

EVALUATING INCOME INEQUALITY IN MALAYSIA: A COMPARATIVE STUDY EMPLOYING GINI AND THEIL INDICES WITH QUANTILE REGRESSION

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Article history

Received date : 10-11-2025

Revised date : 11-11-2025

Accepted date : 1-12-2025

Published date : 3-12-2025

To cite this document:

Kamal, Z. K., Abdullah, M. Z., & Zaharudin, K. Z. (2025). Evaluating income inequality in Malaysia: A comparative study employing Gini and Theil indices with quantile regression. *International Journal of Accounting, Finance and Business (IJAFB)*, 10 (63), 1 - 13.

Abstract: *Despite decades of redistributive policy, income inequality in Malaysia remains persistent. Conventional mean-based analyses fail to capture the distributional structure of inequality, particularly the extent to which disparities arise within, rather than between, demographic groups. Drawing on data from the 2019 Household Income and Expenditure Survey (HEIS2019), this study applies an integrated empirical framework that combines Theil index decomposition with quantile regression to examine the underlying dynamics of income stratification. The results indicate that more than 95 percent of total inequality originates from within-group variation, with demographic penalties intensifying at higher income levels. Between the 25th and 75th percentiles, the gender income gap widens by 69 percent, the ethnic differential increases by 91 percent, and the education-related penalty reaches RM1,435 per month. Returns to age and occupational status also rise with income, reflecting structural advantages concentrated near the top of the distribution. These findings suggest that generalised redistributive instruments are poorly matched to the actual pattern of inequality. More effective policy responses should target high-variance segments through differentiated interventions, including expanded access to tertiary education, enforcement of wage transparency, and the formalisation of employment in low-protection sectors. Precision in policy design is essential to address inequality where it is most acute.*

Keywords: *income inequality, Gini Coefficient, Theil Index, quantile regression*

Introduction

Income inequality in Malaysia remains both persistent and structurally embedded. As of 2019, the top 20 percent of households (T20) captured nearly half of total household income, while the bottom 40 percent (B40) accounted for less than 17 percent (Department of Statistics Malaysia, 2020). These disparities are not simply statistical anomalies. They reflect long-standing frictions in the allocation of resources, returns to human capital, and access to opportunity. Among lower-income households, incentives to invest in education are weaker, and the expected returns from such investments are more uncertain. Over time, this diminishes the prospects for upward mobility and undermines the economy's productive potential. At the macroeconomic level, elevated inequality dampens aggregate demand, increases volatility, and intensifies social tension. These dynamics complicate the equity-efficiency trade-off that features prominently in neoclassical growth theory (Barro, 2000; Aghion et al., 1999).

Malaysia has made repeated efforts to address inequality through redistributive policy, beginning with the New Economic Policy (NEP) and continuing through subsequent reforms. Although these programmes have made some progress, disparities remain widespread across ethnicity, gender, education, and region. One reason for this persistence lies in the limitations of conventional inequality metrics. The Gini coefficient, for example, provides a single-number summary but cannot differentiate between structural and cyclical factors, nor between within-group and between-group variation. In a dual labour market like Malaysia's, where formal and informal employment coexist, this becomes a serious limitation. The returns to similar endowments can vary substantially depending on whether one works in salaried employment, informal jobs, or platform-based gig work.

This paper addresses three methodological shortcomings that continue to limit the empirical literature on inequality in Malaysia. First, the literature remains heavily reliant on average-effects models, which obscure distributional heterogeneity across income levels (Che Mata et al., 2020; Harun et al., 2020; Kasim & Ismail, 2020). Second, although some work has introduced compositional metrics such as the Theil Index (Lee & Seshadri, 2019; Erola & Kilpi-Jakonen, 2022), these approaches are rarely applied to dimensions such as occupation, education, or spatial inequality. Third, despite its widespread use in international research on distributional asymmetries (Koenker & Bassett, 1978; Altunbaş & Thornton, 2019; Mallela et al., 2023), quantile regression remains underutilised in the Malaysian context. This gap is particularly salient for the period following the implementation of the Goods and Services Tax (GST), which may have induced structural shifts in cost-of-living pressures for lower- and middle-income households.

To address these gaps, this paper employs data from the 2019 Household Income and Expenditure Survey (HEIS2019) and applies a multi-method empirical strategy. The Gini coefficient is used as a benchmark to assess aggregate inequality. The Theil Index is then applied to distinguish between within-group and between-group components of inequality. Finally, quantile regressions are estimated at the 25th, 50th, and 75th percentiles to examine how the effects of gender, ethnicity, education, occupation, and location vary across the income distribution.

The analysis is informed by two theoretical perspectives. The first is labour market segmentation theory, which posits that similar individual characteristics yield different returns depending on the segment of the labour market in which one is employed. The second is the literature on skill-biased technological change, which argues that technological advances tend

to favour skilled over unskilled labour. In Malaysia, complementarities between capital and skill may disproportionately benefit highly educated workers at the upper tail of the distribution (Acemoglu, 2002). At the same time, occupational sorting may lock marginalised groups into lower-wage occupations, thereby reinforcing existing disadvantages (Bertrand & Hallock, 2001; Cha & Weeden, 2014).

This study makes three principal contributions. First, it integrates distributional and compositional techniques to move beyond conventional mean-based analyses. Second, it presents novel evidence showing that demographic and occupational disparities widen at higher points in the income distribution. For instance, the gender income gap increases by 69.1 percent between the 25th and 75th percentiles, while the penalty associated with low educational attainment rises from RM749 to RM1,435. Third, the analysis reveals that more than 95 percent of observed inequality originates from within-group variation. This finding raises important questions about the effectiveness of group-based redistributive strategies.

These findings have significant policy implications. Broad instruments such as blanket subsidies or flat-rate tax adjustments, are unlikely to address the structure of inequality revealed in the data. More effective interventions should target within-group disparities. For example, expanding tertiary education access for underrepresented populations, mandating equal-pay and wage-transparency practices, and improving social protections for informal workers through formalisation and portable benefits. Targeted initiatives that align with the conditional heterogeneity observed in this study offer a more coherent and effective policy response.

The remainder of the paper is structured as follows. Section 2 reviews the existing literature on income inequality and its measurement. Section 3 outlines the data and methodology. Section 4 presents the empirical results. Section 5 concludes with implications for policy and future research.

Literature Review

Socioeconomic Drivers of Income Inequality

Identifying the underlying drivers of income inequality is essential for designing policies that align with the structure of distributional outcomes. A large body of Malaysian research has examined how demographic and structural attributes shape income differentials, including education, occupation, ethnicity, gender, and geographic location. Across these studies, human capital emerges as the most consistent explanatory factor. Educational attainment, in particular, is repeatedly found to influence earnings trajectories. Kasim and Ismail (2020), for example, attribute labour market disparities primarily to unequal access to education and formal employment. However, their analysis does not consider how institutional structures condition the returns to education across different population groups.

More recent work has broadened this scope. Aziz and Isa (2021) document persistent ethnic income gaps, noting that Bumiputera households earn significantly less than their Chinese and Indian counterparts, even after controlling for observable characteristics. Gender inequality in earnings remains a parallel concern. Zainuddin et al. (2021) report systematic wage penalties for women, which they attribute to limited opportunities for career progression. Spatial disparities also feature prominently in the literature. Nair (2022) finds that rural households, which tend to be concentrated in low-skill and low-wage sectors, consistently lag behind urban households in income outcomes. These findings suggest that inequality is not only driven by

individual endowments but is also embedded in institutional, occupational, and spatial structures.

Nevertheless, most empirical studies employ models that focus on average effects and treat explanatory factors in isolation. As a result, they overlook how demographic attributes interact or vary across different segments of the income distribution. This limits the ability of such models to capture conditional heterogeneity, particularly in the presence of labour market segmentation and informal employment.

Measurement Approaches: Gini and Theil Indices

A second strand of the literature concerns the tools used to measure income inequality. The Gini coefficient remains the most widely applied indicator, valued for its simplicity, scalability, and intuitive interpretation. It ranges from zero (complete equality) to one (maximum inequality) and allows for straightforward comparisons across time and populations (Zhang, 2016). Its capacity to accommodate negative values further enhances its applicability, particularly in studies involving expenditure or net wealth (Van Den Brakel & Lok, 2021).

However, the Gini coefficient has important limitations. Most notably, it cannot decompose overall inequality into constituent components, such as within-group versus between-group variation. This makes it unsuitable for identifying which sources of inequality are most salient in a given context.

To address this constraint, researchers have turned to entropy-based indices, such as the Theil Index. This measure enables formal decomposition, allowing for analysis of how different subpopulations contribute to total inequality. In stratified societies like Malaysia, such decomposition is critical. Erola and Kilpi-Jakonen (2022) use the Theil Index to examine intergenerational inequality by parental status and educational background. In the Malaysian setting, Lee and Seshadri (2019) apply it to assess the contribution of ethnicity and regional factors to income variation.

Despite these advantages, the Theil Index also faces methodological constraints. It assumes log-linearity and is sensitive to skewness and extreme values, which may distort interpretation in highly unequal distributions (Liao, 2016). Moreover, like the Gini coefficient, it provides only a static summary of inequality and does not account for how covariates influence different segments of the income distribution.

Distributional Methods: The Case for Quantile Regression

To capture inequality that is structured across the income distribution, researchers have increasingly turned to quantile regression. Unlike ordinary least squares (OLS), which estimates the average effect of explanatory variables, quantile regression allows for estimation of conditional effects at different points in the distribution. This method is particularly well suited to identifying whether returns to education, occupation, or demographic characteristics differ between low-income and high-income groups. First formalised by Koenker and Bassett (1978), quantile regression has become a standard approach in inequality research.

Recent international studies illustrate the value of this method. Altunbaş and Thornton (2019) find that financial development increases inequality disproportionately at higher income quantiles across a panel of 121 countries. Mallela et al. (2023) show that the interaction between remittances and financial development has unequal effects along the income spectrum, with

stronger amplification at the tails. In a related context, Wang and Nguyen Thi (2022) demonstrate that the relationship between income inequality and health expenditure varies substantially by income level, underscoring the importance of distribution-sensitive models.

Despite its widespread application elsewhere, quantile regression has not been widely adopted in Malaysian studies. Most domestic analyses continue to rely on mean-based techniques (e.g., Che Mata et al., 2020; Harun et al., 2020; Kasim & Ismail, 2020), which do not account for the segmented nature of the Malaysian labour market. Given the rise of informal employment, platform work, and spatial inequality, this methodological gap limits the relevance of current findings for policy design.

Methodology

Data Description

This subsection examines the dataset used in this study, which is the Household Income and Expenditure Survey 2019 (HEIS2019), conducted by the Department of Statistics Malaysia. The survey employs a two-stage stratified sampling design across urban and rural strata in all Malaysian states. It yields detailed information on household income, expenditure, and demographics. From the original 24,872 observations, the sample is restricted to household heads aged 24–60 to capture the working-age population, reflecting the age bracket in which labour force participation peaks. Furthermore, only those employed in the private or public sectors are retained, since formal employment typically exhibits more reliable income reporting, standardised wage structures and clear occupational classifications. The exclusion of informal, self-employed and unpaid family workers mitigates measurement error and potential bias in the estimation of income inequality. After applying these criteria, the final dataset comprises 12,436 households.

The Gini Coefficient

This subsection defines and operationalises the Gini coefficient as a summary measure of income dispersion. The Gini coefficient, G , is given by:

$$G = \frac{\sum_{i=1}^n \sum_{j=1}^n |x_i - x_j|}{2n^2 \bar{x}}$$

where x_i and x_j denoted the incomes of households i and j , \bar{x} is the sample mean income, and n the sample size. A value of zero corresponds to perfect equality, whereas a value closer to one indicates greater inequality. In this study, we estimate the Gini coefficient for three binary comparisons: ethnicity (Bumiputera versus Non-Bumiputera), gender of head of household (male versus female) and residential strata (urban versus rural). These pairwise estimations facilitate clear, direct comparisons of income dispersion across key demographic segments.

The Theil Index

This subsection introduces the Theil Index, an entropy-based measure capable of decomposing total inequality into between-group and within-group components. The overall Theil Index, T , is defined as

$$T = \frac{1}{n} \sum_{i=1}^n \left(\frac{y_i}{\bar{y}} \ln \left(\frac{y_i}{\bar{y}} \right) \right)$$

where y_i denotes the income of household i and \bar{y} the population mean income. Perfect equality corresponds to $T=0$, and higher values indicate greater dispersion. The Theil Index can be decomposed into between-group and within group inequality,

$$T = \sum_{h=1}^H \left(\frac{n_h}{n} \cdot \frac{\bar{y}_h}{\bar{y}} \ln \left(\frac{\bar{y}_h}{\bar{y}} \right) \right) + \sum_{h=1}^H \left(\frac{n_h}{n} T_h \right)$$

where h indexes each subgroup, n_h its population, \bar{y}_h its mean income, and T_h its within-group Theil index. The first term captures between-group disparity, while the second term aggregates within-group dispersion. We apply this approach to multicategory variables: strata (urban, rural), region (Central, South, North, East Coast, Sabah, Sarawak), gender (Male, Female), ethnicity (Bumiputera, Chinese, Indian, Others), marital status (Single, Married, Divorced/Separated, Widowed), education (seven levels), occupation (eight categories), and industry (six sectors). Such granularity allows insight into the sources of inequality across administrative and demographic dimensions.

Quantile Regression

This subsection presents the quantile regression model used to analyse conditional income effects across the distribution. For a given quantile $\tau \in (0, 1)$, the conditional quantile function is specified as

$$Q_y(\tau|X) = \beta_0(\tau) + \sum_{k=1}^K \beta_k(\tau) X_k$$

where $Q_y(\tau|X)$ denotes the τ -th conditional quantile of household income y , $\beta_0(\tau)$ is the intercept and $\beta_k(\tau)$ is the slope coefficient for the k -th predictor X_k . In this study, the vector of covariates X comprises residential strata and region to capture locational context, together with the head of household's gender, ethnicity, age, marital status, highest educational attainment, occupation and industry. Estimating $\beta_k(\tau)$ for $\tau = 0.25, 0.50$ and 0.75 allows us to document how each characteristic influences income at the lower, median and upper tails of the distribution. This method thus reveals conditional heterogeneity that would remain concealed under an ordinary least squares specification.

Results and Discussion

Income Inequality: Summary Measures

We begin by assessing baseline income inequality using the Gini coefficient, a widely recognised metric of income dispersion. Figure 1 presents Lorenz curves and corresponding Gini values across three primary demographic dimensions: ethnicity (Panels i and ii), gender (Panels iii and iv), and geographic location (Panels v and vi). This graphical representation enables direct comparison of income concentration within and between population groups.

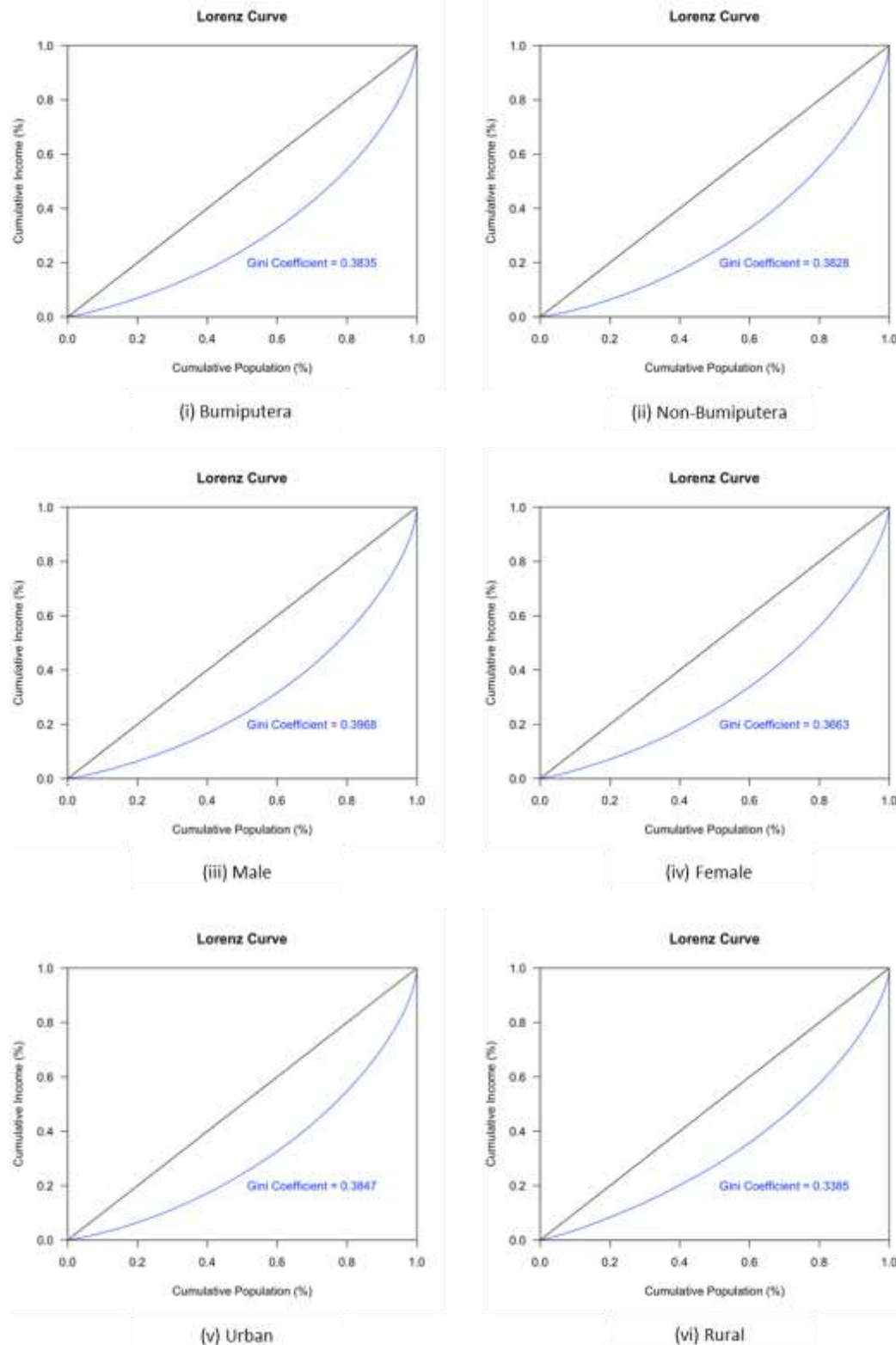


Figure 1: Lorenz curve

The estimated Gini coefficients indicate meaningful variation across strata. Households headed by males exhibit the highest degree of inequality, with a Gini coefficient of 0.3968. In contrast, rural households register the lowest dispersion (Gini = 0.3385), while urban households fall in between (Gini = 0.3847). When comparing by ethnicity, Bumiputera and non-Bumiputera households display nearly identical Gini values (0.3835 and 0.3828, respectively), suggesting that ethnicity, when considered in isolation, contributes little to explaining overall income inequality.

These findings underscore two important limitations of the Gini coefficient. First, its sensitivity to overall distributional shape and sample size may conflate structural segmentation with demographic characteristics. For instance, elevated inequality among male-headed households could reflect labour market stratification rather than gender-specific factors. Second, the Gini measure does not indicate whether inequality is concentrated at the lower or upper end of the income distribution. As a result, it offers limited insight into the structural sources of inequality.

Structural Sources of Inequality: Theil Decomposition

To further investigate the composition of inequality, we apply the Theil Index, which allows for decomposition into between-group and within-group components across various socio-economic categories (Table 1).

The decomposition reveals that the bulk of income inequality originates from variation within groups rather than between them. Gender-based between-group inequality is negligible (Theil = 0.0029), whereas within-gender income dispersion is considerable (Theil = 0.2960). This pattern implies that while average income differences between men and women are modest, there exists significant heterogeneity in earnings within each gender group.

Among the structural variables, occupation and education are the only factors with notable between-group contributions (Theil = 0.1070 and 0.0888, respectively). In contrast, ethnicity, regional location, and marital status each contribute less than 2 percent to total inequality through between-group variation. These findings suggest that the principal segmenting forces in Malaysia's income distribution are linked to occupational status and educational attainment rather than identity-based categories. Accordingly, policy interventions should prioritise reducing disparities within educational and occupational groups.

Table 1: Theil Index Decomposition

Group	Between-Group Theil	Within-Group Theil
Strata	0.0253	0.2737
Region	0.0084	0.2905
Gender	0.0029	0.2960
Ethnic	0.0159	0.2830
Marital Status	0.0039	0.2951
Education	0.0888	0.2102
Occupation	0.1070	0.1919
Industry	0.0400	0.2589

Conditional Inequality: Quantile Regression Evidence

To assess how the impact of socio-demographic characteristics varies across the income distribution, we estimate quantile regressions at the 25th, 50th, and 75th percentiles (Table 2).

These estimates uncover significant conditional heterogeneity that conventional mean-based models fail to capture.

Among demographic factors, gender emerges as the most salient. Female-headed households face an income deficit of RM 1,013 at the 25th percentile, which widens to RM 1,713 at the 75th percentile. This increasing disparity points to structural constraints that intensify at higher income levels, such as vertical occupational segregation and unequal access to senior roles.

Table 2: Quantile Regression Estimates of Household Income Determinants

Variables	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$
Strata	-592.78*** (68.10)	-817.68*** (82.20)	-1127.20*** (128.14)
Region	-44.93 (39.90)	-117.77** (50.37)	-139.29 (75.19)
Gender	-1013.32*** (85.37)	-1405.55*** (121.67)	-1712.75*** (165.29)
Ethnicity	769.83*** (82.19)	1026.81*** (101.76)	1469.85*** (166.35)
Age	53.36*** (3.70)	81.71*** (5.59)	123.23*** (7.44)
Marital Status	57.67 (40.26)	15.55 (57.96)	129.75 (99.87)
Education	-749.27*** (28.99)	-1089.61*** (39.53)	-1434.99*** (56.20)
Occupation	-303.82*** (14.39)	-421.95*** (20.63)	-614.68*** (29.38)
Industry	-15.91** (7.15)	-4.46 (9.75)	-1.91 (13.45)
Constant	7542.65*** (241.86)	10626.56*** (323.42)	13856.42*** (445.32)

Note. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All estimates are based on quantile regression with bootstrapped standard errors. Dependent variable: household income (in RM).

Ethnic disparities exhibit a similar pattern. The income differential between Bumiputera and non-Bumiputera households expands from RM 770 at the lower quartile to RM 1,470 at the upper quartile. This non-uniform pattern is consistent with segmented labour market theory, suggesting that ethnic stratification is more pronounced at the top end of the income distribution.

Among structural variables, educational attainment exhibits the steepest gradient. Households headed by individuals lacking the highest level of formal certification face an income penalty of RM 749 at the 25th percentile, which increases to RM 1,435 at the 75th percentile. This result aligns with theories of skill-biased technological change and occupational sorting, whereby returns to education rise in more advanced segments of the labour market (Acemoglu, 2002; Bertrand & Hallock, 2001; Nogueira & Madaleno, 2023).

Similar amplification is observed for other structural characteristics. The income gap between rural and urban households grows from RM 593 to RM 1,127 across the distribution. Likewise, households engaged in lower-status occupations incur rising income penalties, increasing from

RM 304 to RM 615. In contrast, variables such as marital status, industry, and region exert relatively weak or inconsistent effects across quantiles.

Economic Significance and Policy Implications

The quantile-specific estimates underscore the economic significance of demographic and structural penalties. At the 75th percentile, income shortfalls associated with gender and education each exceed RM 1,400 per month, equivalent to over 12 percent of average income in the upper quartile. Over a working life, these gaps may translate into cumulative losses equivalent to multiple years of earnings.

These findings suggest that uniform policy tools are poorly suited to addressing the multifaceted nature of income inequality in Malaysia. Instead, policy design must be responsive to the conditional heterogeneity revealed in this study.

Targeted interventions are likely to yield greater impact. To mitigate education-based inequality, policymakers could expand need-based scholarships, subsidise tuition for underrepresented groups, and strengthen transitional programmes that bridge secondary and tertiary education. In addressing gender-based disparities, the implementation of wage-transparency legislation, stricter enforcement of equal-pay mandates, and the provision of family-friendly workplace policies such as flexible scheduling and parental leave are key. Occupational disparities may be reduced through structured career pathways and sector-specific upskilling programmes that align training with labour market demand. Embedding clear progression frameworks into these programmes could support upward mobility and mitigate income penalties that disproportionately affect mid- and upper-quartile earners in low-status roles.

Collectively, these precision-focused strategies acknowledge the layered drivers of inequality and offer a coherent policy toolkit to address its most persistent and consequential dimensions.

Conclusion

This study demonstrates that income inequality in Malaysia is primarily driven by disparities within demographic groups and that these disparities become more pronounced at higher points in the income distribution. This finding challenges the effectiveness of group-based redistributive strategies and underscores the importance of empirical approaches that account for the structure of distributional outcomes, not merely average differences.

We make three principal contributions. First, we introduce an integrated empirical framework that combines Theil decomposition with quantile regression, thereby moving beyond conventional mean-based models. This approach reveals heterogeneity in income determinants across the distribution that remains obscured in previous studies (e.g., Che Mata et al., 2020; Harun et al., 2020; Kasim & Ismail, 2020). Second, drawing on data from HEIS2019, we present new evidence on distribution-sensitive disparities related to gender, education, and occupation. The income gap between men and women expands by 69 percent between the 25th and 75th percentiles. The penalty associated with lower educational attainment nearly doubles, and occupational stratification intensifies across the distribution. These patterns are consistent with the theoretical literature on skill-biased technological change and occupational sorting. Third, we show that more than 95 percent of total inequality originates from within-group variation, indicating that group-level averages substantially underestimate the magnitude and sources of income stratification.

These findings carry significant policy implications. Uniform redistributive tools, such as blanket subsidies or across-the-board tax relief, are poorly suited to Malaysia's income structure and are unlikely to address the conditional heterogeneity identified in this study. More effective strategies should target within-group disparities, particularly those that emerge at the upper end of the distribution. These may include expanding access to tertiary and vocational education for underrepresented populations, mandating wage transparency, enforcing anti-discrimination legislation in high-income sectors, and introducing structured career pathways alongside portable protections in occupations characterised by high within-group dispersion. The magnitude of observed income penalties, such as RM1,713 for women at the 75th percentile, demands carefully calibrated interventions that reflect the segmentation and dualism of Malaysia's labour market.

This study has two main limitations. First, the cross-sectional nature of the data restricts our ability to infer causality or observe dynamic trends. Nevertheless, by focusing on distributional heterogeneity, we identify structural patterns that remain relevant for policy design, even in the absence of longitudinal information. Second, the analysis is limited by the exclusion of unobserved factors such as social capital, institutional quality, or implicit bias, which are not captured in the HEIS dataset and may affect the precision of our estimates.

Future research could extend this work in three directions. First, longitudinal data would allow for the examination of how technological change and occupational sorting shape income trajectories over time. Second, simulation-based analysis incorporating distribution-sensitive parameters could generate more accurate forecasts of policy impacts. Third, deeper investigation into informal and platform-based employment, particularly at the extremes of the income distribution, may uncover mechanisms of marginalisation and privilege that lie outside formal institutional boundaries.

Addressing persistent inequality requires diagnostic tools capable of identifying not only who is disadvantaged, but also where and how inequality is produced. In this context, advancing structural equity depends less on aggregate averages, and more on the precision of distributional insight.

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