The Relationship Between Remittance Dependence and Income Inequality: evidence from 1980-2015

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1 Introduction

According to the World Bank (2023), total personal remittances worldwide have increased more than tenfold over the past 30 years, rising from 81.08 billion dollars in 1993 to 409.71 billion dollars in 2008, and reaching 822.32 billion dollars in 2023. This trend highlights remittances as a major source of foreign exchange for many developing countries and underscores the profound impact of migrant workers on the global economic system.

While the growth of international remittances is a global phenomenon, the degree to which countries rely on these inflows varies significantly due to differences in their economic conditions. In general, high-income countries are often the primary destinations for migrant workers and serve as major remittance-sending nations rather than recipients, making them relatively less dependent on remittances. In contrast, low-income countries are more likely to rely on international remittances as a key economic pillar. For example, in Tonga, Tajikistan, and Lebanon, remittances account for more than 30 percent, or even 40 percent, of GDP, highlighting the critical role of migrant income in these economies (World Bank, 2023). However, some other countries with similar economic levels receive little to no reliance on remittances. This raises an important question: why do some countries with comparable levels of economic development depend heavily on remittances, while others are barely affected by them? If these countries share similar overall economic conditions, one possible difference is income distribution. Therefore, this paper aims to examine the relationship between income inequality and remittance dependency, exploring how a country's reliance on international remittances, represented by the ratio of remittances to GDP, affects its income distribution among countries with comparable economic status.

Theoretically, remittances directly support migrant families and improve their living standards. In low-income households, remittances can significantly increase household income, helping to narrow income gaps. However, remittances often flow to middle- and high-income families, as migration opportunities are more accessible to those with greater resources. This uneven distribution of remittance inflows can exacerbate income inequality, leaving the poorest households with limited benefits. Koechlin and León (2006) offered a possible explanation for this debate. Using data from 78 countries between 1970 and 2001, their study demonstrates that the effect of remittances on income inequality follows an inverted U-shaped pattern. This implies that in countries with low dependence on remittances, increasing remittance inflows may widen inequality, whereas in countries highly dependent on remittances, further increases in remittances may reduce inequality. This finding provides important inspiration for this research and serves as the theoretical foundation for hypothesizing a non-linear relationship between remittance dependency and income inequality.

Another paper that explores this topic on a global scale is by Anwar, Mang, and Plaza (2024), a recent study that conducts a meta-analysis of 578 estimates from 45 empirical studies examining the relationship between remittances and income inequality. Overall, they found that remittances slightly reduce income inequality, but the effect is economically small. Additionally, they found significant regional variations. In some regions, remittances increase inequality due to high migration costs limiting access for lower-income households. In the Middle East, North Africa, and Sub-Saharan Africa, remittances have minimal effects on income inequality. In contrast, in Latin America, Eastern Europe, and East Asia, there is evidence that remittances reduce inequality. This finding on regional effects suggests that the relationship between remittances and income inequality may be influenced by other factors, particularly the country or regional context. It motivates the inclusion of variables related to national economic conditions in the analysis to better account for contextual heterogeneity in remittance impacts.

One important factor that can influence both income inequality and remittance inflows is the level of education, as individuals' income is often directly correlated with their educational attainment. Education also plays a key role in shaping who migrates and, consequently, who sends remittances, since migration opportunities and associated costs tend to be more accessible to better-educated individuals. Kratou and Khlass (2021), in their study of developing countries in the MENA region, found that remittances are more likely to reduce income inequality when the rate of brain drain is below 22 percent. When brain drain exceeds this threshold, the redistributive effect of remittances diminishes significantly. Although this research adopts a global scope and cannot incorporate brain drain data directly, this finding underscores the importance of migrant workers' skill composition in shaping the remittance–inequality relationship. It has thus informed the decision to include indicators related to national education levels in the analysis.

This study contributes to the literature in the following ways. Although the relationship between remittances and income inequality has been widely studied, few papers focus specifically on the concept of remittance reliance, which refers to the extent to which countries depend on remittance inflows, rather than remittance volume alone. Furthermore, this study adopts a different approach to controlling for education. Specifically, it uses two distinct control variables to capture both basic and higher education levels. It also incorporates a quadratic term for the education-related variables in the regression analysis, revealing a possible non-linear relationship between education and inequality, which may have been overlooked in previous work. Lastly, while prior studies have included controls for a country's economic conditions, they often rely on only one or two common indicators. In contrast, this paper includes a broader set of economic variables, providing a more nuanced control for national economic context.

The ideal dataset for this research would be a panel dataset covering all countries from 1983 to 2023. It should include income inequality measures such as the Gini coefficient, as well as indicators of remittance dependence, primarily remittances as a percentage of GDP, which serve as the outcome and key explanatory variables, respectively. In addition, it should contain essential control variables that reflect economic development and macroeconomic conditions, such as GDP, GDP per capita, inflation rate, financial inclusion, trade openness, and government expenditure. It would also be ideal to include control variables capturing the education levels of migrant workers. However, no single dataset provides complete coverage of all these variables across countries and over time. Therefore, the dataset used in this study is assembled from multiple sources, including the World Bank, the United Nations, and the International Monetary Fund. This data compilation approach inevitably results in gaps and inconsistencies. Moreover, due to the global scope of the study, it is particularly difficult to obtain data on the education levels of migrant workers. As a result, national-level education indicators are used as a proxy. These limitations should be kept in mind when interpreting the findings of this research.

The rest of the paper is organized as follows. The next two sections introduce the data and the empirical strategy, respectively. Section 4 presents and interprets the results of both grouped and non-grouped panel data regression analyses. Finally, Section 5 provides discussions, conclusions, and closing remarks.

2 Data

The inequality measure used in this research is the WIID Companion dataset from the United Nations (2023). This dataset provides information on annual per capita income distributions at both the country and global levels. The variables of interest are the standardized Gini Index and the difference in income share of the top and bottom 20 percent earners. The dataset partially covers 201 countries from 1890 to 2022. These two variables are chosen because the Gini Index offers a comprehensive measure of overall income inequality, while the income shares of the top and bottom 20 percent highlight disparities in wealth distribution, allowing us to assess inequality from both a comprehensive and a distribution-sensitive perspective, and to check whether the results are specific to one particular measure.

Our explanatory variable, which is the reliance of a country's economy on remittances, is represented by the personal remittances received as a percentage of GDP (World Bank, 2024). These values are based on World Bank staff estimates, using IMF balance of payments data as well as World Bank and OECD GDP estimates. IMF data on worker remittances is based on official banking reports and may underestimate actual flows, as informal transfers are not accounted for. Consequently, the estimated coefficients likely represent a lower bound of remittances' true impact on income inequality (Koechlin and Leon, 2006). The dataset partially covers 266 countries from 1890 to 2023.

Following Murodova (2018), the skill composition of migrant workers is considered an important factor when examining the impact of international remittances on inequality. To account for this, I use school life expectancy as a proxy for education levels across countries. School life expectancy refers to the total number of years of schooling a child entering the education system can expect to receive, assuming current age-specific enrollment ratios remain unchanged. The data are drawn from two datasets covering expectancy for ISCED levels 1–3 and ISCED levels 5–8 (United Nations, 2016). ISCED levels 1–3 correspond to primary through high school level education, while ISCED levels 5–8 are equivalent to short-cycle tertiary education through to doctoral studies. The former reflects general accessibility to basic education, whereas the latter indicates the availability and development of higher education. Both datasets provide partial coverage for the period 1975–2016, with the ISCED 1–3 dataset covering 216 countries and the ISCED 5–8 dataset covering 193 countries.

Additionally, we aim to include data that reflect a country's overall economic conditions. For this purpose, we use the World Economic Outlook database (IMF, 2024), which provides partial coverage of 44 different economic indicators across 196 countries from 1980 to 2023. To ensure cross-country and temporal comparability, we retain only those variables expressed in indices, percentages, or purchasing power units. These variables are included in the regression as control variables to account for differences in economic status across countries. While they serve a similar role to country fixed effects by capturing country-specific heterogeneity, their advantage lies in avoiding potential collinearity with time fixed effects. In addition, to minimize multicollinearity among the control variables themselves, we performed a correlation check and excluded variables with pairwise correlations exceeding 0.6. The final set of control variables includes Real GDP, GDP per capita, Total investment, Gross national savings, Inflation, Unemployment rate, General government total expenditure, General government net lending/borrowing, and Current account balance.

It is important to note that all the datasets we use are incomplete. Therefore, our final research dataset is constructed as the intersection of all the aforementioned datasets and transformed into a panel data format. After processing and cleaning, the final dataset consists of 58 observations, covering 73 different countries over the period from 1980 to 2015. The definitions of all datasets are provided in the Variable Descriptions Table.

3 Methods

This study adopts a cross-country least squares regression on panel data as its benchmark method. The specification of this regression will be as follows:

$$y_i = \alpha_0 + \alpha_1 \left(\frac{rem}{GDP}\right)_i + \alpha_2 \left(\frac{rem}{GDP}\right)_i^2 + \beta_1 edu\_13_i + \beta_2 edu\_13_i^2 + \beta_3 edu\_58_i + \beta_4 edu\_58_i^2 + \epsilon_i.$$

In the equation above, y_i is our income inequality indicator, represented by two measures: the standardized Gini coefficient (gini_std), and the difference between the income share of the top 20 percent earners and the bottom 20 percent earners (top20-bottom20). Our variable of interest, which is the share of international remittance in GDP (Remittance_as_percent), is denoted as $\left(\frac{rem}{GDP}\right)_i$. According to previous theoretical and empirical literature on remittances and inequality, an inverted U-shaped relationship is expected (Koechlin and Leon, 2006). Therefore, I include both the linear and quadratic terms of remittances in the regression model. Following this assumption, we expect a positive sign for the linear coefficient α_1, and a negative sign for the quadratic coefficient α_2.

The control variable in this regression is education level, represented by two separate indicators (detailed in the Data section). These variables are used to capture both the general level of educational attainment in a country and the proportion of the population receiving higher education, allowing us to examine their influence on the relationship under study.

The use of quadratic terms in the regression is motivated by the assumption that the relationship between educational expansion and income inequality may vary across different stages of development. In the early phases of expansion, access to education is typically limited to specific groups—such as individuals from higher-income backgrounds, urban residents, or particularly high-performing students. By contrast, when education becomes widely accessible, further expansion may influence inequality in a fundamentally different way. In both low- and high-coverage contexts, marginal changes in educational attainment are unlikely to alter the underlying structure of access. Therefore, the relationship between education and inequality may evolve nonlinearly over the course of development, justifying the inclusion of squared terms in the model.

Time fixed effects are incorporated through the construction of 14 multi-year periods, rather than using yearly fixed effects. This approach is adopted because many individual years—particularly in the earlier part of the dataset—contain too few observations to support reliable year-specific fixed effects. By grouping years into broader periods, each time unit contains at least 20 to 30 observations, thereby ensuring the stability and credibility of the fixed-effects estimates. Additionally, the periods are defined to avoid splitting across major historical or economic events—such as the 1991 dissolution of the Soviet Union and the 2008 global financial crisis—thereby preserving temporal coherence and improving the accuracy of estimation.

The detailed period definitions and corresponding observation counts are shown in the table below. Notably, many periods after the year 2000 are defined at the single-year level. This choice reflects two key considerations. First, these years contain sufficient observations individually, eliminating the need to aggregate them to ensure statistical reliability. Second, single-year periods offer greater temporal precision—particularly important given the accelerated growth of personal international remittances in the post-2000 era, as documented by the World Bank. Where data availability allows, shorter periods are used to better capture changes in remittance dynamics and improve the accuracy of the estimated time effects.

Table 1: Number of Observations by Time Period

Time Period	**Observations**
1980–1990	23
1991–1996	50
1997–2000	56
2001–2003	55
2004	29
2005	31
2006	27
2007	35
2008	36
2009	31
2010	38
2011	39
2012	40
2013–2015	68

4 Results

This section presents the main estimation results. Table 2 reports the OLS estimates based on Equation (1) from the Methods section, excluding economic control variables and time-related factors. Both the linear and squared terms of remittances as a share of GDP are statistically significant, with the squared term being negative. This indicates an inverted U-shaped relationship between remittances and income inequality, consistent across both inequality measures. This finding aligns with previous literature suggesting that remittances may initially increase inequality but reduce it as they become more widespread and accessible.

Turning to the education variables, the coefficient for ISCED 5–8 (higher education) is negative and statistically significant, indicating that greater access to higher education is associated with lower income inequality. In contrast, the linear term for ISCED 1–3 (basic education) is statistically insignificant, suggesting a weaker or more ambiguous relationship. Additionally, the squared terms for both ISCED 1–3 and ISCED 5–8 are not statistically significant, indicating no evidence of a nonlinear association between educational attainment and inequality in the baseline model. These patterns are consistent across both inequality indicators.

While the baseline regressions reveal a statistically significant nonlinear effect of remittances, the relatively modest R-squared values (0.228 and 0.222) suggest that a substantial portion of the variation in inequality remains unexplained. This may be attributed to the lack of controls for economic structure and time trends. Given the cross-country nature of this analysis, it is important to account for macro-level heterogeneity. As discussed in the Methods section, country or region fixed effects are not applicable due to the sparse and uneven distribution of observations. Instead, a set of ten economic control variables is introduced to better capture structural differences across countries. The results are shown in Table 3.

After including economic control variables, the linear term of remittances becomes negative and remains statistically significant, while the squared term turns insignificant. This indicates that the previously observed inverted U-shaped relationship no longer holds once broader economic conditions are taken into account, and that remittances may be linearly associated with lower inequality. For education, ISCED 1–3 becomes significant in both its linear and squared forms, forming an inverted U-shape—suggesting that basic education may initially exacerbate inequality before reducing it as access expands. One possible explanation is that, prior to the inclusion of economic controls, cross-country variation in structural economic conditions may have played a more dominant role in shaping inequality outcomes than education itself—thereby obscuring the independent effect of basic education. The coefficient for ISCED 5–8 remains negative and significant, while its squared term is positive but not statistically significant at conventional levels, suggesting a potential U-shaped relationship. The increases in R-squared and F-statistics confirm that the updated model exhibits stronger explanatory power and a better overall fit.

Table 4 builds upon this model by incorporating time-period fixed effects. The core findings remain robust: the linear effect of remittances remains negative and significant, while the squared term remains insignificant; ISCED 1–3 continues to exhibit an inverted U-shaped pattern; and the linear term for ISCED 5–8 remains negative and significant. Notably, the squared term for ISCED 5–8, which was previously only suggestive, now becomes statistically significant and positive, confirming a U-shaped relationship. This should not be interpreted as a fundamental change in the nature of the relationship, but rather as a clearer identification of a pattern that was previously obscured. One plausible explanation is that the effect of tertiary education on inequality may evolve over time. When time effects are not accounted for, this temporal variation may weaken the estimated nonlinearity. Once time-period fixed effects are introduced, the differences across time are better isolated, making the U-shaped relationship more detectable.

To further assess the robustness of the findings, Tables 4 and 5 implement more parsimonious specifications using a reduced set of economic control variables. Table 5 is based on the same model structure as Table 3, but only retains control variables that are statistically significant. The results show that the direction of the remittance and education variables remains consistent with previous models, with only minor differences in significance. The R-squared values decrease slightly, while the F-statistics increase notably, indicating that the simplified model is more efficient and statistically stable. Although these results suggest room for optimizing the selection of control variables, the consistency of the findings across specifications reinforces the credibility and robustness of the core conclusions.

Table 6 extends this simplified model by incorporating time-period fixed effects. The results closely mirror those of Table 4: the remittance variable remains negative and significant, education variables retain their direction and significance, and the squared term of ISCED 5–8 continues to be significant—further confirming the presence of a U-shaped relationship under a streamlined model. These findings demonstrate that the core conclusions do not depend on any particular set of control variables and remain structurally consistent across different model specifications.

In order to visualize and further examine the conclusions drawn from the regression results, we generate residual plots. For Remittances/GDP and the two education-related variables, we estimate reduced models that exclude the variable of interest, compute the residuals, and then plot their relationship with the excluded variable. This approach allows us to assess whether the residuals are systematically associated with the omitted variable—and, more importantly, whether the functional form observed in the main regression (such as a linear, inverted U-shaped, or U-shaped relationship) is visually supported.

To reduce visual clutter due to the large number of observations, we employ binned scatter plots. Each graph overlays both a linear and a quadratic fitted line: the red solid line represents a linear fit, and the green dashed line represents a quadratic fit. These visualizations are based on regression models that include all economic controls and time-period fixed effects, consistent with the specification in Table 4.

Since the regression results are largely consistent across the two inequality measures (the Gini index and the top 20% minus bottom 20% income share difference), we focus on the Gini index as the dependent variable in this section.

Figures 1 to 3 visualize the relationships between the omitted variables and the residuals from the reduced models, focusing respectively on Remittances/GDP, basic education coverage (ISCED 1–3), and higher education coverage (ISCED 5–8). In Figure 1, the red and green fitted lines nearly overlap, consistent with the regression finding that the squared term for remittances is small and statistically insignificant. This supports the conclusion that the relationship between remittances and inequality is monotonic and negative.

By contrast, Figures 2 and 3 display visible differences between the linear and quadratic fits. These patterns visually reinforce the nonlinear relationships identified in the main regressions: an inverted U-shaped relationship for basic education and a U-shaped relationship for higher education.

Table 2: Effect of Remittances on Income Inequality without Controlling for Economic Variables and Fixed Effects

	Standardized Gini	**Top20 − Bottom20**
Remittances/GDP	0.315*	0.270**
	(0.156)	(0.104)
(Remit./GDP)^2	−0.014*	−0.010*
	(0.006)	(0.004)
ISCED 1–3	2.693	1.749
	(2.255)	(1.497)
ISCED 1–3^2	−0.151	−0.102$^+$
	(0.093)	(0.062)
ISCED 5–8	−5.202**	−2.936**
	(1.708)	(1.134)
ISCED 5–8^2	0.443	0.243
	(0.321)	(0.213)
Constant	36.111**	29.393***
	(12.996)	(8.629)
Economic Controls	No	No
Time Period FE	No	No
Observations	594	594
R-squared	0.228	0.222
F statistic	27.071	26.188

Note: Standard errors in parentheses. $^+p < 0.1$, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 3: Effect of Remittances on Income Inequality with Economic Controls (No Fixed Effects)

	Standardized Gini	**Top20 − Bottom20**
Remittances/GDP	-0.331^{**}	-0.172^{*}
	(0.119)	(0.076)
(Remit./GDP)^2	0.005	0.003
	(0.004)	(0.003)
ISCED 1–3	6.907^{***}	4.557^{***}
	(1.589)	(1.018)
ISCED 1–3^2	-0.245^{***}	-0.162^{***}
	(0.065)	(0.042)
ISCED 5–8	-4.116^{***}	-2.126^{**}
	(1.211)	(0.775)
ISCED 5–8^2	0.506^{*}	0.280^{+}
	(0.226)	(0.144)
Constant	21.686^{*}	19.327^{***}
	(9.087)	(5.820)
Economic Controls	All	All
Time Period FE	No	No
Observations	594	594
R-squared	0.640	0.663
F statistic	64.344	71.073

Note: Standard errors in parentheses. $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Included economic controls: Real GDP, GDP per capita, Total investment, Gross national savings, Inflation, Unemployment rate, General government total expenditure, General government net lending borrowing, Current account balance.

Table 4: Effect of Remittances on Income Inequality with Economic Controls and Time Fixed Effects

	Standardized Gini	**Top20 − Bottom20**
Remittances/GDP	-0.504^{*}	-0.273^{*}
	(0.171)	(0.117)
$(\text{Remit./GDP})^2$	0.009	0.006
	(0.006)	(0.004)
ISCED 1–3	7.709^{***}	5.099^{***}
	(1.622)	(1.151)
ISCED $1\text{–}3^2$	-0.277^{***}	-0.185^{***}
	(0.060)	(0.044)
ISCED 5–8	-6.037^{**}	-3.244^{**}
	(1.456)	(0.918)
ISCED $5\text{–}8^2$	0.709^{**}	0.404^{**}
	(0.214)	(0.133)
Economic Controls	All	All
Time Period FE	Yes	Yes
Observations	594	594
R-squared	0.679	0.695
Within R-squared	0.656	0.673
Std. Errors	by: period	by: period

Note: Standard errors in parentheses, clustered by time period. $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 5: Effect of Remittances on Income Inequality with Full Economic Controls (No Fixed Effects)

	Standardized Gini	**Top20 − Bottom20**
Remittances/GDP	-0.277^{*}	-0.136^{+}
	(0.118)	(0.076)
$(\text{Remit./GDP})^2$	0.003	0.002
	(0.004)	(0.003)
ISCED 1–3	5.827^{***}	3.921^{***}
	(1.590)	(1.016)
ISCED $1\text{–}3^2$	-0.199^{**}	-0.135^{**}
	(0.065)	(0.042)
ISCED 5–8	-3.281^{**}	-1.602^{*}
	(1.206)	(0.770)
ISCED $5\text{–}8^2$	0.359	0.187
	(0.225)	(0.144)
Constant	23.221^{*}	20.350^{***}
	(9.166)	(5.857)
Time Fixed Effects	No	No
Economic Controls	Partial	Partial
Observations	594	594
R-squared	0.625	0.650
F statistic	82.724	92.210
RMSE	5.32	3.40

Note: Standard errors in parentheses. $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Included economic controls: Real GDP, GDP per capita, Inflation, General government total expenditure, General government net lending borrowing.

Table 6: Effect of Remittances on Income Inequality with Partial Economic Controls and Time Fixed Effects

	Standardized Gini	**Top20 − Bottom20**
Remittances/GDP	-0.448^{*}	-0.237^{+}
	(0.158)	(0.110)
$(\text{Remit./GDP})^2$	0.007	0.004
	(0.005)	(0.004)
ISCED 1–3	6.737^{**}	4.548^{**}
	(1.671)	(1.169)
ISCED 1–3^2	-0.239^{**}	-0.163^{**}
	(0.063)	(0.045)
ISCED 5–8	-5.120^{***}	-2.689^{**}
	(1.191)	(0.768)
ISCED 5–8^2	0.566^{**}	0.318^{*}
	(0.185)	(0.117)
Time Fixed Effects	Yes	Yes
Economic Controls	Partial	Partial
Observations	594	594
R-squared	0.663	0.683
Within R-squared	0.640	0.660
Std. Errors	by: period	by: period

Note: Standard errors in parentheses, clustered by time period. $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Included economic controls: Real GDP, GDP per capita, Inflation, General government total expenditure, General government net lending borrowing.

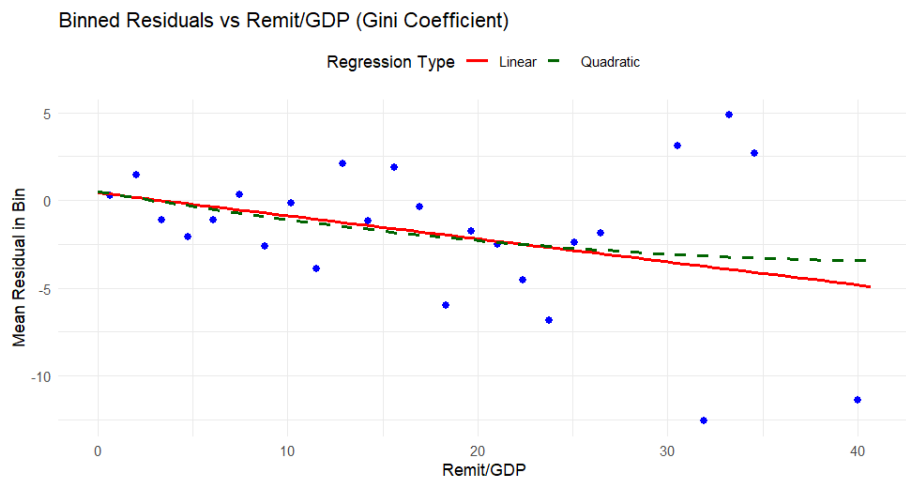

Figure 1: Binned residuals vs Remittances as % of GDP

5 Discussion and Conclusion

The findings of my study differ notably from those of Koechlin and León (2006), who identify an inverted U-shaped relationship between international remittances and income inequality. In contrast, I find a consistently negative and statistically significant association, suggesting that higher remittance dependence corresponds to lower levels of income inequality across the full range of observations.

This divergence likely stems from differences in empirical strategy. While both studies include macroeconomic controls, Koechlin and León use only GDP growth and money supply (M3). In contrast, I incorporate a broader set of macroeconomic indicators, many of which show significant effects. Regarding education, their model includes only secondary schooling. I, however, distinguish between basic education (ISCED 1–3) and higher education (ISCED 5–8), and I include squared terms to capture potential nonlinear relationships. This approach enables a more nuanced understanding of how education levels shape inequality.

Despite this, my model omits certain elements included in their framework. For instance, they use the Polity index to account for political structure, which can influence both remittance flows and inequality through institutional and monetary channels. They also address potential endogeneity by using the cost of obtaining a passport as an instrumental variable—an approach I do not apply here. These differences in variable choices and estimation techniques may help explain the contrasting results. Future research could explore which specific factors are responsible for these discrepancies.

I also uncover important nonlinearities in how education coverage affects

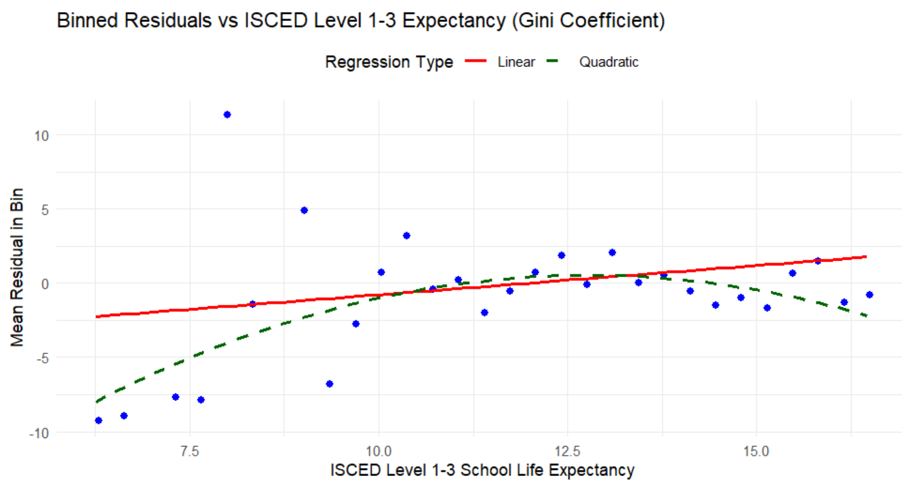

Figure 2: Binned residuals vs ISCED Level 1–3 School Life Expectancy

inequality, with distinct patterns for basic and higher education. In the early stages of expansion, basic education tends to benefit urban or higher-income areas that gain preferential access to educational resources, potentially increasing inequality. As coverage broadens and reaches lower-income populations, however, inequality tends to decline—producing the observed inverted U-shaped pattern. The relationship between higher education and inequality appears more complex. Early expansion may promote upward mobility and reduce inequality, but as access becomes more widespread, stratification increases. Privileged groups are more likely to dominate high-quality institutions, which can erode or even reverse the equalizing effect of higher education, leading to a U-shaped relationship. Although not the central focus of this study, these results highlight the importance of accounting for heterogeneity within different levels of education when analyzing inequality outcomes.

Finally, my study faces some limitations. The panel dataset used here lacks full temporal and geographic balance. Although it includes 594 observations, most data points are concentrated in more recent years—particularly after 2000—and in high-income countries. In contrast, earlier periods and low-income regions are underrepresented. This imbalance may introduce selection bias and limits the generalizability of the findings. As such, the estimated effects likely reflect dynamics in modern, high-income economies more than in lower-income or earlier-stage contexts.

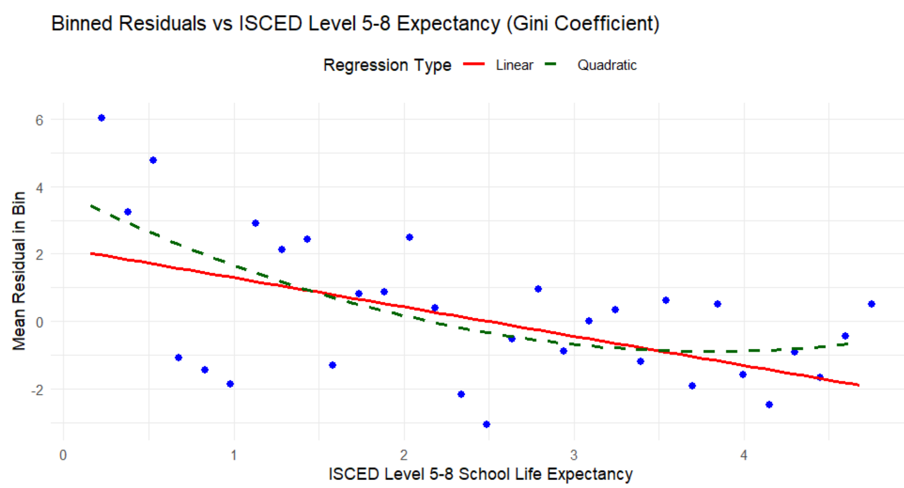

Figure 3: Binned residuals vs ISCED Level 5–8 School Life Expectancy