global prosperity and poverty reduction. For decades, poverty rates have started to increase again, and the 2020s is increasingly appearing to be a lost decade(World Bank Group, 2024). Income mobility and its determinants remain central to understanding economic inequality across the globe, particularly in regions characterized by significant disparities such as Sub-Saharan Africa. Within this context, South Africa presents a unique case study owing to its legacy of apartheid, deeply entrenched racial inequalities, and ongoing gender disparities in labour market participation and income levels (Morrell et al., 2012). Income dynamics which basically looks into how individuals' earnings change over time are crucial for evaluating economic resilience and social mobility, yet they are influenced by intersecting demographic factors, including gender, race, and marital status (Klasen & Woolard, 2005).

Research has consistently demonstrated that in South Africa, racial disparities continue to shape income inequality, with historically marginalized groups such as Black Africans experiencing lower income mobility compared to their White counterparts (Kiggundu & Mwenda, 2021). Simultaneously, gender disparities manifest in wage gaps and employment opportunities, impacting income trajectories differently for men and women (Cantor & Wainwright, 2022). Marital status further complicates these patterns by influencing household income composition, access to resources, and social support structures (Leibbrandt et al., 2010). Despite these insights, there remains a paucity of comprehensive, longitudinal analyses that examine how these factors intersect to influence income mobility over time within the South African context.

This study utilizes the 2023 South African General Household Survey (GHS) to analyse the interplay of gender, race, and marital status in shaping income dynamics. By leveraging recent nationally representative data, this research aims to capture current patterns and provide empirical evidence on the differential income trajectories among various demographic groups. Understanding these nuanced dynamics is vital for crafting targeted policies aimed at reducing inequality, promoting inclusive economic growth, and fostering social cohesion.

The findings of this research will contribute to the broader literature on income mobility in Sub-Saharan Africa, offering insights into the persistent structural barriers faced by marginalized groups and highlighting pathways toward equitable economic participation. This analysis not only advances academic understanding but also informs policy discussions aimed at addressing inequality in a post-pandemic economic landscape.

LITERATURE REVIEW

The study of income is a venerable field in economic and social sciences, tracing its origins back centuries due to its unparalleled utility as a direct and immediate measure of individual and household well-being, or conversely, as a critical indicator of poverty (Sherman et al., 2024; Atkinson, 1970). Income serves as a fundamental metric because it quantifies the resources available to individuals and households for consumption, savings, and investment, thereby directly reflecting their command over goods and services and their overall standard of living (Sen, 1999). Consequently, a vast body of literature across economics, sociology, and public policy has been dedicated to understanding not only the levels of income but also its distribution, its determinants, and the factors contributing to disparities within and across societies (Piketty, 2014; Fields, 2007). Research in this area frequently explores the drivers of income variation, such as human capital attributes (e.g., education, experience), demographic characteristics (e.g., age, gender, race), and labour market structures, all of which are crucial for formulating effective policies aimed at poverty reduction and inequality alleviation.

Given income's central role as an indicator of socio-economic well-being, a significant branch of this extensive literature delves into the determinants of income variation, seeking to unravel the individual and systemic factors that shape earnings and contribute to disparities. Among the myriad variables explored, race and gender have consistently emerged as paramount demographic characteristics profoundly influencing income trajectories and distribution across diverse contexts. These two factors, often intertwined with historical legacies, social structures, and labour market dynamics, are central to understanding patterns of inequality. The following sections will therefore delve specifically into the existing body of research on income and gender, followed by an examination of the literature on income and race, laying the groundwork for the empirical analysis presented in this study within the South African context.

Income and Gender

Gender-based income inequality remains a deeply entrenched global phenomenon, and South Africa, despite its progressive constitutional framework and robust labour reforms aimed at promoting gender equality, continues to grapple with substantial wage disparities between men and women. The persistence of this gap signifies that formal legal protections alone are insufficient to dismantle deeply rooted socio-economic structures.

Empirical evidence consistently demonstrates a significant earnings gap in South Africa. For instance, Statistics South Africa's Quarterly Labour Force Survey (QLFS) data frequently indicates that women earn approximately 75 to 78 cents for every rand earned by men, even when controlling for factors like education and experience (Statistics South Africa, 2023). This "unexplained" portion of the gap points towards underlying systemic biases and non-economic factors. As noted by Casale and Posel (2005), this disparity is often attributed to several interconnected factors, including pronounced occupational segregation, where women are disproportionately concentrated in lower-paying sectors such as care, administrative, and service industries, while men dominate higher-paying fields like engineering and IT. Furthermore, differences in hours worked and women's heavier, often invisible, burden of unpaid care work – including household chores, childcare, and eldercare – significantly constrain their capacity for full-time formal employment and career progression (Budlender & Lund, 2011). Time-use surveys consistently show South African women spending significantly more hours daily on unpaid care activities than men, directly impacting their economic participation and earning potential.

In the post-apartheid era, while female labour force participation has indeed increased, a considerable portion of this growth has been concentrated in low-paying, informal, or precarious employment sectors (Casale, 2012). This phenomenon means that even as more women enter the workforce, they often remain confined to jobs with limited benefits, job security, and opportunities for advancement, perpetuating their economic vulnerability. Moreover, gender-based income inequality in South Africa is critically compounded by intersecting factors such as race and family status. As Posel and Rogan (2019) highlight, Black African women face the compounded disadvantage of higher unemployment rates and a greater likelihood of working in the informal sector. For example, in Q1 2024, the official unemployment rate for women stood at approximately 35%, notably higher than the 30% for men, with Black African women experiencing some of the highest rates across all demographic groups (Statistics South Africa, 2024). This intersectionality means that policy interventions must be multifaceted to address the layered forms of discrimination and disadvantage.

Despite the implementation of progressive policy measures, such as affirmative action and gender-sensitive labour policies, structural barriers continue to impede the achievement of full economic parity. These barriers include, but are not limited to, limited access to quality, affordable childcare services, persistent patriarchal social norms that assign specific roles to men and women, and the pervasive issue of gender-based violence, which undermines women's safety, mobility, and ability to participate fully in the economy (UN Women, 2015). Addressing these deeply entrenched structural issues is fundamental to genuinely closing the gender income gap and fostering equitable economic opportunities for all South Africans.

Income and Race

Racial income inequality in South Africa is not merely a contemporary issue but a deeply entrenched legacy of the country's colonial and apartheid history. For centuries, discriminatory policies systematically excluded the majority Black African population from access to quality education, skilled employment, land ownership, and asset accumulation, deliberately impeding their economic advancement. Even more than three decades into democracy, race remains an overwhelmingly significant determinant of income, casting a long shadow over the promise of economic redress. As Leibbrandt et al. (2010) empirically demonstrate, the average earnings of Black South Africans remain substantially lower than those of their White counterparts, even when accounting for crucial human capital factors such as education and experience. This persistent disparity highlights that the issue extends beyond individual attributes to systemic imbalances.

The perpetuation of these racial disparities is sustained by complex structural inequalities within the South African socio-economic fabric. These include starkly unequal access to quality education, with historical underinvestment in schools serving Black communities continuing to affect educational outcomes and future earning potential. Furthermore, spatial segregation, a direct consequence of apartheid planning, forces many Black individuals to live far from economic hubs, incurring higher travel costs and limiting access to better employment opportunities. Labour market discrimination, both overt and subtle, continues to hinder career progression. Burger and Jafta (2006) provide evidence of persistent occupational stratification by race, with White South Africans remaining significantly overrepresented in high-paying management, professional, and technical professions. Disturbingly, even among university graduates, research by Mlatsheni and Rospabe (2002) reveals that Black professionals consistently tend to earn less than their White peers, underscoring that educational attainment alone does not fully equalize labour market returns across racial lines. More recent studies have further emphasized the importance of inherited advantages, with intergenerational transfers of wealth, property ownership, and access to powerful social and professional networks disproportionately benefiting White South Africans, thereby entrenching and perpetuating existing income gaps across generations (Zizzamia et al., 2019). Despite the implementation of corrective policy measures such as affirmative action and Black Economic Empowerment (BEE), the sheer scale of historical disadvantage means that these initiatives have, thus far, been insufficient to fully dismantle these deeply entrenched income inequalities.

Beyond race, marital status significantly influences income dynamics in South Africa, reflecting both economic efficiencies within household structures and the impact of policy design. Single-earner households, which are disproportionately headed by women, frequently face higher effective tax burdens due to the country's tax rebate structure. For instance, a concrete example illustrates this disadvantage: a single mother earning R17,000 per month could pay significantly more in annual taxes compared to a dual-income household with the same total income, essentially missing out on the benefit of a second tax-free threshold and rebate that a dual-earner couple would receive. This effectively means that for the same household income, a single-earner family can contribute substantially more in taxes, impacting their disposable income (Steencamp 2014).

Furthermore, employment patterns themselves vary by marital status, contributing to income differentials. Data often indicate that divorced individuals, possibly driven by the economic necessity of supporting themselves or their dependents independently, exhibit some of the highest employment rates among various marital categories. Conversely, (Dunga 2017) found that widowed and never-married individuals tend to have lower employment rates, which can be influenced by factors such as age, caregiving responsibilities, or lack of established professional networks These differences collectively suggest that marital status plays a multifaceted role, affecting both an individual's engagement with the labour market and their resultant income levels. Moreover, the burden of caregiving responsibilities disproportionately falls on women, particularly those heading single-parent households. This often limits their capacity to engage in full-time employment, pursue demanding career advancements, or even participate in lucrative but time-consuming informal economic activities, thereby directly constraining their income potential and perpetuating cycles of economic vulnerability.

Building on the insights gleaned from the extensive literature on income determination and inequality, particularly regarding the persistent disparities linked to race, gender, and marital status, it becomes evident that a rigorous empirical approach is essential to quantify these relationships within the South African context. The following section, Methodology, outlines the research design, data sources, variables, and econometric techniques employed to empirically investigate the factors influencing household head labour salary, thus providing a foundation for the robust analysis presented in this study.

This study makes both theoretical and practical contributions to the literature. Theoretically, it extends existing research on income inequality by jointly examining the intersection of gender, race, and marital status using recent nationally representative data, thereby providing updated empirical evidence in a post-pandemic context. Practically, the findings offer important policy insights for addressing persistent labour market inequalities, particularly racial income disparities and vulnerabilities associated with different household structures. These insights are critical for informing targeted interventions aimed at promoting inclusive economic growth and reducing income inequality in South Africa.

METHODOLOGY AND RESULTS

This study employs data from the 2023 General Household Survey (GHS), conducted annually by Statistics South Africa. The GHS is a crucial national survey designed to gather comprehensive data from households on a wide array of socio-economic variables, offering invaluable insights into living conditions and serving as a primary tool for assessing the overall well-being of households across the country. The 2023 GHS dataset, specifically utilized in this research, comprises a robust sample of 10,883 households. This extensive sample is meticulously designed to ensure national representativeness, proportionally reflecting the population distribution across all nine provinces of South Africa and aligning with the demographic composition of various population groups.

A detailed examination of the sample's distribution, crucial for understanding the representativeness of the data, is presented in the following tables. As detailed in Table 1, the provincial distribution of respondents shows Gauteng with the highest representation, consistent with its relative population size, while the Northern Cape has the smallest. Similarly, Table 2 illustrates the sample's proportional alignment with the national population distribution across different population groups (Statistics South Africa, 2023). The representative nature of this dataset is fundamental to ensuring the external validity and generalizability of the study's findings on labour salary determinants.

Table 1: Provincial representation of the sample

Province	Freq.	Percent	Cum.
Western Cape	1186	10.90	10.90
Eastern Cape	1118	10.27	21.17
Northern Cape	479	4.40	25.57
Free State	667	6.13	31.70
KwaZulu-Natal	1717	15.78	47.48
North-West	640	5.88	53.36
Gauteng	3106	28.54	81.90
Mpumalanga	879	8.08	89.98
Limpopo	1091	10.02	100.00
Total	10883	100.00	

Table 2 presents the sample's racial distribution, which is meticulously designed to reflect the demographic makeup of South Africa. As expected, African/Black households constitute the largest portion of the sample, representing 82.27% of the total. This robust representation aligns closely with their significant proportion in the national population, which was approximately 81.4% according to Statistics South Africa's 2022 mid-year population estimates (Statistics South Africa, 2022a; Demographics of South Africa, 2024). Following this proportional approach, the sample includes 6.56% White households, a figure aligned with their share of the total population, estimated at around 7.3% in 2022. The representation of Coloured (mixed race) and Indian/Asian households in the sample likewise mirrors their respective national population percentages (approximately 8.9% for Coloured and 2.3% for Indian/Asian in 2022, according to Statistics South Africa's mid-year estimates) to ensure the survey accurately reflects the country's diverse demographics (Statistics South Africa, 2022a; Data First, 2024).

This proportional sampling by population group is a cornerstone of the GHS methodology. Statistics South Africa employs a stratified two-stage sample design, with subsequent weighting procedures that calibrate the collected data to national-level population estimates cross-classified by age groups, gender, and race (Data First, 2024; Statistics South Africa, 2023). This rigorous process ensures the reliability and validity of the insights derived from the survey concerning the well-being and living conditions of households across all population groups in South Africa (Statistics South Africa, 2017).

Table 2: Distribution of race

Population group of household head	Freq.	Percent	Cum.
African/Black	8953	82.27	82.27
Coloured	971	8.92	91.19
Indian/Asian	245	2.25	93.44
White	714	6.56	100.00
Total	10883	100.00	

Beyond the demographic characteristics, the General Household Survey (GHS) collects a rich array of variables pertinent to household well-being. For the purpose of this analysis, labour salary will be utilized as a key income variable, in preference to total household income. This deliberate choice addresses the potential volatility and diverse components of total income, which can encompass social grants, remittances, and other non-labor related transfers (Statistics South Africa, 2023a). Focusing on labour salary provides a more direct measure of earned income from employment, reflecting an individual's or household's consistent earning capability. This approach is favored because employment, and consequently labour salary, tends to exhibit greater stability over time compared to other income sources that might be subject to short-term fluctuations or temporary movements, such as casual work or sporadic remittances (Leibbrandt et al., 2010; Posel & Rogan, 2017).

A significant methodological advantage of using the 2023 GHS data for this study is its cross-sectional nature, captured at a single point in time. This ensures that all sampled households were exposed to a similar set of external economic and social circumstances prevailing in 2023, thereby enhancing the comparability of income data across the sample (Hair et al., 2010). Furthermore, the GHS is particularly valuable because it involves the direct collection of actual income data. This contrasts with many studies that are often compelled to deduce or impute income from expenditure patterns or asset ownership, methods that can introduce significant measurement error and reduce the precision of income estimates (Po et al., 2012; Deaton & Zaidi, 2002). The availability of directly reported labour salary data thus significantly strengthens the robustness and validity of the income analysis presented in this paper.

Table 3: Descriptive statistics for Salary

Variable	Obs	Mean	Std. Dev.	Min	Max
Salary	10883	13370.213	21392.842	100	420000

Another crucial variable presented in Table 4 is the distribution of gender within the sampled households. As gender is a key factor in explaining variations in income, it is essential to assess the representation of different gender groups within the dataset. The results indicate that the sample comprises 34.62% females and 65.38% males. This observed distribution suggests that a majority of the sampled households are headed by males, a common pattern in many patriarchal societies, including South Africa (Statistics South Africa, 2023; Budlender, 2007).

Despite the lower percentage of female representation compared to males in terms of household headship, the absolute number of female-headed households in the sample provides a sufficiently robust basis for meaningful analysis of gender dynamics in income. The General Household Survey (GHS) is specifically designed to collect comprehensive data that allows for disaggregated analysis, including by gender, to understand various socio-economic outcomes (Data First, 2024.).

Extensive literature consistently highlights a recurring gender disparity in income and labour market outcomes across numerous countries. Research universally demonstrates that women are often paid less than men, even for comparable work, a phenomenon known as the gender pay gap (Lurie & Stier, 2022; Blau & Kahn, 2017). This disparity can be attributed to a complex interplay of factors, including occupational segregation, differences in human capital accumulation, discriminatory practices, and the uneven burden of care responsibilities that disproportionately fall on women (UN Women, 2019; World Bank, 2018). In the South African context, studies have also identified persistent gender wage gaps, often exacerbated by racial inequalities and historical disadvantages (Casale & Posel, 2002; Kachingwe & Mabaso, 2020). Therefore, the data's gender distribution, even with a higher proportion of male-headed households, offers a valuable opportunity to investigate these crucial income dynamics and disparities within the South African household context.

Table 4 Gender of head of household

Sex of household head	Freq.	Percent	Cum.
Male	7115	65.38	65.38
Female	3768	34.62	100.00
Total	10883	100.00	

Model specification

The relationship between labour salary and the selected explanatory variables is estimated using an Ordinary Least Squares (OLS) regression model. Labour salary of the household head is specified as the dependent variable. The model includes age, gender, race, marital status, and employment status as key explanatory variables. Robust standard errors are applied to account for heteroskedasticity commonly present in cross-sectional income data.

Data and Variable Definition

The study uses cross-sectional data from the 2023 General Household Survey (GHS) conducted by Statistics South Africa. The analysis focuses on household heads and examines the factors associated with labour income across gender, race, and marital status. The dependent variable is **labour salary of the household head**, which captures earnings from wages and salaries. Labour salary is preferred to total household income in order to focus on stable, earned income and to avoid conflating labour market outcomes with transfers such as social grants, remittances, or other non-labour income sources (Statistics South Africa, 2023; Posel & Rogan, 2017).

The key explanatory variables include age, gender, race, and marital status of the household head. Gender, race, and marital status are categorical variables and are included in the regression model using dummy variables with clearly defined reference categories.

Empirical Model Specification

To examine the relationship between labour salary and the selected explanatory variables, the study employs an Ordinary Least Squares (OLS) regression framework. The baseline model is specified as follows:

$$Y_i = \beta_0 + \sum_{k=1}^{K} \beta_k X_{ik} + \sum_{j=1}^{J} \theta_j D_{ij} + \varepsilon_i \qquad (1)$$

where:

- Y_i denotes the labour salary of household head i;
- β_0 is the intercept term;
- X_{ik} represents a vector of continuous explanatory variables (such as age);
- D_{ij} represents a vector of dummy variables capturing categorical characteristics (gender, race, and marital status);
- β_k and θ_j are parameters to be estimated;
- ε_i is the error term.

Equation (1) is expanded to explicitly incorporate the variables of interest as follows:

$$Salary = \beta_0 + \beta_1 Age_i + \theta_1 gender_j + \theta_2 Mixedrace_j + \theta_3 Indian/asian_j + \theta_4 White_j + \theta_5 MS2_j + \theta_6 MS3_j + \theta_7 MS4_j + \theta_8 \mathrm{MS5}_j + \theta_9 MS6_j + \varepsilon \ldots \quad (2)$$

where:

- $Female_i$ is a dummy variable equal to 1 if the household head is female (male is the reference category).
- $MixedRace_i$, $IndianAsian_i$, and $White_i$ are race dummy variables, with African/Black as the reference category;
- MS_{2j} to MS_{6i} represent marital status categories, with legally married as the reference group.

Estimation Strategy and Robust Standard Errors

OLS estimation relies on the assumption of homoscedastic error terms. However, in cross-sectional income data, heteroscedasticity is common due to substantial variation in earnings across individuals, ranging from very low incomes to high-earning households.

To address this concern, all regression models are estimated using heteroscedasticity-robust standard errors. This approach relaxes the homoscedasticity assumption and ensures valid statistical inference in the presence of heteroscedasticity.

Accordingly, coefficient estimates are obtained using OLS, while inference is based on robust standard errors:

$$\hat{\beta} = (X'X)^{-1}X'Y \qquad (3)$$

with variance–covariance matrix given by:

$$Var(\hat{\beta}) = (X'X)^{-1}X'\hat{\Omega}X(X'X)^{-1} \qquad (4)$$

where $\hat{\Omega}$ is a diagonal matrix containing squared residuals. This estimator provides consistent standard errors under heteroscedasticity.

The General Household Survey employs a stratified two-stage sampling design to ensure national representativeness. In the first stage, primary sampling units are selected, followed by households within each unit. Sampling weights are applied to adjust for unequal probabilities of selection and to align the sample with national population estimates. The study employs Ordinary Least Squares (OLS) regression as the primary estimation technique, which is appropriate for modelling continuous income outcomes. Robust standard errors are used to correct for heteroscedasticity commonly present in cross-sectional income data, ensuring reliable statistical inference.

Interpretation of Results

The estimated coefficients capture associations between labour salary and the explanatory variables rather than causal effects. This interpretation is consistent with the cross-sectional nature of the data and the absence of an explicit identification strategy. All results are therefore discussed in terms of observed income differentials by gender, race, and marital status.

RESULTS AND DISCUSSION

The overall statistical significance of the model is robust, with a p-value less than 0.001, indicating that the model as a whole provides a statistically significant explanation of variation in labour salary. The R-squared value of 21.4 percent suggests that the included independent variables explain a meaningful share of the variability in household head labour salary. While modest, this level of explanatory power is typical for cross-sectional income regressions in the social sciences, particularly when modelling complex and heterogeneous outcomes such as individual earnings (Hair et al., 2010; Brooks, 2019). Income is influenced by a wide range of factors, many of which are unobservable or difficult to quantify, making very high R-squared values uncommon in this context.

It is acknowledged that the inclusion of additional human capital variables, such as education level or sector of employment, could potentially enhance the model's explanatory power and provide a more comprehensive understanding of salary variation. These variables are well established in the economic literature as important determinants of income (Mincer, 1974; Becker, 1964). However, the primary focus of this study is to highlight differences in labour salary attributable to gender, race, and marital status, which guided the current model specification and selection of explanatory variables.

Upon examining the individual coefficients, all variables included in the model are statistically significant with the notable exception of gender, which exhibits a p-value of 0.629. This indicates that, within the current model specification and holding other factors constant, gender is not statistically significant in explaining variation in household head labour salary. This finding should not be interpreted as evidence of the absence of gender-based income inequality in South Africa. Rather, it may reflect the conditioning effects of race, marital status, and employment status, as well as the limitations of cross-sectional data in capturing occupational segregation, sectoral differences, and variations in hours worked (GCIS, 2013). While this result differs from some international and historical South African evidence on gender pay gaps (Blau & Kahn, 2017; Casale & Posel, 2002), it may reflect the specific context of the 2023 GHS data and the set of control variables employed.

The age of the household head is found to be highly significant, with a p-value below 0.01. The positive coefficient on age indicates that increases in age are associated with higher labour salary. This finding is consistent with the Mincerian earnings function, where age often serves as a proxy for accumulated work experience and human capital development when included linearly. Although the Mincerian framework typically incorporates a quadratic age term to capture diminishing returns to experience later in life (Biyase & Zwane, 2015; Fiaschi & Gabbriellini, 2013; Patrinos, 2016), the positive linear relationship observed here suggests that the benefits of experience remain prominent within the age range captured by the dataset.

Table 5: Robust Linear Regression Results (Dependent variable: Monthly labour salary, ZAR)

Salary	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Head age	81.145	19.943	4.07	0.00	42.053	120.237	***
Female	-216.241	447.118	-0.48	.629	-1092.674	660.192	
Coloured	5201.989	651.698	7.98	0.00	3924.543	6479.435	***
Indian/Asian	20326.272	1241.747	16.37	0.00	17892.221	22760.322	***
White	30165.502	759.016	39.74	0.00	28677.694	31653.311	***
Living together not married	-6733.059	591.621	-11.38	0.00	-7892.744	-5573.374	***
Divorced	-6553.026	1071.706	-6.11	0.00	-8653.766	-4452.286	***
Separated, but sti~r	-8563.75	1562.918	-5.48	0.00	-11627.355	-5500.145	***
Widowed	-6154.649	787.836	-7.81	0.00	-7698.951	-4610.348	***
Single, but have l~	-9465.391	1037.719	-9.12	0.00	-11499.509	-7431.272	***
Single and have ne~i	-7734.986	505.329	-15.31	0.00	-8725.524	-6744.449	***
Unemployed	-5930.315	824.147	-7.20	0.00	-7545.794	-4314.836	***
Not economically a~e	-5397.774	632.997	-8.53	0.00	-6638.564	-4156.985	***
Constant	12537.072	979.171	12.80	0.00	10617.719	14456.426	***

Mean dependent var	13370.213	SD dependent var	21392.842
R-squared	0.214	Number of obs	10883
F-test	227.022	Prob > F	0.000
Akaike crit. (AIC)	245321.954	Bayesian crit. (BIC)	245424.083

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

Notes: Robust standard errors reported. Reference categories are Male, African/Black, Legally married, and employed.

The results in Table 5 indicate that race/population group and marital status are among the strongest correlates of labour salary. All marital status categories are statistically significant relative to the reference group of legally married household heads, indicating substantial income differentials across marital arrangements. To illustrate the relative magnitude of these differences, illustrative predicted income values were calculated using the estimated regression coefficients. These values are derived by holding all other covariates at their reference categories and adding the relevant marital status coefficient to the intercept term. While these figures do not represent sample averages, they provide a useful comparison of relative income differences across marital status groups within the estimated model.

Formally, the illustrative predicted income is given by:

$$Y = \beta_0 + \theta_j \text{MaritalStatus}_j \quad (4)$$

For the reference category (legally married), the predicted income is:

$$Y = \beta_0 + \theta_j(0) \quad (5)$$

$$Y = 12{,}537.072 \quad (6)$$

Applying the same approach to the remaining marital status categories yields the illustrative predicted income values reported in Table 6.

Table 6: Average incomes by marital status

To further illustrate the association between marital status and labour salary, illustrative predicted income values were calculated using the estimated regression coefficients. These values are obtained by holding all other covariates at their reference categories and adding the relevant marital status coefficients to the intercept term. While these figures do not represent sample averages, they provide a useful comparison of relative income differences across marital status groups within the model framework.

Table 6: Average incomes by marital status

Marital status	Calculation (ceteris paribus)	Average income
Legally married	$Y = 12537.072 + 0$	12,537.07
Widow	$Y = 12537.072 - 6{,}154.649$	6,382.42
Divorced	$Y = 12537.072 - 6{,}553.026$	5,984.05
Single and never lived with a partner	$Y = 12537.072 - 7{,}734.986$	4,802.09
Separated	$Y = 12537.072 - 8{,}563.75$	3,973.32
Single but lived with a partner	$Y = 12537.072 - 9{,}465.39$	3,071.68

Source: Authors calculations

Note: Values reported are illustrative predicted income values derived from regression coefficients, holding all other covariates at their reference categories. These values do not represent sample averages.

The illustrative predicted income values in Table 6 indicate that, holding other characteristics at their reference categories, legally married household heads are associated with higher labour salary relative to other marital status groups. The second group are the widows with an average income of R6,332.42[i]. The lowest category are the never married but have lived with a partner. This is in agreement with the literature that shows that being legally married improves ones income compared to the other categories (Dunga, 2017).

Average incomes by population group (Race)

A similar approach is applied to examine income differentials across population groups. Illustrative predicted income values were calculated by holding all covariates at their reference categories and adding the relevant population group coefficients to the intercept. This approach allows for a clear comparison of relative income differences by race within the estimated model.

Table 7: Average incomes by population group (Race)

Marital status	Calculation (ceteris paribus)	Average income
African/Black	$Y = 12{,}537.072 + 0$	12,537.07
Coloured	$Y = 12{,}537.072 +$ 5,201.98	17,739.06
Indian/ Asian	$Y = 12{,}537.07 + 20{,}326.27$	32,863.34
White	$Y = 12{,}537.07 + 30{,}165.50$	42,702.57

Note: Values reported are illustrative predicted income values derived from regression coefficients, holding all other covariates at their reference categories. These values do not represent sample averages.

The results presented in Table 7 show substantial income differentials across population groups. Relative to African/Black household heads, all other population groups are associated with higher illustrative predicted labour income, with the largest differentials observed for White household heads. These findings are consistent with South Africa's historical and structural inequalities in access to education, employment opportunities, and high-paying occupations, which continue to shape labour market outcomes in the post-apartheid period (Armstrong & Burger, 2009; Statistics South Africa, 2018).

CONCLUSION

The findings of this study indicate that labour market outcomes in South Africa are primarily shaped by structural factors, particularly race and marital status, while gender effects appear to be mediated through broader socio-economic dynamics.

This study examined the determinants of labour salary among household heads using data from the 2023 General Household Survey. By focusing specifically on labour income rather than total household income, the analysis provides a more precise assessment of income differentials associated with demographic characteristics, population group, marital status, and employment status. The results reveal substantial and persistent disparities across these dimensions.

Race emerges as a particularly strong determinant of labour income. African/Black household heads earn significantly lower labour salaries compared to other population groups, even after controlling for key socio-demographic characteristics. This finding underscores the enduring influence of historical and structural inequalities in shaping labour market outcomes. Marital status is also significantly associated with income, with legally married individuals exhibiting higher predicted earnings relative to those in other marital categories. This suggests that marriage may confer economic advantages, potentially through income pooling, stability, and household-level complementarities.

In contrast, gender does not exhibit a statistically significant direct effect in the estimated model. However, this result should be interpreted with caution. It may reflect the influence of other covariates included in the model or limitations inherent in cross-sectional data, which may not fully capture gendered labour market dynamics such as occupational segregation, wage differentials within sectors, or unpaid care burdens. As such, the absence of a direct gender effect does not necessarily imply the absence of gender inequality in labour market outcomes.

Overall, the findings highlight the continued importance of structural and institutional factors in shaping income inequality in South Africa. From a policy perspective, the results point to the need for targeted interventions aimed at reducing racial income disparities and addressing the vulnerabilities associated with different household structures. Policies that promote equitable access to quality employment opportunities, reduce labour market segmentation, and support individuals outside stable marital arrangements are essential for advancing inclusive economic growth.

This study is subject to several limitations. The use of cross-sectional data restricts causal inference and limits the ability to examine income dynamics over time. In addition, the exclusion of variables such as education, occupation, and sector of employment may constrain the explanatory power of the model. Future research should incorporate more detailed measures of human capital and labour market characteristics, and where possible, utilise longitudinal data to better understand income mobility and persistence.

The analysis yielded several critical insights

The empirical analysis yields several important insights into the determinants of labour income among household heads.

First, the age of the household head emerges as a statistically significant and positive determinant of labour salary. This finding is consistent with human capital theory, which posits that accumulated experience, skills acquisition, and productivity gains over the life cycle translate into higher earnings. The result reflects the role of labour market experience in enhancing income-generating capacity over time.

Second, the analysis reveals persistent and substantial racial disparities in labour income within South Africa. Even after controlling for key socio-demographic factors—including age, gender, marital status, and employment status—significant income differentials remain. African household heads earn an estimated average monthly labour salary of R12,537.07, compared to R42,702.57 for White household heads, resulting in a pronounced income gap of approximately R30,165.50. This disparity underscores the enduring legacy of historical inequalities and the continued influence of structural constraints in the labour market. These findings are consistent with existing literature documenting entrenched racial income disparities in South Africa (Leibbrandt et al., 2010; Burger & Jafta, 2006), and reflect the long-term effects of institutionalised inequality and unequal access to economic opportunities.

Third, marital status is found to be a significant predictor of labour income, with results indicating a clear "marriage premium." Legally married household heads consistently earn higher incomes than those in other marital categories, including cohabiting, divorced, separated, widowed, and single individuals. This may reflect several mechanisms, including economies of scale within households, labour specialisation, and positive selection into marriage. The finding aligns with prior empirical evidence highlighting the income advantages associated with marital unions (Dunga, 2017), and supports theoretical insights from intra-household bargaining frameworks regarding the economic benefits of shared resources and joint decision-making.

Finally, gender—measured as female household headship—does not exhibit a statistically significant direct effect on labour income within the current model specification. While this result may suggest some convergence in earnings across gender in this specific context, it should be interpreted with caution. It contrasts with a substantial body of literature documenting persistent gender wage gaps globally (Blau & Kahn, 2017), and may reflect the influence of other covariates included in the model, such as education, employment status, or occupational sorting. This finding points to the need for further investigation into the indirect and interaction effects of gender, particularly in relation to labour market segmentation and access to high-paying sectors. As expected, employment status remains a key determinant of income, reinforcing the central role of labour market participation in shaping economic outcomes.

Overall, the results highlight that labour income in South Africa is primarily shaped by structural and institutional factors, with race and marital status emerging as particularly salient determinants. While the absence of a direct gender effect in this model provides an interesting point of discussion, the persistence of racial disparities underscores the continued need for policy interventions aimed at addressing deep-rooted inequalities in the labour market. Future research should further explore the interaction between gender and human capital variables, examine the underlying drivers of racial and marital income differentials, and incorporate more detailed measures of education, occupation, and sectoral employment to deepen understanding of income dynamics in South Africa.

Recommendations

This study's findings highlight critical areas for policy intervention to foster a more equitable South African labour market. The persistent and significant racial income disparities, particularly the substantial gap favoring White over African household heads, demand intensified efforts to dismantle structural barriers through robust enforcement of employment equity laws and targeted skills development for historically disadvantaged groups. Concurrently, leveraging the positive impact of experience on earnings necessitates ongoing investment in human capital through expanded lifelong learning and vocational training initiatives. Furthermore, policies aimed at broad-based job creation and economic inclusion remain paramount to integrate the unemployed and economically inactive into the labour force.

For future research, a deeper dive into gender income dynamics is warranted, as this study's model did not find a direct significant effect; this requires more granular data on education and occupation, along with exploration of interaction effects. Further investigation into the mechanisms behind the "marriage premium" is also recommended. Methodologically, the development and utilization of longitudinal datasets, like those potentially emerging from the Labour Market Information System (LMIS), are crucial to establish causality and provide a more comprehensive understanding of income mobility and household well-being over time in South Africa.

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[i] All the calculations are done in Rand the currency of South Africa. US$1 is approximately R18 in 2025