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BẤT BÌNH ĐẲNG THU NHẬP SAU THUẾ: ĐÁNH GIÁ TÁC ĐỘNG CỦA HỆ THỐNG THUẾ THU NHẬP CÁ NHÂN TẠI CÁC QUỐC GIA CHÂU Á

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Tóm tắt

Sau cú sốc COVID-19, bất bình đẳng thu nhập tại nhiều quốc gia châu Á ngày càng trầm trọng. Nghiên cứu này xem xét hiệu quả của một hệ thống thuế thu nhập cá nhân (TNCN) mạnh mẽ trong việc giảm phân cực thu nhập, được đo bằng tỷ lệ phần chia thu nhập giữa 10 % người giàu nhất và 10% người nghèo nhất. Sử dụng khung hồi quy bảng với xếp hạng cố định theo mức thu nhập, nhóm tác giả phân tích bộ dữ liệu cân bằng giai đoạn 2010-2023 của 30 nền kinh tế châu Á, kết hợp chỉ số tài khoá từ các nguồn đáng tin cậy như IMF, OECD, World Inequality Database và World Bank Data. Kết quả cho thấy, cứ thu TNCN tăng thêm 1 điểm phần trăm GDP thì tỷ lệ phân cực giảm trung bình 0,07%, đặc biệt rõ nét ở nửa dưới phân phối thu nhập. Tác động thu hẹp khoảng cách càng lớn khi trình độ học vấn cao, trong khi tăng trưởng GDP cao nhưng thiếu chính sách tái phân phối lại làm bất bình đẳng thu nhập gia tăng. Đối với Việt Nam và các nước lân cận, điều này hàm ý cần mở rộng cơ sở thu TNCN, tăng cường tuân thủ ở nhóm thu nhập cao và ưu tiên nguồn thu bổ sung cho bảo trợ xã hội cùng phát triển nguồn nhân lực để thúc đẩy phát triển toàn diện.

Từ khoá: thuế thu nhập cá nhân (TNCN), bất bình đẳng thu nhập, tái phân phối thu nhập, các nước châu Á

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INCOME INEQUALITY AFTER TAXES: ASSESSING THE IMPACT OF PERSONAL INCOME TAX SYSTEMS IN ASIAN COUNTRIES

Abstract

Income inequality has widened in many Asian economies, especially after the COVID-19 shock. This research aims to evaluate whether stronger personal income tax (PIT) systems curb distributional polarization, defined as the income-share ratio of the top 10 percent to the bottom 10 percent. The study applies a fixed-income-based ranking panel-regression approach to a balanced 2010-2023 dataset of 30 Asian economies, integrating fiscal indicators from the fiscal indicators from reliable sources such as IMF, OECD, World Inequality Database, and World Bank Data. A one-percentage-point rise in PIT revenue (share of GDP) lowers the polarization ratio by approximately 0.07 percent on average, with the strongest compression below the median of the distribution. Higher educational attainment reinforces the equalizing effect, whereas increasing GDP without matching redistribution widens disparities. Policy implications for Vietnam and neighboring economies underline the need to broaden PIT bases, tighten upper-income compliance, and direct additional revenue toward social-protection and human-capital programmes to achieve inclusive growth.

Keywords: personal income tax (PIT), income inequality, income redistribution, Asia countries

1. Introduction

Income inequality has become a defining challenge of the twenty-first century. After three decades of globalization and technological advancement, the richest 10 percent of the world's population now capture over half of all income, while the poorest half receive less than 10 percent of global income (IMF, 2022). In Asia, this trend has become more visible in recent decades, particularly after the COVID-19 pandemic, which disproportionately impacted low-income groups through job losses and income shocks (IMF, 2020). These developments raise questions about the long-term inclusiveness of growth in the region.

Direct taxation, especially personal income tax (PIT), is widely acknowledged as a principal tool for redistribution. In the Asia-Pacific region, PIT comprises only about 15.9 percent of total tax revenues, well below the OECD average of 23.7 percent, limiting fiscal space for equity-enhancing transfers and services (OECD, 2024). This difference reflects not only lower progressivity in tax design but also limited administrative capacity and weaker enforcement. Countries with higher PIT revenues and more progressive structures generally achieve greater post-tax equality, as these revenues can be directed toward targeted social spending. Yet many Asian governments rely heavily on indirect taxes, which are less effective at narrowing income gaps.

This study has two main objectives. First, it will measure how much additional PIT revenue (as a share of GDP) narrows the income gap between the richest 10 % and the poorest 10 % across thirty Asian economies over 2010-2023, while controlling for growth, external balances, interest

rates, education levels, and overall redistribution effort. Second, it will test how factors such as the size of transfer programs and interactions between PIT and other fiscal tools affect those results, and whether PIT's impact differs at various points in the income distribution. Therefore, the expected outcomes of this study are quantified elasticities showing by how much each extra percentage point of PIT revenue reduces the top-to-bottom income-share ratio and data-driven policy recommendations for Vietnam and similar economies to achieve a more inclusive growth.

2. Literature review

2.1. Income inequality

The absolute autonomy of the free market and speculation, as aptly addressed by Pope Francis back in May 16th of 2013, contributes to the phenomenon of "the income of a minority is increasing exponentially, that of the majority is crumbling", or income inequality in free-rein. That was the narrative from more than a decade ago, but how much has changed? Income has generally and profoundly converged since the 1990s, but within-country inequality also seemed to grow for most, particularly so for advanced economies, insofar as applicable for 90% of them, and even more exacerbated by the COVID-19 crisis (IMF, 2024).

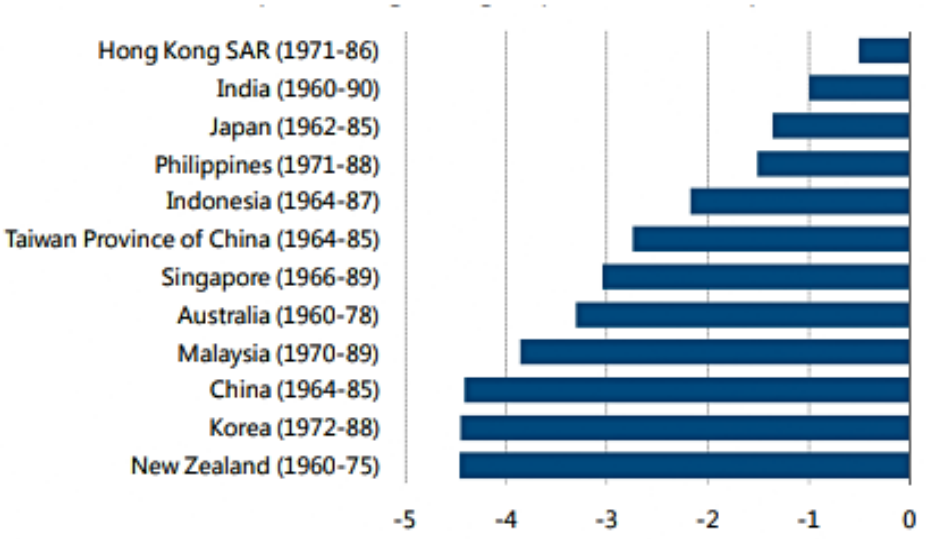

Figure 1. Selected Asia: Income Inequality, pre-1999

Source: IMF Working Paper

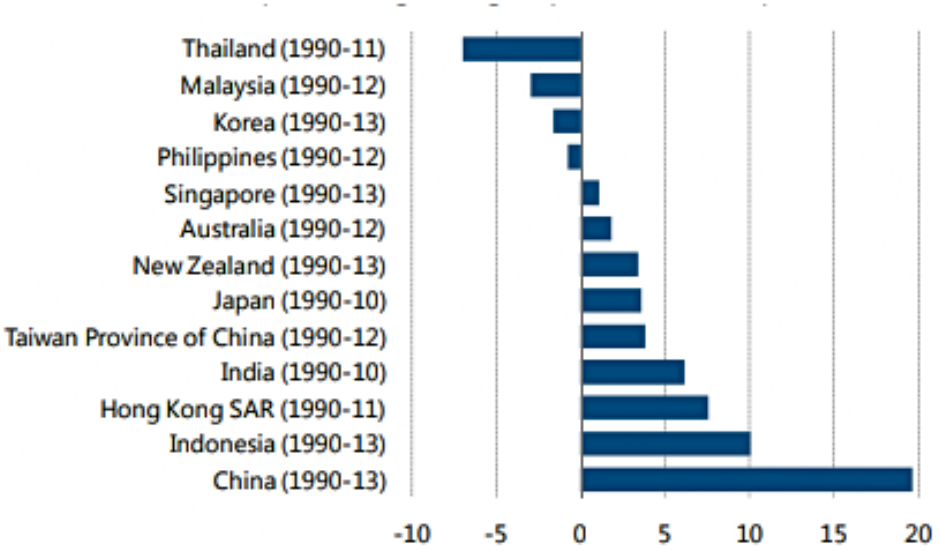

Figure 2. Selected Asia: Income Inequality, 1990-2016

Source: IMF Working Paper

For region-specific countries, Asia's experience with inequality has visibly flipped around 1990. The "Golden Age" of broadly shared gains yields in the 1990s all the way to 2016 in which booming growth has often coincided with widening gaps between rich and poor (Figure 1 & 2), this pivot points to a shift away from an inclusive "Miracle" growth, when policies regarding taxation, transfers, and labor markets will determine whether Asian growth can once again be broadly shared.

2.2. Personal Income Tax (PIT) as a regressor on income inequality

Utilized as a fiscal tool, PIT was believed to alleviate the burden of inequality between income levels (Datt et al., 2022), of which "progressivity capacity" can be measured by several metrics, including and exemplifying by following literature: fixed-income based ranking (Bishop et al., 1990; Norregaard 1990); log-normal simplification in a paper by Vellutini and Benítez (2021) involving Gini and mean income; similarly, Sabirianova-Peter et al. (2010) also computed 100 points of marginal and average PIT rates (4 - 400 percent of GDP per capita) and regressed these against log income; showing a positive slope signals greater structural progressivity. All in all, these approaches allow cross-country and over-time comparisons of PIT design, revealing that high progressivity (steeply rising average rates) must be paired with sufficiently high average PIT burdens to achieve meaningful redistribution.

Research on the impact of the tax on inequality may still come up with mixed evidence. Using panel regressions across a broad sample of countries, Martínez-Vázquez, Vulovic and Moreno-Dodson (2012) find that progressive PIT systems significantly lower Gini indices, even after accounting for social welfare spending and globalization effects. Similarly, Causa and

Hermansen (2017) show that, in the OECD, PIT and social security contributions jointly mitigate over one quarter of pre-tax market inequality, with PIT alone shouldering a large share in countries with weaker transfer systems. Regression-based studies in developing contexts largely reaffirm these findings: Clifton et al. (2020) and Maina (2017) both documented a negative and statistically significant relationship between higher effective PIT burdens and lower disposable-income inequality, while Oboh and Eromonsele (2018) provided a contrasting ECM-based result for Nigeria. In a World Bank research (2023), the authors have also comparably pointed out, countries like Uganda and Tanzania exhibit very steep PIT progressivity but low average rates, and thus only modest net redistribution, whereas OECD economies combine moderate progressivity with higher average PIT to deliver far larger cuts in post-tax inequality.

2.3. Fiscal redistribution

Fiscal redistribution, or taxes and social benefits, sharply narrowed income gaps in OECD countries, but their redistributive impact has waned. Before the 2008 crisis, market-income inequality was flat, yet cuts in tax-and-benefit generosity allowed take-home inequality to rise. Early crisis relief briefly eased this, but as recovery sputtered, fiscal consolidation trimmed unemployment pay and social spending, stripping away that cushion and pushing disposable-income inequality back upward (OECD, 2015).

It should also be noted that progressivity and redistributive power of taxes are two distinct but highly either complementary or substitutional concepts, with the former measures the departure from proportionality (Kakwani, 1977) and the latter – the total reduction in income inequality achieved by moving from the pre-tax distribution to the post-tax distribution (Reynolds-Smolensky, 1977). An example for the exploitation of the two indices is a paper from Verbist & Figari (2014), where they concluded that countries might differ sharply in both dimensions: high progressivity (e.g. France: 0,445 to 0,432) does not always coincide with high average tax levels (19.4% to 21.2% as of time of research), as some nations achieve strong redistribution through steeply rising rates but modest overall PIT burdens. Conversely, other countries (e.g., Denmark, Sweden) raise a large share of income in PIT yet exhibit lower progressivity, often because of broad-based allowances or caps. This empirical pattern suggests that moderately progressive systems with higher average tax burdens may ultimately reduce inequality more effectively than highly progressive systems that collect proportionally less income.

2.4. Other control variables

Table 1. Compiled literature by the Author

Variable	Main Findings	Reference
GDP	Using the system GMM to estimate both cross-country variation and within-country evolution, it was deduced that: higher initial net-income inequality shaves roughly 0.8-1.3% points off subsequent five-year GDP-per-capita growth, and reversely, a reduction in inequality at the bottom of the distribution can boost it by 0.3% points over a 25-year period.	[OECD, 2015]
	Panel data supported that high-income nations each additional percentage point of GDP growth is associated with a small yet significant decline in inequality, whereas in developing and moderately developed countries growth correlates positively (though insignificantly) with inequality.	[Mohamed & Karim, 2018; Rachel & Ahmed, 2024]
Account balance	Income inequality and external balances are tightly linked, but that the sign and magnitude of the effect depend crucially on a country's level of development, financial liberalization, and the shape of its inequality (whether driven by the very rich versus the middle class or versus the poor).	[Blomme & Héricourt, 2023]
Educational attainment	Education-inequality matters most as more and better education helps tamp down income gaps. A wider dispersion in years of schooling (i.e., higher Gini of education) is robustly associated with higher disposable-income inequality.	[Benhabib & Spiegel, 1994; Coady & Dizioli, 2017]
Real interest rate	Lower real interest rates induce a revaluation of existing financial assets that boosts the fortunes of the wealthiest and widens gaps in financial but not total wealth, thereby exacerbating the inequality of financial resources even as broader measures of household welfare remain more resilient.	[Greenwald et al., 2021]

Source: Authors

2.5. Research gap

Despite growing interest in the relationship between personal income tax (PIT) and income inequality, several important gaps remain in the existing literature, particularly concerning developing and emerging economies in Asia.

Most prior studies use outdated data and do not account for the economic and social effects of recent global disruptions such as the COVID-19 pandemic. Key works like Martínez-Vázquez et al. (2012), Verbist and Figari (2014), and Vellutini and Benítez (2021) focus on data from before 2010 or, at best, up to 2018. As a result, they cannot assess how recent fiscal policies or income dynamics have affected inequality in the last decade, particularly in rapidly changing economies.

Additionally, existing empirical research tends to focus on OECD or European countries, while non-Middle Eastern Asian countries remain underrepresented. For example, studies by Causa and Hermansen (2017) and Verbist and Figari (2014) rely heavily on European datasets, and although some IMF and World Bank papers discuss inequality in Asia, they often do not provide region-specific regression models. This limits the applicability of their findings to the unique fiscal structures and developmental stages of Asian economies.

Many studies rely on conventional inequality measures such as the Gini index or top-income shares, but rarely examine the ratio between the top 10% and bottom 10% income groups. This ratio offers a direct view of income polarization, which is especially relevant in countries where middle-class growth is unstable or shrinking. By focusing on broader or aggregate metrics, previous research may overlook important changes at the extremes of the income distribution. Moreover, most models analyze PIT in isolation without including other variables that affect redistribution. For instance, the role of actual redistributive outcomes, such as the difference between pre- and post-tax Gini coefficients, is often ignored. Similarly, variables like educational attainment or external sector imbalances are frequently excluded, which can lead to omitted variable bias.

In this study, we address these gaps by: (1) using updated post-2010 data covering 30 non-Middle Eastern Asian countries through 2023, (2) including a broader set of control variables like education, redistribution, and current account balance, (3) applying a logarithmic income ratio between the top 10% and bottom 10% as the inequality measure, and (4) focusing specifically on Asia to generate regionally relevant findings. As such, it contributes new evidence to the literature on how PIT and related fiscal tools affect income distribution in an under-studied region.

3. Conceptual framework

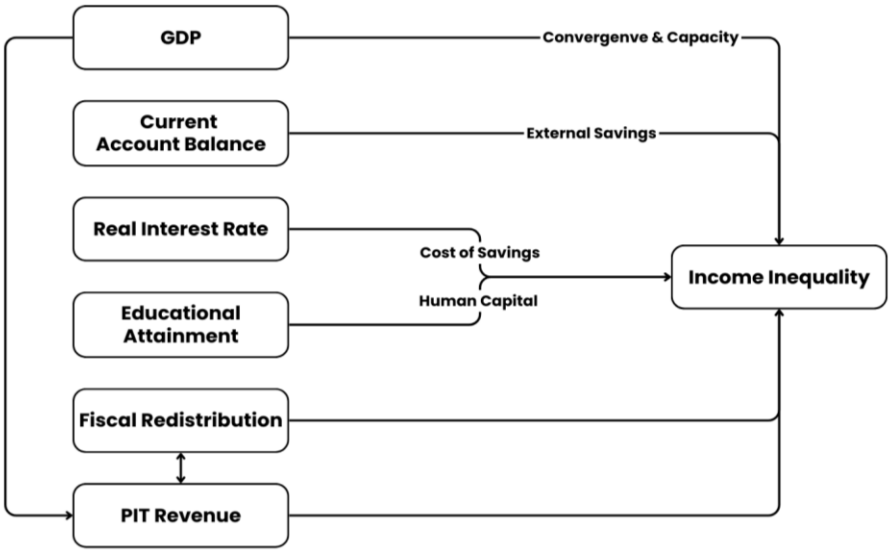

Figure 3. Conceptual framework

Source: Author

Herein, we unified a framework revolving around a transparent system of both direct fiscal channels (PIT revenue and progressivity) and indirect macro-economic channels (growth, human capital, interest rates, external balances). Differing to previous models, we acknowledge the multi-pathway structure to the relationship between the redistributive power of taxes and PIT revenue, as well as the confounding effect from GDP on the aforementioned tax. Moreover, the direct incorporation of real interest rates and current-account balance into the model such as ours has not been accommodated by existing literature.

4. Methodology

4.1. Research methodology

This study adopts the Multiple Linear Regression (MLR) model, a statistical method used to estimate the relationship between one dependent variable and multiple independent variables. The aim is to analyze how personal income tax revenue, GDP, current account balance, real interest rate, educational attainment, and estimated absolute redistribution influence income inequality. The Ordinary Least Squares (OLS) method is utilized to estimate the model parameters, given its efficiency in minimizing the sum of squared residuals and its widespread use in empirical economic research.

The dataset includes 30 Asian countries over a 14-year period from 2010 to 2023, totaling 420 observations. This panel dataset allows for a comprehensive view of regional trends and variations across time.

After collecting the data, we proceed with the OLS estimation to evaluate the model's explanatory power and statistical significance, ensuring the results align with theoretical expectations and previous empirical studies. The analysis integrates knowledge from econometrics, macroeconomics, and quantitative methods, supported by software tools such as STATA, Microsoft Excel, and Microsoft Word throughout the research process

4.2. Research model

4.2.1 Variable description

Table 2. Data description and data sources

Variable	Abbreviation & Hypothesized relationship	Description	Source of data
Dependent variable			
Income inequality (*Logarithm*)	$lninc\_inequality$	The logarithm of $\frac{Post-tax\ national\ income\ of\ the\ top\ 10\%}{Post-tax\ national\ income\ of\ the\ bottom\ 10\%}$	WID
Independent variable			
Personal income tax revenue (*Logarithm*)	$lnPIT\_rev$ **(-)**	The logarithm of personal income tax revenue, measured in local currency units	OECD
Gross Domestic Product (*Logarithm*)	$lnGDP$ **(+)**	The logarithm of GDP at purchasing power parity (PPP), current prices	IMF
Current account balance	$acc\_balance$ (-)	The difference between a country's savings and investment as a share of GDP	IMF
Real interest rate (%)	int_rate (+)	Nominal interest rate adjusted for inflation	World Bank Data

Variable	Abbreviation & Hypothesized relationship	Description	Source of data
Independent variable			
Educational attainment	edu_attain (-)	Percentage of population aged 25+ that completed upper secondary education or higher	World Bank Data
Estimated absolute redistribution	abs_re (-)	Gini coefficient of market income (before taxes and benefits) minus the Gini coefficient of disposable income (after taxes and benefits)	SWIID

Source: Author

4.2.2 Model development

Building upon the model proposed by Taghizadeh-Hesary et al. (2019), and drawing from the theoretical foundations and empirical evidence provided by numerous prior studies, the research team has formulated a model to examine the influence of relevant factors on income inequality, including gross domestic product, current account balance, real interest rate, educational attainment, estimated absolute redistribution, and personal income tax revenue.

The functional relationship can be expressed as:

$$inc\_inequality = f(GDP, acc\_balance, int\_rate, edu\_attain, abs\_re, PIT\_rev)$$

Based on this, we construct the following population regression model:

$$lninc\_inequality = \beta_0 + \beta_1.lnGDP + \beta_2.acc\_balance + \beta_3.int\_rate + \beta_4.edu\_attain + \beta_5.abs\_re + \beta_6.lnPIT\_rev + u_i$$

Where:

β_0: the intercept term of the model

β_{1-6}: the intercept term and the corresponding coefficients of each variable

u_i: the disturbance term of the model, represents other factors that affect the dependant variable but not mentioned in the model

4.2.3 Data description

Using the corr command in STATA to analyze the correlation between variables, we have:

Table 3. Correlation matrix

	$lninc\_inequalit$	$lnGDP$	$acc\_balance$	int_rate	edu_attair	abs_re	$lnPIT\_rev$
$lninc\_inequalit$	1.0000						
$lnGDP$	0.2952	1.0000					
$acc\_balance$	0.0796	0.5771	1.0000				
int_rate	0.0198	-0.1501	-0.2891	1.0000			
edu_attain	-0.2959	-0.4189	-0.1653	0.1388	1.0000		
abs_re	-0.5358	-0.0988	0.0218	-0.1137	0.0677	1.0000	
$lnPIT\_rev$	0.0051	0.6701	0.2163	0.0831	-0.3505	-0.3218	1.0000

Source: Author

A correlation matrix was constructed to examine the linear relationships between $lninc\_inequality$ and the independent variables. The correlation coefficient ranges from -1 to +1, where values closer to ±1 indicate stronger linear relationships.

- $lninc\_inequality$ vs. $lnGDP$ (r = 0.2952): Weak to moderate positive correlation, suggesting that higher GDP may be associated with increased income inequality.
- $lninc\_inequality$ vs. $acc\_balance$ (r = 0.0796): Weak positive correlation, suggesting little to no apparent linear relationship between the current account balance and income inequality at the bivariate level.
- $lninc\_inequality$ vs. int_rate (r = 0.0198): Weak positive correlation, suggesting a minimal linear connection between real interest rates and income inequality when considered on their own.
- $lninc\_inequality$ vs. edu_attain (r = -0.2959): Weak to moderate negative correlation, suggesting that higher levels of educational attainment may be linked to somewhat lower income inequality.
- $lninc\_inequality$ vs. abs_re (r = -0.5358): Moderate negative correlation, suggesting that redistribution policies might play a role in narrowing income disparities.

- $lninc\_inequality$ vs. $lnPIT\_rev$ (r = 0.0051): Very close to zero positive correlation, suggesting that there is no meaningful correlation between personal income tax revenue and income inequality in the simple linear context.

However, this does not rule out the possibility that $acc\_balance$, int_rate and $lnPIT\_rev$ could have a significant effect when considered in a multivariate regression model. Therefore, we retain these variables in the model. The low correlation coefficient only indicates a weak bivariate relationship, but it does not capture the variable's potential impact after controlling for other explanatory variables (Wooldridge, 2012).

5. Results

5.1. Estimated model

5.1.1 OLS Estimation Results

The model was estimated using the Ordinary Least Squares (OLS) technique implemented in STATA, applying a significance level of α = 5%. The resulting estimates are presented below:

Table 4. OLS regression result

Source	SS	df	MS
Model	6.6402	6	1.1067
Residual	3.5521	78	0.0455
Total	10.1923	84	0.1213

Statistic	Value
Number of obs	85
F(6, 78)	24.30
Prob > F	0.0000
R-squared	0.6515
Adj R-squared	0.6247
Root MSE	0.2134

lninc_inequa	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
lnGDP	0.129259	0.0193021	6.70	0.000	0.0908315	0.1676864
acc_balance	-0.0100721	0.0044294	-2.27	0.026	-0.0188903	-0.0012539
int_rate	0.005944	0.0041525	1.43	0.156	-0.002323	0.0142111
edu_attain	-0.0044773	0.0013669	-3.28	0.002	-0.0071985	-0.001756
abs_re	-0.0660811	0.0069611	-9.49	0.000	-0.0799396	-0.0522226
lnPIT_rev	-0.0685782	0.0087812	-7.81	0.000	-0.0860602	-0.0510962
_cons	6.865466	0.1394443	49.23	0.000	6.587854	7.143079

Source: Author

5.1.2 Sample regression model

After using the result from STATA, we have the sample regression model as follows:

$$lninc\_inequality = 6.865466 + 0.129259.lnGDP - 0.0100721.acc\_balance + 0.005944.int\_rate - 0.0044773.edu\_attain - 0.0660811.abs\_re - 0.0685782.lnPIT\_rev + \widehat{u_i}$$

Where:

$\widehat{\beta_0}$ = 6.865466: When all the values of independent variables equal 0, the predicted value of $lninc\_inequality$ is 6.865466.

$\widehat{\beta_1}$ = 0.129259: The relationship between $lnGDP$ and $lninc\_inequality$ is positive, as expected. Holding other variables constant, a 1- unit increase in $lnGDP$ is associated with an increase of 0.129259 units in $lninc\_inequality$.

$\widehat{\beta_2}$ = - 0.0100721: The relationship between $acc\_balance$ and $lninc\_inequality$ is negative, as expected. Holding other factors constant, a 1 percentage point increase in $acc\_balance$ is associated with a 0.0100721 unit decrease in $lninc\_inequality$.

$\widehat{\beta_3}$ = 0.005944: The relationship between int_rate and $lninc\_inequality$ is positive, as expected. Holding other variables constant, a 1 percentage point increase in int_rate is associated with an increase of 0.005944 units in $lninc\_inequality$.

$\widehat{\beta_4}$ = - 0.0044773: The relationship between edu_attain and $lninc\_inequality$ is negative, as

expected. Holding other variables constant, a 1 percentage point increase in edu_attain is associated with a decrease of 0.0044773 units in $lninc\_inequality$.

$\widehat{\beta_5}$ = - 0.0660811: The relationship between abs_re and $lninc\_inequality$ is negative, as expected. Holding other variables constant, a 1- unit increase in abs_re leads to a 0.0660811 unit decrease in $lninc\_inequality$.

$\widehat{\beta_6}$ = - 0.0685782: Holding other variables constant, a 1- unit increase in $lnPIT\_rev$ is associated with a 0.0685782 unit decrease in $lninc\_inequality$.

5.1.3 Simultaneous-quantile regression

To explore the relationship between PIT revenue and income inequality more comprehensively, this study employs Quantile Regression (QR). Besides the Ordinary Least Squares (OLS) method, which estimates the average effect across the entire population, QR allows us to examine how this relationship varies at different points of the income distribution. This is particularly useful given the heteroskedasticity and skewness typical in inequality data.

The analysis focuses on the impact of the logarithm of PIT revenue ($lnPIT\_rev$) across the 10th, 20th, 50th, 80th, and 90th income quantiles, thereby capturing effects on low-, middle-, and high-income groups.

Table 5. Quantile regression result

$lninc\_inequalit$	**Qtile**	**Coefficient**	**Std. err.**	**t**	**P>|t|**	**[95% conf. interval]**	
	Q(0.1)	-0.0646687	0.004446	-14.55	0.000	-0.0735199	-0.0558174
	Q(0.2)	-0.0700684	0.0072362	-9.68	0.000	-0.0844746	-0.0556622
$lnPIT\_rev$	**Q(0.5)**	-0.0696547	0.0078632	-8.86	0.000	-0.0853093	-0.0540002
	Q(0.8)	-0.0461303	0.0226766	-2.03	0.045	-0.091276	-0.0009846
	Q(0.9)	-0.0166175	0.0376876	-0.44	0.660	-0.0916477	0.0584127

Source: Author

At the 10th and 20th Quantiles (Low-Income Group): At the lower end of the income distribution, personal income tax (PIT) revenue has a statistically significant negative effect on income inequality. Specifically, the coefficient is -0.064 at the 10th quantile and -0.070 at the 20th quantile (p-value < 0.05). This indicates that increases in PIT revenue are associated with a modest but meaningful reduction in inequality among low-income earners. This outcome reflects the

progressive structure of PIT, which taxes higher incomes at greater rates, enabling income redistribution through public spending and social welfare programs.

At the 50th Quantile (Middle-Income Group): At the median income level, PIT revenue continues to have a statistically significant negative effect on income inequality, with a coefficient of -0.696 (p-value < 0.05). While the absolute value of this coefficient appears larger, the practical difference compared to lower quantiles may not be substantial. Nevertheless, the result reinforces the redistributive role of PIT for the broad base of low to middle income earners.

At the 80th and 90th Quantiles (High-Income Group): At the higher income levels, the effect of PIT revenue on inequality weakens significantly. At the 80th quantile, the coefficient remains negative (-0.046) but is much smaller in magnitude, indicating a relatively weak reduction in inequality among high-income earners. At the 90th quantile, the coefficient is statistically insignificant (p-value = 0.660), suggesting no meaningful effect of PIT revenue on inequality among the very top earners. This limited impact may result from tax avoidance strategies employed by high-income individuals, such as converting taxable wages into capital gains taxed at lower rates, and the fact that a significant portion of their income derives from assets and investments not subject to PIT. Consequently, increases in PIT revenue alone are insufficient to address inequality at the highest income levels, underscoring the limitations of personal income tax as a tool for tackling extreme income disparities

5.2. Hypotheses testing

5.2.1 Testing the significance of an individual regression coefficient

To assess the statistical significance of each independent variable in the regression model, the P-value approach was employed. The hypotheses for each coefficient test are as follows:

H_0: $\beta_i = 0$ (The coefficient is not statistically significant)

H_1: $\beta_i \neq 0$ (The coefficient is statistically significant)

Refer to the Table 4, at the 5% significance level ($\alpha = 0.05$), most of the explanatory variables are found to be statistically significant. Specifically, $lnGDP$ (p = 0.000), $acc\_balance$ (p = 0.026), edu_attain (p = 0.002), abs_re (p = 0.000), and $lnPIT\_rev$ (p = 0.000) all have p-values lower than 0.05, leading to the rejection of the null hypothesis for each, indicating that these variables have a statistically significant influence on $lninc\_inequality$ and contribute meaningfully to the model's explanatory power.

On the other hand, int_rate (p = 0.156) exceeds the 5% threshold, meaning the null hypothesis cannot be rejected for this variable. As a result, real interest rate is not considered a significant predictor of income inequality in this regression model. This outcome can be attributed to the fact that although interest rates play a crucial role in controlling inflation and stimulating investment, they may not have directly influenced income distribution across Asian countries.

Interest rate channels primarily impact the economy through changes in investment and consumption behavior, effects that often take time to materialize and are unevenly distributed across different population groups due to varying levels of access to credit and institutional structures (Mishra & Montiel, 2012). Furthermore, in many developing and emerging Asian economies, a significant portion of the population remains outside the formal financial system, limiting the effectiveness of interest rate adjustments in influencing the incomes of lower-income groups (Mehrotra & Yetman, 2015). Consequently, structural factors such as access to education or fiscal instruments like taxation and social transfers tend to have a more immediate and substantial impact on income inequality than monetary variables.

5.2.2 Testing overall significance

To test the overall significance of the regression model, we establish the following hypotheses:

H_0: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = 0$

H_1: $\beta_1^2 + \beta_2^2 + \beta_3^2 + \beta_4^2 + \beta_5^2 + \beta_6^2 \neq 0$ (or at least one $\beta_i \neq 0$)

This can also be expressed in terms of the R-squared statistic:

H_0: $R^2 = 0$

H_1: $R^2 \neq 0$

The coefficient of determination, R^2, measures the extent to which the variation in the dependent variable is explained by the independent variables in the model. In this regression, an R^2 value of 0.6515 indicates that approximately 65.15% of the variation in $lninc\_inequality$ can be attributed to the combined effects of $lnGDP$, $acc\_balance$, int_rate, edu_attain, abs_re, and $lnPIT\_rev$. The remaining 34.85% is likely driven by other unobserved factors, which, in accordance with economic theory, are captured by the error term (u).

Furthermore, the STATA output reports a p-value for the F-statistic of 0.0000, which falls well below conventional thresholds for statistical significance (1%, 5%, and 10%). Consequently, we reject the null hypothesis that all coefficients are jointly equal to zero. This strongly supports the conclusion that the overall model is statistically significant, and the explanatory variables collectively exert a substantial influence on income inequality.

5.3. Testing for model assumptions

In conducting linear regression analysis, it is essential to perform a series of diagnostic tests to verify that the model adheres to its underlying assumptions and to detect any potential flaws in the research framework.

5.3.1 Variable omission test for omitted variables

Omitting a theoretically relevant independent variable can lead to biased and misidentified models, despite appearing linear. To address this, the authors performed a Ramsey test, with the results as follows: (Gujarati & Porter, 2009).

Table 6. Ramsey reset test for omitted variables

F(3, 75)	= 1.95
Prob > F	= 0.1290

Source: Author

The table above indicates that the p-value is 0.1290, which is greater than $\alpha = 0.05$, falling within the non-rejection region of the null hypothesis (H_0). Therefore, the model does not suffer from variable omission.

5.3.2 Jacque-Bera test for normally distributed residuals

Residuals that deviate from a normal distribution can yield linear yet inefficient estimations. To assess the normality of residuals, the Jacque–Bera test was applied, producing the following results:

Table 7. Jacque-Bera test for normal distribution of residuals

Variable	Obs	Pr(skewness)	Pr(kurtosis)	Adj chi2(2)	Prob>chi2
u	85	0.0000	0.0000	30.60	0.0000

Source: Author

The table above shows a p-value of 0.0000, with both Pr(Skewness) and Pr(Kurtosis) falling below the significance level $\alpha = 0.05$. These results lead to the rejection of the null hypothesis H_0, indicating that the model's residuals are not normally distributed. Despite this violation of the normality assumption, the model remains reliable due to the sufficiently large sample size (85 observations), which mitigates the impact of non-normal residuals (Wooldridge, 2012).

5.3.3 VIF test for multicollinearity

Multicollinearity occurs when independent variables are highly correlated with one another, thereby breaching the assumptions of the classical linear regression framework. To assess the presence of multicollinearity, the research team employed the Variance Inflation Factor (VIF) and obtained the following results: All VIF values fall within the range of 1.15 to 3.09, with a mean VIF of 1.78. This indicates that multicollinearity is not a concern in our model, as the commonly accepted threshold for VIF is 10. The relatively low VIF values suggest that the independent

variables are not highly correlated with each other, thereby supporting the reliability and stability of the regression estimates (Wooldridge, 2012).

5.3.4 White test for Heteroskedasticity

A key assumption of the classical linear regression model is that the random error terms u_i exhibit constant variance (homoscedasticity) across observations. To verify the efficiency of the Ordinary Least Squares (OLS) estimators, the White test is applied to detect any presence of heteroskedasticity in the error terms. The following table presents the test results.

Table 8. White test for heteroscedasticity of residuals

chi2(27)	= 50.93
Prob > chi2	= 0.0035

Source: Author

The White test results reveal a p-value of 0.0035, which is lower than the significance level α = 0.05. This leads to the rejection of the null hypothesis H_0, suggesting that the model suffers from heteroskedasticity - a violation of the classical linear regression assumption that the variance of the error terms remains constant across observations.

To mitigate this issue, the research team re-estimated the model using robust standard errors, which are designed to provide valid standard errors even in the presence of heteroskedasticity. The robust regression output maintains a high level of model fitness, with an R-squared of 0.6515, indicating that approximately 65.15% of the variation in $lninc\_inequality$ is explained by the independent variables in the model.

Furthermore, all key variables remain statistically significant at the 10%, 5%, or 1% levels, and the model continues to display strong explanatory power. This confirms that, despite the presence of heteroskedasticity, the adoption of robust standard errors ensures that the model's inferences remain reliable and valid.

6. Discussion

Our OLS estimates largely mirror the broader empirical consensus that GDP has a significant negative relationship with income inequality (supported as a Kuznets-style convergence in the previous literature by OECD in 2015), educational attainment strongly reduces income disparities; and most noticeably, both redistributive power and PIT revenue demonstrate robust negative impacts on inequality. Another contention as appraised in our literature review is the inconstant relation between current-account surpluses and with lower post-tax inequality, on which our verdict reflects as negative over our Asian sample, spanning both financially less developed and

more advanced economies, this negative estimate suggests that the advanced/open regime predominates in the region.

Besides these findings, we also intend to discover the relationship between fiscal redistribution and PIT revenue as established in our conceptual framework through the means of regressing an interaction variable of $c.abs\_re\#c.pit\_rev$, as adapted from Voto & Ngepah (2023):

Table 9. Interaction of fiscal redistribution and PIT revenue

$lninc\_inequality$	**Coefficient**	**Std. err.**	**t**	**P>|t|**
abs_re	-.0611395	0.0102862	-5.94	0.000
pit_rev	-4.58e-90	7.41e-10	-6.18	0.000
$c.abs\_re\#c.pit\_rev$	-5.44e-10	1.44e-10	-3.76	0.000

Source: Author

It is revealed that fiscal redistribution creates a nonlinear relationship between inequality (Gini) and PIT revenue. This is clearly demonstrated in our marginal effect calculation, where the partial effect of PIT revenue on log Gini is expressed as:

$$\frac{\partial ln(Gini)}{\partial pit\_rev} = \beta pit\_rev + \beta pit\_rev \times abs\_re = -4.58e-9 - 5.44e-10 \times abs\_re$$

The equation shows that the impact of PIT on inequality isn't constant but rather contingent on the magnitude of fiscal redistribution (abs_re). As fiscal redistribution increases, the inequality-reducing effect of PIT revenue becomes progressively stronger. The negative interaction term (−5.44e−10) indicates that each additional unit of fiscal redistribution enhances PIT's effectiveness in reducing inequality, creating a compounding effect that explains why some tax systems achieve greater equity outcomes despite similar revenue levels.

7. Conclusion and Limitations

7.1. Conclusion and Implications

This study investigates the determinants of income inequality across 30 Asian countries over a 14-year period from 2010 to 2023, with a particular focus on the role of personal income tax (PIT) revenue. Our findings highlight that PIT revenue has a strong and statistically significant

effect in reducing income inequality, especially among low and middle-income individuals, but its impact diminishes substantially for high-income individuals.

For low-income individuals, increased PIT revenue is associated with meaningful reductions in income inequality, reflecting the progressive structure of income taxation and its redistributive potential. The effect is even more pronounced for middle-income individuals, reinforcing the importance of robust tax collection and redistribution mechanisms for promoting equity among the majority of the population. However, for high-income individuals, the effectiveness of PIT in curbing inequality is markedly weaker (at 80th quantile) and statistically insignificant (at 90th quantile), suggesting that these earners may reduce taxation through legal optimization strategies or derive most of their income from non-taxed sources such as capital gains or investments.

Additionally, the study confirms the significance of other macroeconomic and social variables such as GDP, current account balance, educational attainment, and estimated absolute redistribution in shaping income inequality patterns across countries. These findings suggest that addressing inequality requires a multidimensional policy approach. For example, promoting educational attainment can improve long-term income mobility, while responsible macroeconomic management can support more inclusive growth. The real interest rate, however, does not exhibit a statistically significant effect, possibly due to its indirect or lagged influence on income distribution.

Policy implications from these findings are twofold. First, governments should strengthen PIT systems, not only by improving tax compliance and enforcement but also by expanding tax bases to include income sources disproportionately earned by the wealthy. Second, complementary policies such as investing in education, fostering equitable economic growth, and strengthening social protection are necessary to reinforce the redistributive power of taxation and ensure broader income equity.

7.2. Limitations

Despite its contributions, this study has several limitations. The analysis is limited to 30 Asian countries due to data availability, which may restrict the generalizability of the findings to regions with different fiscal structures, governance systems, and levels of economic development. This constraint might be particularly limiting when considering PIT policies, as existing literature has established that PIT often exerts a strong equalizing effect within countries. Nevertheless, our research provides compelling evidence that PIT revenue significantly shapes income inequality patterns, especially for low and middle-income segments of the population. Therefore, future research should be encouraged to develop more sophisticated within-country models that account for country-specific tax architectures, compliance behaviors, and the interactions between formal and informal economic sectors in determining redistributive outcomes. Moreover, extending the analysis to include wealth inequality, nontaxable income, and other fiscal instruments such as

value-added taxes or social transfers would provide a more comprehensive picture of inequality dynamics in different contexts.

REFERENCES

Bishop, J.A., Formby, J.P. & Thistle, P.D. (1990) "International comparisons of tax and transfer progressivity: new evidence from the Luxembourg Income Study". *Luxembourg Income Study Working Paper No.52*. Available at: https://www.lisdatacenter.org/wps/liswps/52.pdf

Blomme, O. & Héricourt, J. (2025) "Inequality, current account imbalances, and middle incomes", *Journal of International Money and Finance*, Vol 152 p103267. doi:10.1016/j.jimonfin.2025.103267.

Bouincha, M. & Karim, M. (2018) "Income inequality and economic growth: An analysis using a panel data", *International Journal of Economics and Finance*, Vol 10 No 5 p242. doi:10.5539/ijef.v10n5p242.

Causa, O. & Hermansen, M. (2017) "Income Redistribution Through Taxes and Transfers Across OECD Countries", *OECD Economics Department Working Papers*, No. 1453. Available at: https://www.oecd.org/en/publications/income-redistribution-through-taxes-and-transfers-across-oecd-countries_bc7569c6-en.html?

Clifton, J., Díaz-Fuentes, D. & Revuelta, J. (2020) "Falling inequality in Latin America: the role of fiscal policy", *Journal of Latin American Studies*, Vol 52 p317–341.

Jain-Chandra, S., Kinda, T., Kochhar, K., Piao, S. & Schauer, J. (2016) "Sharing the Growth Dividend: Analysis of Inequality in Asia". IMF Working Paper. Available at: https://www.imf.org/external/pubs/ft/wp/2016/wp1648.pdf

Jurzyk, E.M., Aoyagi, C., Clements, B., Gupta, S. & Kang, J. (2020) "Covid-19 and inequality in Asia: Breaking the vicious cycle". IMF Working Paper. Available at: https://www.imf.org/en/Publications/WP/Issues/2020/10/16/COVID-19-and-Inequality-in-Asia-Breaking-the-Vicious-Cycle-49807.

Kakwani, N. (1977a) "Measurement of Tax Progressivity: An International Comparison", *Economic Journal*, Vol 87 p71–80.

Maina, W.A. (2017) "The effect of consumption taxes on poverty and inequality in Kenya", *International Journal of Accounting and Taxation*, Vol 5 No 2 p56–82.

Martínez-Vázquez, J., Vulovic, V. & Moreno-Dodson, B. (2012) "The impact of tax and expenditure policies on income distribution: evidence from a large panel of countries", *Hacienda Pública Española*, IEF, Vol 200 No 1 p95–130.

Mishra, P. & Montiel, P.J. (2012) “How effective is monetary transmission in low-income countries?: A survey of the empirical evidence”. Washington, D.C: International Monetary Fund. Available at: https://www.imf.org/external/pubs/ft/wp/2012/wp12143.pdf?

OECD (2015) “In It Together: Why Less Inequality Benefits All”. OECD Publishing. doi:https://doi.org/10.1787/9789264235120-en.

OECD (2024) “Revenue Statistics in Asia and the Pacific 2024: Tax Revenue Buoyancy in Asia”. Paris: OECD Publishing. doi:10.1787/e4681bfa-en.

Sabirianova Peter, K., Buttrick, S. & Duncan, D. (2010) “Global Reform of Personal Income Taxation, 1981−2005: Evidence from 189 Countries”, *National Tax Journal*, Vol 63 No 3 p447–478.

Stanley, A. (2022) “Global Inequalities”. [online] International Monetary Fund. Available at: https://www.imf.org/en/Publications/fandd/issues/2022/03/Global-inequalities-Stanley.

Steenbrink, R. & Skali, A. (2024) “Wealth Inequality and Economic Growth: Evidence from the World Inequality Database”, *GLO Discussion Paper*, No. 1417. Essen: Global Labor Organization (GLO). Available at: https://www.econstor.eu/bitstream/10419/289584/1/GLO-DP-1417.pdf?

T., O. & E.P., E. (2018) “Taxation and income inequality in Nigeria”, *NG-Journal of Social Development*, Vol 7 No 1 p64–72. doi:10.12816/0046771.

Thomas, A.G. (2023) “Measuring tax progressivity in low-income countries” [Preprint]. doi:10.1596/1813-9450-10460.

Vellutini, C. & Benítez, J.C. (2021) “Measuring the Redistributive Capacity of Tax Policies”, *IMF Working Paper*, No. WP/21/252. Available at: file:///C:/Users/Admin/Downloads/wpiea2021252-print-pdf.pdf

Verbist, G. & Figari, F. (2014) “The redistributive effect and progressivity of taxes revisited: An international comparison across the European Union”, *FinanzArchiv*, Vol 70 No 3 p405. doi:10.1628/001522114x684529.

Voto, T.P. & Ngepah, N. (2023) “Personal income tax, redistribution and income inequality in Sub-Saharan Africa”, *International Review of Economics*, Vol 71 No 2 p205–223. doi:10.1007/s12232-023-00440-9.

Yetman, J. (n.d.) “Financial inclusion - issues for central banks”. [online] Available at: https://www.bis.org/publ/qtrpdf/r_qt1503h.pdf