MASTER'S THESIS

Beyond the Tipping Point: When Financial Institutional Depth Transforms Remittances from Consumption Buffers to Poverty Reduction Catalyst

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ABSTRACT

Remittances, money transfers from migrant workers to their origin countries, have become a dominant external finance source for many developing economies, often exceeding foreign direct investment inflows (FDI) and official development assistance (ODA). While remittances are often associated with short-term welfare gains through consumption smoothing, their role in sustained poverty reduction remains contingent. This study investigates whether such longer-term impacts depend on the level of financial institutional development. Grounded in absorptive capacity and financial complementarity theory, it argues that remittances contribute meaningfully to structural poverty reduction only after a country's financial system surpasses a critical development threshold.

Using panel data from 96 developing countries (2002-2021), the study applies fixed-effects, instrumental variable (IV), and dynamic threshold error correction models (TECM). Domestic credit to the private sector by banks (% of GDP) proxies financial institutional depth and serves as the threshold variable. A binding threshold is identified at approximately 20.26% of GDP, above which remittances have significantly stronger poverty-reducing effects. This inflection point marks the financial readiness needed to transform remittances from consumption flows into financial development capital.

Mechanism testing supports this interpretation: in high-depth regimes, remittances are positively associated with increased gross savings (% of GNI), while in low-depth regimes, they do not, suggesting a continued role in short-term consumption smoothing. A squared remittance term confirms diminishing marginal returns. Instrumental Variable (IV) estimates reinforce the plausibility of financial mediation, even if strict exogeneity is not claimed.

The findings reposition financial development not as a linear moderator but as a structural precondition for effective remittance absorption. They offer policy relevance for SDG 1 (No Poverty), SDG 10.c (Remittance Cost Reduction), and SDG 8.10 (Financial Institution Strengthening). Robustness checks using non-monetary poverty indicators such as undernourishment and electricity access confirm the threshold effect, underscoring the systemic role of financial institutions in unlocking the full developmental potential of remittance flows.

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CHAPTER 1
INTRODUCTION

In 2024, the World Bank reported $685 billion in remittance flows to low and middle-income countries (LMICs), a figure surpassing both foreign direct investment inflows and official development assistance (ODA) (World Bank, 2024). Remittances often help families meet essential needs, especially during economic shocks. They are widely seen as a buffer that supports household consumption and access to basic services (Giuliano & Ruiz-Arranz, 2009). Yet, a persistent puzzle remains as to why some remittance-receiving countries experience rapid poverty reduction while others stagnate, despite comparable inflow volumes. As shown in Figure 1, the disparity among remittance-receiving countries suggests that remittances do not uniformly lead to poverty reduction; rather, their effectiveness appears contingent on country-specific financial conditions.

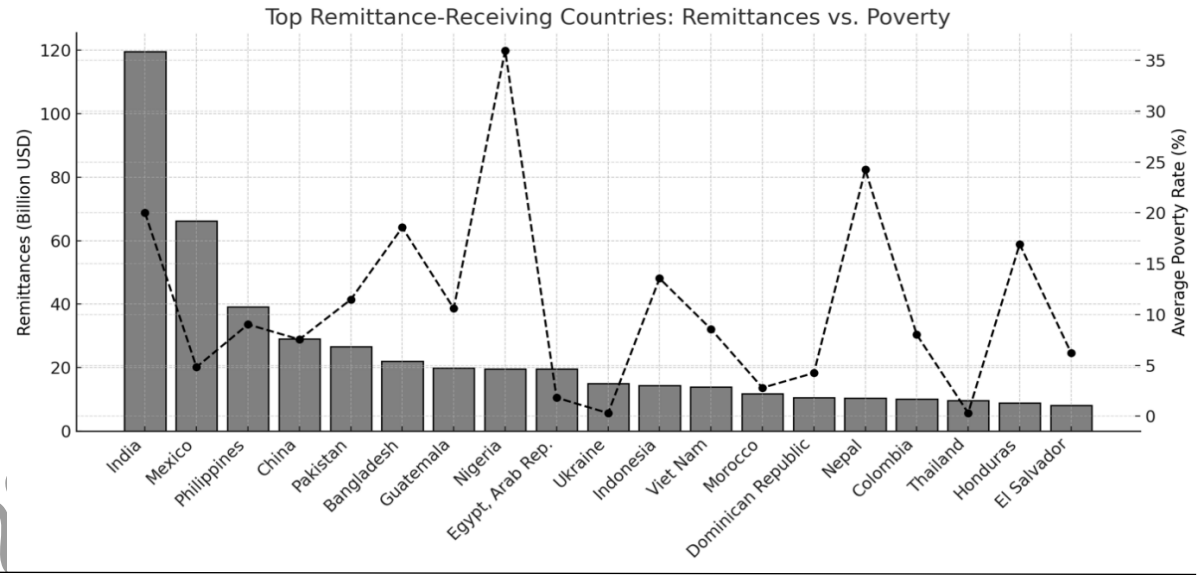

Figure 1. 1 Average Poverty Rates and Remittance Inflows (% of GDP) by Countries, Author's calculation using World Bank data (2025).

Financial development may be one such condition. In some contexts, remittances serve as substitutes for missing financial services; in others, they complement existing systems by supporting savings, credit access, and productive investment. However, most existing studies

treat it either as a linear control or a background condition, rather than a structural factor. This study departs from that view, hypothesizing that remittances support basic consumption and subsistence needs in low-FID regimes, but only in high-FID regimes do they catalyze structural poverty reduction, particularly through savings behavior. This transformation occurs as households gradually shift from consumption to savings and investment behavior once financial environments improve.

Using a panel of 96 developing countries, the study tests the following questions: (1) Is there a threshold level of financial institutional development beyond which the poverty-reducing effect of remittances shifts structurally or changes sign? (2) How does the marginal effect of remittances differ in countries below vs. above this threshold? (3) Do remittance effects transition from consumption to structural accumulation only after surpassing a financial threshold, as evidenced through savings behavior? (4) Does this regime-dependent pattern persist when poverty is measured using structural and social indicators such as access to electricity and child undernourishment?

By combining financial institutional theory, threshold modelling, short and long-run dynamics, this analysis offers both methodological innovation and policy-relevant insight on the evolving paradigm in the nonlinear effects of remittances-financial development, and its effects on poverty reduction.

The remainder of this thesis is organized as follows: Chapter 2 reviews the related literature, presenting the key theoretical perspective and empirical findings that have shaped the remittance, financial development, and poverty debate. Chapter 3 outlines the methodological approach and data sources, and descriptive analysis. Chapter 4 presents and interprets the empirical results. Finally, chapter 5 discusses their broader implications and offers concluding reflections on theory and policy.

CHAPTER 2
RELATED LITERATURE

This chapter provides a structured synthesis of the theoretical and empirical literature relevant to the intersection of remittances, financial development, and poverty. As remittance inflows continue to rise across developing economies, serving as a vital source of household income and stability, it becomes increasingly important to determine the financial conditions under which their poverty-reducing effects are either transitory or amplified. This chapter also establishes the conceptual foundations for this paper, situating it within current research and delineating the empirical and theoretical gaps it seeks to address.

2.1 Theory: Foundations of Remittance-Finance-Poverty Nexus

Historically, remittances have been believed to reduce poverty directly by augmenting household income and smoothing consumption. This view, often referred to as the substitution hypothesis, posits that remittances serve as informal alternatives to missing or inefficient formal financial services. In financially underdeveloped contexts, remittances effectively replace credit, savings, or insurance mechanisms that are otherwise inaccessible to low-income households (R. H. Adams & Page, 2005; Giuliano & Ruiz-Arranz, 2009). This view, rooted in the New Economics of Labor Migration (NELM), conceptualizes remittances as part of a household's strategy to mitigate market failures. However, this theory emphasizes the lack of ripple effects of these transfers on long-term development, as they substitute rather than complement to financial institutional growth (Barajas et al., 2009.)

As financial systems in developing countries began to expand, another body of literature emerged as the complementarity hypothesis. It posits that remittances are more effective when paired with robust financial development. In this framework, financial institutions facilitate the productive use of remittances in lowering transaction costs, enabling savings, and creating

credit multipliers (Aggarwal et al., 2011). The same remittance inflows may lead to productive investment in one context and consumption in another, depending on the accessibility and efficiency of financial intermediaries. Proponents of this hypothesis show that remittances significantly increase deposits and credit only in countries with more developed financial systems. It further states that financial infrastructure is a necessary channel for remittance transmission into productive investment and income smoothing. These studies, however, do not specify the rate at which the degree of financial development mutes or amplifies the effects of remittances in remittance-receiving countries.

Because of the empirical gaps presented by the two contending hypotheses above, recent developments in theory introduced a nonlinear perspective, suggesting that the poverty-reducing effect of remittances may depend on whether financial development has surpassed a critical threshold. Below it, remittances may have neutral or even adverse effects, such as fostering dependency, moral hazard, and inequality (Chami et al.,2005). Above it, financial system can transform remittance inflows into capital for development. This idea fits with broader theories in development, like the financial Kuznets Curve (Greenwood & Jovanovic, 1990), which shows that financial growth doesn't always reduce inequality right away. That is, the same remittance inflow may yield different poverty outcomes depending on institutional, financial, and social maturity. This nonlinear relationship is best understood through the lens of absorptive capacity, elaborated in the next section.

2.2 Concept: Threshold Effects and the Role of Absorptive Capacity

Rather than treating remittances as uniformly effective, this study builds on the premise that their impact is conditional on the receiving country's structural capacity to absorb and channel inflows productively. This logic draws on the broader concept of absorptive capacity in development economics. Absorptive Capacity refers to a system's ability to internalize

external inputs and transform them into sustained developmental outcomes (Cohen & Levinthal, 1990).

While this concept is a well-established theme in aid and FDI literature (Alfaro et al., 2004; Cohen & Levinthal, 1990; Guillaumont & Chauvet, 2001), its usage in remittance-related studies is more limited and often implicit. A few studies, including (Chami et al., 2005) and (Barajas et al., 2009) do mention the term directly, typically in discussions of macroeconomic constraints or remittance ineffectiveness in low-capacity environments. However, most of the empirical literature refers to its components, particularly financial development, as mediating mechanisms without labeling them under the unifying construct of absorptive capacity. For instance, Giuliano & Ruiz-Arranz (2009) argue that remittances stimulate growth only when financial systems are developed, while Bettin & Zazzaro (2012) highlight the role of banking depth and quality. Similarly, Aggarwal et al., (2011) and Fajnzylber et al., (2007) emphasize financial infrastructure but do not explicitly invoke absorptive capacity.

This study advances the conversation by conceptualizing and formalizing the mechanism of absorptive capacity. While it does not introduce a new theory, it synthesizes and formalizes scattered insights into a threshold-based framework. Specifically, absorptive capacity is conceptualized in this study across three dimensions: First, institutional absorptive capacity. It refers to the legal-regulatory infrastructure, banking supervision, macroeconomic stability, and property rights that ensure remittances flow through secure, formal channels and incentivize productive use (Acemoglu et al., 2004; Aggarwal et al., 2011). Second is financial absorptive capacity that involves the reach, efficiency, and depth of the financial system, including remittance-linked savings products, mobile banking, and credit intermediation mechanisms (Beck et al., 2007; Bettin & Zazzaro, 2012.; Giuliano & Ruiz-Arranz, 2009). The third one is social absorptive capacity that encompasses household-level traits such as financial literacy, trust in banks, and market access, which shape how remittances are allocated post-receipt

(Demirgüç-Kunt & Klapper, 2012; Karlan et al., 2014). While these components have been discussed individually in past studies, this paper synthesizes them into a unified framework and explicitly formalizes their interaction as a threshold condition for the developmental transformation of remittances. While the framework covers institutional, financial, and social dimensions, only financial absorptive capacity is empirically tested in this study due to cross-country data limitations and its theorized primacy in enabling remittance intermediation.

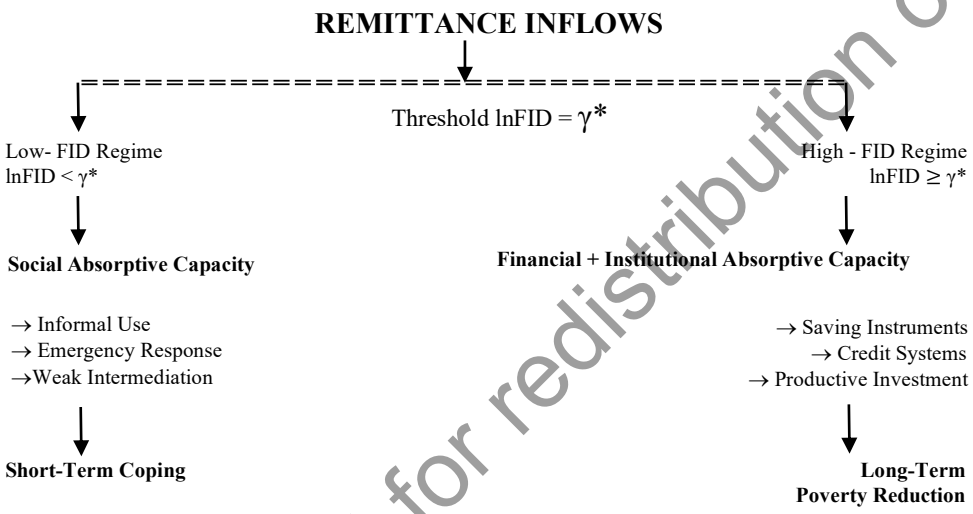

Figure 2. 1 Conceptual Transformation of Remittance Utility across Financial Development Regimes via Absorption Capacity channels.

Figure 2.1 illustrates the framework. At low levels of financial institutional development, remittances tend to support basic consumption and emergency coping, with little transformation into investment or long-term poverty reduction. As absorptive capacity improves, particularly in its financial dimension, remittances shift toward catalyzing savings and capital formation; thus, the observed impact follows a threshold effect rather than a linear path.

While Figure 2.1 positions social absorptive capacity within the low-FID regime, this does not imply that social factors exclusively operate at low financial depth or that they inherently constrain long-term transformation. Rather, the figure reflects that in low-FID environments, household-level traits, such as financial literacy, trust in institutions, and risk preferences, often

dominate the remittance decision-making process due to the absence of institutional and financial infrastructure. In such contexts, even where remittances are received, their allocation remains shaped by informal mechanisms and short-term coping needs. In contrast, in high-FID regimes, institutional and financial absorptive capacities become the dominant channels through which remittances are transformed into savings and productive investment. Social absorptive capacity remains relevant in both regimes but is more binding in low-capacity settings where formal intermediation is weak or inaccessible.

This conceptual framework anchors the study's empirical strategy, which seeks to identify the financial threshold at which remittances transition from consumption buffers to drivers of structural poverty reduction.

2.3 Empirics: Evidence of Heterogeneity and Nonlinearity

Evidence for the substitution hypothesis is widespread in contexts with weak financial systems. Adams & Page (2005) found that a 10% increase in remittances per capita leads to a 3.5% decline in the share of people living in poverty across a large set of countries. However, subsequent research revealed that this effect is not uniform. For instance, Anyanwu & Erhijakpor, (2010) and Gupta et al., (2009) showed the strong poverty-reducing effects of remittances in Sub-Saharan Africa but cautioned that these effects diminish where financial systems are weak. This evidence in the substitution hypothesis and these theoretical assumptions fail to consider the growing financial institutions in these countries.

Then, empirical literature records a shift where remittances begin to flow through formal channels, increasing savings and investment, supporting the complementarity hypothesis. Aggarwal et al., (2011) show that remittances significantly increase deposits and credit only in countries with more developed financial systems. Bettin & Zazzaro (2012) and Fromentin (2018) similarly find that financial infrastructure is a necessary channel for remittance

transmission into productive investment and income smoothing. These findings suggest that financial development not only mediates but also amplifies the impact of remittances.

Because of the evolving mechanism of institutional and financial literature, recent studies provide empirical support for nonlinear dynamics and absorptive capacity mechanisms. Bangake & Eggoh (2020) used a system GMM and Panel Threshold Regression (PTR) approach for developing countries from 1985 to 2015 in identifying the critical financial development threshold. The study found that financial development should surpass the threshold between 28.7% and 46.3% of GDP, beyond which remittances shift from neutral to growth effects. This confirms both complementary and conditional threshold hypotheses. Similarly, Ofori et al., (2022) show that remittances promote inclusive growth only when financial institutional depth exceeds 22.3 % of GDP. Their dynamic System GMM model suggests remittances are neutral or inequality-worsening until financial systems reach critical efficiency and depth thresholds. Another study by Lartey (2008) provides robust evidence that rising remittance inflows contribute to Dutch Disease symptoms in developing countries. Specifically, the study finds that increases in remittance lead to real exchange rate appreciation and a reallocation of resources away from tradable sectors, while manufacturing and agriculture, toward services. These effects are significantly more pronounced under fixed exchange rate regimes, proposing structural adjustment pressures as economies adapt to persistent remittance flows. This suggests periods of adjustment as economies reorient around remittance flows.

2.4 Mechanisms: Financial Frictions and Behavioral Channels

The existing empirical literature, such as above, often treats financial development as a unified concept. In practice, however, it comprises two distinct components: financial institutions (such as banks, credit unions, and microfinance) and financial markets (such as

equities, bonds, and capital accounts). These components operate through separate channels and affect different economic agents. Prior studies, including Beck et al., (2007) using a cross-country panel from 1960 to 2005, found that financial institutions disproportionately benefit poor and underserved populations through broader access, while Aggarwal et al., (2011) emphasized how remittances amplify this effect in banked economies. As a result, markets exert their effects through aggregate capital formation rather than through household-level inclusion.

This study explicitly differentiates between the two financial structures to avoid conflating their effects. It disaggregates financial development into financial institutions and financial markets to test whether one channel exhibits a stronger moderating effect on remittance absorption. This structural disaggregation allows for a more accurate assessment of which financial pathways support remittance effectiveness in poverty alleviation.

A second channel shaping remittance effectiveness is the behavioral and financial context in which households operate. In settings with low financial depth, informal intermediaries such as ROSCA (Rotating Savings and Credit Associations) and Hawala networks often substitute for formal financial systems. These informal arrangements provide immediate liquidity but lack scalability, regulation, and long-term capital formation capacity. Households operating under such systems often use remittances for consumption or emergency spending, with limited conversion into savings or investment. The shift from consumption-driven to investment-driven remittance use requires formal infrastructure, trust in financial products, and minimal transaction barriers, conditions typically present only in systems with adequate financial depth.

Moreover, financial deepening may exhibit transitional frictions. As financial systems expand, formalization may expose previously informal incomes to taxation (La Porta & Shleifer, 2014), households may face learning costs in navigating formal institutions (Beck et al., 2007), and benefits may initially accrue to already-included populations, widening

inequality before convergence occurs (Honohan, 2008). These transitional dynamics are especially relevant for understanding early-stage financial expansion in lower-FID regimes.

These financial and behavioral frictions reinforce the earlier claim that financial maturity shapes the development impact of remittances. Rather than assume convergence across countries, this study disaggregates financial structures to identify which specific channels, household-serving institutions vs. market-based intermediaries, most effectively mediate remittance absorption.

2.5 Methodology: Dynamic Structures and Threshold Estimation Approaches

While recent studies confirm that financial development conditions the effectiveness of remittances, few identify the short and long-run dynamics simultaneously or specify the role of financial system components. This study incorporates ECM-based threshold framework to provide sharper identification of regime shifts and clearer policy implications for financial sector strengthening in remittance-dependent economies.

However, any empirical attempt to evaluate this relationship must first confront several structural and econometric challenges. First, there is growing evidence of bidirectional causality between remittances and financial development. While remittances can deepen financial access, the state of financial infrastructure also affects the cost, frequency, and formalization of remittance flows as shown in study by (Fromentin, 2018) in the context of Latin America and the Caribbean (2000 to 2015). Second, remittances may undermine credit market expansion by relaxing household borrowing needs or by shifting banks' liquidity preferences away from risk-bearing loans. Third, remittance flows often move through informal channels in financially underdeveloped countries, resulting in underreported volumes and a disconnect between remittances and the formal credit system. These features generate

potential endogeneity, measurement error, and financial heterogeneity, all of which standard panel regression fails to capture.

To address these challenges, this study adopts a threshold cointegration framework that explicitly tests whether the poverty-reducing effects of remittances shift discontinuously at a critical degree of financial development. This empirical design incorporates dynamic structures and lags, allowing for delayed responses and mitigating simultaneity. Moreover, regime splitting based on financial institutional thresholds enables a structural distinction between contexts where financial systems amplify or mute remittances' effects. Finally, instrumental variables are carefully selected to ensure exogeneity of remittance variations, borrowing methodological insight from recent regime-stage literature such as R. H. Jr. Adams & Cuecuecha (2010). The model divides countries into distinct regimes based on the observed threshold: whether financial institutional depth exceeds an estimated threshold (upper regime opposite to lower regime) and estimates regime-specific relationships between remittance and poverty. This approach not only isolates the financial conditions under which remittances are effective but also embeds structural nonlinearity and long-run adjustment dynamics.

2.6 Controls: Structural Covariates and Theoretical Expectations

To isolate the conditional effects of remittances and financial development on poverty, several structural and institutional controls are included in the empirical models. These include GDP per capita (expected negative sign), trade openness (ambiguous effect depending on institutional and financial quality, Control of Corruption (expected negative relationship with poverty), and FDI inflows (ambiguous). These variables are grounded in the development literature and help capture non-remittance drivers of poverty variation across countries and time.

These theoretical foundations, empirical findings, and econometric challenges justify the empirical strategy adopted in the next chapter, which models remittance-poverty interactions under dynamic, nonlinear, and threshold-dependent conditions.

CHAPTER 3
METHODOLOGY & MODELS

This chapter outlines the empirical methodology used to evaluate the conditional effects of remittances on poverty reduction across varying levels of financial institutional development. It presents the dataset, key variables, and model specifications, followed by threshold estimation procedures and robustness checks to ensure internal validity.

3.1 Data Overview and Descriptive Patterns

The estimations use a panel of 96 developing countries from 2002 to 2021. Table 3.1 presents a summary of the main variable definitions, sources, and descriptive statistics.

TABLE 3.1
MAIN VARIABLES DEFINITION, SOURCE, AND DESCRIPTIVE ANALYSIS

Variable	Short Description	Sources	Mean	SD	Min	Max
ln(POV)	Pov. headcount ratio at $2.15/day	WDI, WB	0.89	2.81	-6.91	4.52
ln(REM)	Rem. Inflows received (% of GDP)	WDI, WB	0.37	2.6	-6.91	3.91
ln(FID)	Dom. Credit by banks (% of GDP)	IMF	3.1	0.91	-6.91	5.21
ln(FMD)	Financial Market Depth Index	IMF	-3.85	2.02	-6.91	-0.05
ln(GDP)	GDP per capita (con. 2015, USD)	WDI, WB	7.75	0.95	5.52	9.55
ln(TRADE)	Trade (% of GDP)	WDI, WB	4.22	0.46	1.42	5.86
ln(CC)	Control of Corruption: Estimate	WDI, WB	-0.56	0.61	-1.94	1.62
ln(FDI)	FDI inflows (% of GDP)	WDI, WB	1.64	1.14	-4.31	5.33

Note: WDI stands for World Development Indicators; WB means World Bank ; IMF is International Monetary FundAll variables except CC (Control of Corruption) are log-transformed to reduce skewness and improve interpretability. The inverse hyperbolic sine (HIS) transformation, applied to FDI, handles zeros and negative values while keeping the results comparable to log-linear models. Unlike standard logarithms, HIS does not require strictly positive values, however, its behavior can diverge significantly from logs at lower magnitudes (Bellemare & Wichman, 2020). This method is also increasingly used in development and migration studies, where variables with many zeros are common. See Appendix B for full variable construction and squared terms.

Absorptive capacity, as defined earlier, comprises institutional, financial, and social dimensions. This study empirically operationalizes only the financial dimension, proxied by domestic credit to the private sector by banks (% of GDP), due to data constraints and its central role in enabling remittance intermediation through formal savings, credit access, and liquidity mechanisms.

The variable (lnFID) captures the extent to which banks allocate credit to private agents (excluding central banks and non-bank credits) and reflects the economy's capacity to absorb

and intermediate financial inflows productively. It allows a sharper distinction between contexts where remittances remain outside the formal system and those where they contribute to long-term development. Domestic credit to the private sector by banks (% of GDP), henceforth referred to as lnFID, is selected as the threshold variable, offering both empirical tractability and theoretical coherence, particularly in a long-run dynamic panel context.

The summary statistics in Table 3.1 further reflect heterogeneity across developing economies, aligning with theoretical expectations outlined in the previous chapters. On average, countries show moderate to high poverty rates (lnPOV), with wide dispersion. The variance in lnREM highlights divergent reliance on remittances, reflecting structural migration patterns, financial, and institutional differences, patterns also noted by Acosta et al., (2009), who linked remittances to Dutch disease dynamics, and Maimbo & Ratha (2005), who emphasized how financial constraints shape remittance channeling. The financial variables, which were modeled using two distinct constructs to acknowledge the distinctive impacts of their dimensions, show asymmetries. lnFID (financial Institution) is more centralized, while lnFMD (financial markets) exhibits lower means and higher variability, consistent with dual-track financial development in studies by Beck et al., (2007).

3.2 Diagnostic Correlation Analysis

Table 3.2 presents pairwise correlations among key variables. The strong negative correlation between poverty (lnPOV) and gross domestic product (lnGDP) of -0.46 aligns with the well-documented inverse relationship between income levels and poverty (Dollar & Kraay, 2000). The correlation between remittances and poverty (lnREM vs. lnPOV) is weakly positive at 0.03, while the squared term lnREMsq shows a slightly negative association (-0.01). Although modest, this reversal in sign provides a preliminary signal of potential nonlinearity

in the remittance-poverty relationship, supporting the rationale for including higher-order terms and adopting a threshold estimation strategy.

TABLE 3. 2
PAIRWISE CORRELATION MATRIX

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
(1) lnPOV	1.00										
(2) lnREM	0.03	1.00									
(3) lnREMsq	-0.01	-0.38	1.00								
(4) lnFID	-0.33	0.09	-0.03	1.00							
(5) lnFIDsq	0.01	-0.03	-0.02	-0.41	1.00						
(6) lnFMD	-0.19	-0.31	-0.16	0.49	-0.03	1.00					
(7) lnFMDsq	-0.12	-0.22	-0.11	0.28	0.15	0.41	1.00				
(8) lnGDP	-0.46	-0.24	-0.14	0.48	-0.07	0.46	0.12	1.00			
(9) lnTRADE	-0.29	0.32	0.01	0.18	-0.03	-0.15	-0.14	-0.02	1.00		
(10) CC	-0.06	-0.05	-0.18	0.36	-0.03	0.22	0.09	0.41	-0.02	1.00	
(11) ihsFDI	-0.07	0.16	-0.07	0.03	-0.04	-0.01	-0.08	0.04	0.41	0.12	1.00

Note: All squared terms (e.g., lnREMsq, lnFIDsq, lnFMDsq) are derived from their respective base variables. To mitigate multicollinearity in subsequent estimations, these components are mean-centered prior to inclusion in the correlation matrix and estimation models. Additional variables used in robustness checks and their extended statistics are provided in Appendix Table C. Variance Inflation Factors is in Appendix D.

The financial development indicators exhibit patterns that align with structural expectations. Financial institutional depth (lnFID) and financial market depth (lnFMD) are moderately positively correlated (0.49), and both show moderate positive associations with lnGDP (0.48 and 0.46, respectively), reflecting the co-evolution of financial sector development and income levels. Squared terms such as lnFIDsq and lnFMDsq maintain moderate associations with their base variables but remain below levels that would trigger serious multicollinearity concerns. To note, squared terms were mean-centered before calculation, further reducing the risk of artificial inflation in standard errors during estimation.

Trade openness (lnTRADE) correlates positively with remittances (0.32) and with foreign direct investment (0.41), suggesting that trade and capital flows may co-move with labor migration and remittance patterns. Control of corruption (CC) shows moderate positive associations with lnFID (0.36) and lnGDP (0.41), consistent with literature linking financial quality to financial and economic development.

Importantly, none of the pairwise correlations exceed conventional thresholds (above 0.80) that would raise multicollinearity concerns.

3.3 Model Construction and Estimation Strategy

This study's empirical design proceeds in three systematic phases. First, a series of preliminary regressions (6 models) are estimated to diagnose structural patterns, endogeneity, and nonlinearities in the remittance-poverty relationship. Second, a formal threshold modeling strategy is employed to identify whether the effects of remittances shift structurally across levels of financial institutional development. Third, regime-specific estimations are performed to test whether remittance effects differ across high- and low-financial contexts, followed by complementary diagnostics focused on financial accumulation. Each phase contributes a distinct layer of insight while preserving internal coherence across specifications.

3.3.1 Preliminary Regressions and Endogeneity Considerations

The first step involves estimating a series of fixed effects (FE) and instrumental variable (IV) panel regressions using six model specifications. These regressions aim not to produce causal inference but to reveal underlying interactions that justify regime-based estimation. Specifically, they aim: (1) to detect nonlinearity in remittance effects, (2) to assess interaction patterns with financial development, (3) to provide baseline coefficients for comparison, and (4) to assess the possible endogeneity of remittance inflows. The core specification is given by

$$lnPOV_{it} = \alpha_i + \beta_1 \cdot lnREM_{it} + \beta_2 \cdot lnFID_{it} + \beta_3 \cdot lnFMD_{it} + \beta_4 \cdot X_{it} + \varepsilon_{it} \quad (1)$$

Variants include nonlinear terms (lnREMsq, lnFIDsq), interaction terms (lnREM x lnFID), and different financial development measures. All equations and specifications are provided in Appendix E.

To address endogeneity common in remittance studies, a Bartik-style instrument was constructed exploiting exogenous variations in destination-country conditions and satisfying both relevance and exclusion restrictions. It follows the structure introduced by Timothy Bartik (1991), where local exposure to external shocks is constructed by interacting fixed shares (e.g.,

migration patterns), allowing for plausibly exogenous variations across units. The Bartik instrument in this study is constructed with the equation

$$bartik\_remittance_{i,t} = \sum_{i,t}(s_{i,j} \times remittance\_paid_{j,t}) \quad (2)$$

where $s_{i,j}$ represents the normalized migration share from origin country i to destination country j, and $remittance\_paid_{j,t}$ captures the total remittance outflows from country j in year. The exclusion restriction in the Bartik instrument assumes that destination-country remittance outflows affect origin-country poverty only through changes in remittance inflows, not through other channels such as trade, aid, or geopolitical alignment. This is a strong assumption. While the use of fixed migration shares ($s_{i,j}$) controls for persistent bilateral linkages, unobserved time-varying shocks in destination countries, such as changes in aid or foreign policy, may still exert residual influence. To mitigate this concern, the study controls for GDP per capita, trade openness, and FDI inflows, reducing the risk of omitted variable bias. Nonetheless, future research should explore alternative instruments or use shift-share designs with multiple interacting shocks to strengthen exogeneity claims.

3.3.2 Threshold Modeling Strategy

Based on the evidence of heterogeneity from the calculation above, the next phase uses the threshold panel model developed by Seo and Shin (2016) to detect whether a structural break in remittance effects occurs around a critical level of financial institutional development. Unlike Hansen's (1999, 2000) static models, this method allows for endogenous regressors, dynamic processes, and mixed integration orders.

3.3.2.a Conceptual Foundation

To find the threshold value, this analysis adopts a threshold panel model (TECM) patterned through Seo & Shin (2016) to test whether remittances work better or worse after a country

reaches a certain degree of financial development. The approach, unlike Hansen (1999, 2000), which assumes strict exogeneity and no dynamics, accommodates nonlinear long-run equilibria and short-run error correction processes under endogenous regressors and mixed I (0) and I (1) variable structures. This is particularly suitable for the current dataset, which includes both trend, stationary, and unit root variables, and where remittance flows and poverty dynamics likely evolve with threshold effects. Moreover, Seo and Shin (2016)'s extended approach allows for cointegrated variables, regime-dependent adjustment speeds, and endogenous regressors, making it more suitable for remittance-finance-poverty interactions over time.

3.3.2.b Selecting and Estimating the Threshold

The threshold variable is lnFID, proxied by domestic credit to the private sector by banks (% of GDP). A grid search within the 10th to 90th percentile range of lnFID estimates the optimal threshold (γ*) by minimizing regime-wise residuals from the following panel TECM with the equation as follows:

For Regime_L (lnFID < γ), estimate:

$$\Delta lnPOV_{it} = \theta L\, X_{it} + \lambda L\, ECM_{it-1} + \mu_i + \varepsilon_{it} \quad (3)$$

For Regime_H (lnFID ≥ γ), estimate:

$$\Delta lnPOV_{it} = \theta H\, X_{it} + \lambda H\, ECM_{it-1} + \mu_i + \varepsilon_{it} \quad (4)$$

Here, X_{it} includes short-run differenced covariates such as D_lnREM, D_lnREMsq, and controls. The addition of lnREMsq comes from two logical rationales: (1) the theoretical evidence that remittances are nonlinear, and (2) the consistently significant coefficient of the variable (lnREMsq) in the 6-model preliminary regressions. The lagged error term ECM_{it-1} ensures that short-run deviations from long-run equilibrium are modeled dynamically.

For each threshold candidate, the sum of squared residuals (SSR) from both regimes is computed. Finally, the optional threshold γ* is selected as the value that minimizes the total

SSR, subject to a minimum number of 30 observations per regime to preserve statistical validity.

3.3.2.c Cointegration Testing and Threshold Inference

Cointegration is confirmed using a combination of Fisher-type ADF/PP tests, the Kao (1999) test, and the Westerlund (2007) error correction-based test. These establish the presence of long-run equilibrium relationships among variables. The statistical validity of the threshold estimate is assessed using a bootstrap Likelihood Ratio (LR) test with 1,000 replications, as proposed by Seo and Shin. A significant LR statistic confirms that the threshold structure is not spurious and that the data-generating process indeed features a regime shift based on financial depth.

3.3.3 Regime-Specific estimation and IV strategy

After confirming γ*, short-run Threshold Error Correction Models (TECMs) are re-estimated separately for both regimes (below and above the observed threshold). Endogeneity is addressed using both FE and FEIV models, incorporating regime-specific instruments. Full instrument design logic is documented in Appendix I. These specifications evaluate whether the marginal impact of remittances on poverty dynamics varies across financial development regimes. The differenced model estimated in each regime is expressed as:

$$\Delta lnPOV_{it}^{L} = \alpha_i^{L} + \beta_1^{L}\Delta lnREM_{it} + \beta_2^{L}\Delta lnFID_{it} + \beta_3^{L}\Delta X_{it} + \lambda^{L}ECM_{it} - 1 + \varepsilon_{it}^{L} \quad (5);$$

$$\Delta lnPOV_{it}^{H} = \alpha_i^{H} + \beta_1^{H}\Delta lnREM_{it} + \beta_2^{H}\Delta lnFID_{it} + \beta_3^{H}\Delta X_{it} + \lambda^{H}ECM_{it} - 1 + \varepsilon_{it}^{H} \quad (6)$$

where Regime_L is defined by $lnFID_{it} < \gamma^*$ and Regime_H is $lnFID_{it} \geq \gamma$. To assess whether the effect of remittances is conditioned by financial institutional depth, an interaction term between $\Delta lnREM$ and $lnFID$ in both regime is introduced as:

$$\Delta lnPOV_{it} = \alpha_i + \beta^1 \cdot \Delta lnREM_{it} + \beta^2 \cdot \Delta lnFID_{it} + \beta^3 \cdot \Delta lnREM_{it} \times \Delta lnFID_{it} + \beta^4 \cdot \Delta X_{it} + ECM_{1_{it}} + \varepsilon_{it} \quad (7)$$

The inclusion of an interaction term allows the model to detect whether the marginal effect of remittances on poverty is conditioned by financial institutional depth. A significant and negative coefficient on the interaction term would imply that remittances are more effective in reducing poverty in countries with more developed financial systems, consistent with the theory of absorptive capacity and financial intermediation. Together, these models allow for a robust test of the hypothesis that remittances operate differently depending on the financial context in which they are received.

3.3.3.a Complementary Diagnostics: Financial Accumulation Channels

To deepen the understanding of remittance dynamics beyond core threshold estimations, the study incorporates a series of complementary diagnostic tests. These are not auxiliary but serve to reinforce, contextualize, and qualify the central findings regarding financial conditionality and remittance effectiveness. This tier of analysis aims to address critical gaps left by conventional regime splitting or simple interaction modeling, specifically, whether the effect of remittances is statistically coherent and nonlinear.

First, to test for the structural relevance of remittances under differing financial institutional regimes, the study evaluates their joint statistical significance using Wald tests. This test aims to identify whether the poverty-reducing impact of remittances remains statistically robust and non-monotonic across levels of financial maturity.

Second, to probe the underlying channels through which remittances operate, this study proceeds to estimate regime-specific fixed-effects models on alternative dependent variables representing financial accumulation (Gross Savings as % of GNI). This model reveals whether remittances translate into structural behaviors, such as increased household savings or whether

their effects are confined to contemporaneous consumption. By comparing these mechanisms across regimes, the analysis evaluates whether financial depth conditions the functional use of remittances, not merely their immediate impact on poverty.

Together, these diagnostic strategies serve as complementary checks and interpretive lenses for the primary results. They refine the identification of financial thresholds not just as statistical breakpoints but as behavioral inflection points in remittance utility.

3.4 Robustness Framework and Specification Checks

The study then conducts robustness checks to assess whether the identified threshold effects and interaction structures are stable across alternative model specifications and welfare indicators. The goal is to determine whether the observed conditionality in the remittance-poverty relationship, namely, that remittances reduce poverty more effectively in high-financial contexts, is a consistent feature of the data or an artifact of specific measurement choices.

To address this, two principal strategies are used. First, the model is re-estimated using alternative, non-income-based poverty indicators: access to electricity (lnELEC) and undernourishment prevalence (lnUNDER). These indicators extend the scope of analysis to multidimensional poverty, capturing infrastructure and nutritional deprivations not directly reflected in income measures. Both are commonly used proxies in SDG tracking (e.g., SDG 7.1 and SDG 2.1), and their inclusion helps test whether remittance effects generalize beyond monetary outcomes.

Second, the same threshold estimation approach is applied to these alternative indicators. Cointegration tests confirm that lnREM, lnFID, and the structural poverty variables move together in the long run.

Together, the robustness tests are run to confirm that the threshold effect is not confined to a single model specification or dependent variable. Rather, it reflects a deeper structural relationship between financial maturity and the transmission of remittance inflows into poverty reduction. This enhances the internal validity of the empirical approach and strengthens the case for threshold estimation.

CHAPTER 4
EMPIRICAL RESULTS

This chapter presents the empirical results derived from the methodological framework outlined in the previous chapter.

4.1 Baseline Regression and Evidence of Nonlinearity

Table 4.1 presents preliminary regression results examining the relationship between remittances, financial development, and poverty. These models are not intended to establish causal claims, but rather to provide initial evidence guiding the subsequent threshold analysis.

TABLE 4. 1
PRELIMINARY REGRESSION RESULTS (KEY VARIABLES)

VARIABLES	MODEL 1		MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6
	FE	FE-IV	FE-IV	FE-IV	FE-IV	FE-IV	FE-IV
lnREM	-0.202	-1.501*	-1.536**	-1.468**	-1.609*	-1.495*	-1.622**
	(0.148)	(0.836)	(0.859)	(0.707)	(0.827)	(0.823)	(0.719)
lnREMsq				-0.184**			-0.204**
				(0.087)			(0.088)
lnFID	0.312	0.356*	0.514	0.477*	0.637*	0.353*	0.901**
	(0.223)	(0.205)	(0.429)	(0.266)	(0.354)	(0.200)	(0.436)
lnREM*lnFID			-0.124				
			(0.292)				
lnFIDsq					0.040		0.059*
					(0.034)		(0.039)
lnFMD	0.131	0.111	0.107	-0.042	0.072	0.098	-0.116
	(0.107)	(0.204)	(0.203)	(0.154)	(0.209)	(0.195)	(0.165)
lnFMDsq						0.023	
						(0.060)	
lnGDP	-6.166***	-5.973***	-6.013***	-6.017***	-6.265***	-6.006***	-6.449***
	(0.879)	(0.834)	(0.835)	(0.848)	(0.932)	(0.862)	(0.967)
lnTRADE	1.530**	2.328**	2.367**	2.177**	2.297**	2.310**	2.114**
	(0.627)	(0.967)	(0.984)	(0.878)	(0.976)	(0.951)	(0.880)
R^2	0.4768	0.2978	0.4157	0.4075	0.2692	0.1763	0.389

Note: Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1; Full Results is in the Appendix F.

Model 1 (FE-IV) provides the benchmark estimate where a 1% increase in remittances (lnREM) is associated with a 1.501% reduction in poverty, significant at the 10% level. The effect is notably stronger than in the basic FE model which did not reach significance. This highlights how failing to account for simultaneity biases downward the estimated effect. This

supports claims in the literature that remittances appear more poverty-reducing once endogeneity and heterogeneity are addressed.

Models 2 to 6 introduce nonlinearities. Model 2 incorporates an interaction term between remittances and financial institutional depth (lnREM x lnFID), offering a direct test of whether the effect of remittances on poverty is conditioned by the degree of financial institutional development. While the main effect of remittance is significant, the interaction term is negative but did not reach significance. This insignificance signifies the heterogeneity of remittance and financial development that cannot be revealed by simple linear models. Model 3 adds a squared remittance term (lnREMsq), which is negative (-0.184), and significant at 5% suggesting diminishing returns where the initial poverty-reducing effect of remittances weakens as flows increase. This is consistent with saturation dynamics in the context of consumption smoothing identified by Combes & Ebeke (2011) who found that remittances-induced consumption smoothing effects decline as household inflows increase, especially in financially constrained environments. Models 4, 5, and 6 reinforce this nonlinear (concave relationship) through the consistent lnREM and lnREMsq's statistically significant and negative coefficients. The same can be said with lnFID and lnFIDsq, which show a convex relationship from their positive and statistically significant coefficients. These positive coefficients across all specifications of Financial institutional depth (lnFID), while initially appearing counterintuitive, likely reflect the complex structural relationship that threshold modelling can clarify. This further supports the use of a threshold model where lnFID operates not as a nonlinear marginal effect, but as a regime-switching variable. Notably and quite expectedly, financial market depth (lnFMD) and its squared term show consistently insignificant effects across all models. This aligns with the theoretical distinction between financial institutions and markets, where the former is more directly relevant for poverty reduction than the markets in developing countries.

Control variables, on the other hand, largely align with theoretical expectations. GDP per capita (lnGDP) is robustly negative and significant at 1% (ranging from -6.0 to -6.7), reflecting income's inverse correlation with poverty. The consistent positive coefficient for Trade Openness (lnTRADE) is surprising but well-written in the literature. While trade is often assumed to reduce poverty, in weak financial contexts, it can also exacerbate distributional imbalances, a point raised by Rodrik (1998).

Several findings in the preliminary regressions merit careful interpretation due to their initially counterintuitive nature. Most notably, the positive coefficient on Financial Institutional Depth (lnFID) may appear paradoxical, suggesting that deeper financial systems are associated with higher poverty. This seemingly paradoxical result is consistent with transitional dynamics outlined in Chapter 2, where financial deepening may initially raise measured poverty due to formalization effects (La Porta & Shleifer, 2014), adjustment costs (Beck et al., 2007), and compositional gains favoring already-included populations (Honohan, 2008).

In a similar vein, the consistently positive and significant coefficient on Trade Openness (lnTRADE) also requires contextualization. While trade liberalization is often associated with economic growth, Rodrik (1998) argues that in weak institutional environments, openness can aggravate poverty by increasing volatility and exposing vulnerable populations to market shocks, job displacement, or wage suppression without adequate compensatory policies. These dynamics are especially relevant in developing economies lacking robust labor protections, fiscal buffers, or social insurance systems.

These preliminary results establish three key patterns that justify the subsequent threshold approach. First, the turning points (concave for remittances, convex for financial institutional depth) in its separate models (models 3, 5, and 6) underscore the conditional nature of remittance effectiveness. The significance of the squared terms (lnREMsq and lnFIDsq)

indicates that linear specifications may obscure critical dynamics, particularly saturation effects and financial institutional inflection points, one reason why lnREMsq is added in the threshold model. Second, the consistently larger magnitude of remittance coefficients in the FE-IV models (relative to standard FE), especially when moderated by financial institutional depth in the same equation, hints that heterogeneity across financial environments matters. Third, the insignificance of financial market variables justifies the choice of lnFID as a threshold variable in the next subsections. These patterns point to non-constant marginal effects of remittance inflows, motivating a more flexible, segmented approach to modeling remittance-poverty dynamics across degrees of financial development.

Taken together, these counterintuitive findings underscore the importance of adopting a threshold modeling framework. Linear specifications risk obscuring the conditional and nonlinear nature of these relationships. The remainder of the empirical strategy is thus designed to explicitly capture these non-linear dynamics.

4.2 Cointegration Diagnostics and Long-Run Dynamics

Following the preliminary regressions that reveal a nonlinear, financial institutionally contingent remittance-poverty relationship, it is essential to determine whether a long-run equilibrium relationship exists between the variables before running the threshold model. Table 4.2 presents evidence of cointegration among the key variables, validating the use of an error correction framework in subsequent threshold modeling.

TABLE 4. 2
PANEL COINTEGRATION TEST

Test	Statistic	p-value	Result
ADF (Fisher-type)	P= 29.43	0.043	Reject H_0 (5% level)
PP (Fisher-type)	P= 36.92	0.005	Reject H_0 (1% level)
Kao (DF t-statistic)	-2.686	0.004	Reject H_0 (1% level)
Westerlund (Error Correction)			
Pt	-12.943	0.000	Reject H_0 (1% level)
Gt	-2.924	0.100	Weak evidence
Pa	-8.168	0.090	Borderline
Ga	-5.335	1.000	Fail to reject H_0

Note: Null Hypothesis (H_0) is **no cointegration** in all tests.

The Phillips-Perron test shows strong rejection of the null (p = 0.005), indicating stationarity of the error correction term. This is corroborated by Kao's (1999) test (t = -2.686, p = 0.004) and the Westerlund ECM test, where the Pt statistic remains significant even with bootstrapped p-values. ADF tests also support residual stationarity. These results confirm cointegration and validate the Threshold Error Correction Model (TECM) for further analysis.

4.3 Threshold Identification: Financial Institutional Depth

With the integration confirmed in the previous section, the investigation now moves to formally identify the degrees of financial institutional depth at which the remittance-poverty relationship undergoes a structural change. The result in Table 4.3 targets nonlinearity in the relationship among remittances, financial development, and poverty.

TABLE 4. 3
THRESHOLD IDENTIFICATION RESULTS FOR LNFDI IN TECM FRAMEWORK

Specification	Value
Threshold search percentiles	10th to 90th
Total thresholds tested	300
Estimated threshold value (γ^*)	3.00812
Minimum Total SSR	446.39685
95% conf. interval	[0.2395, 39.9807]
Bootstrap replications	1000
Observed LR statistic	20.11
Empirical p-value	p > 0.002
Regime 1 sample size (lnFID ≤ 3.00812)	68 ; 16.45%
Regime 2 sample size (lnFID > 3.00812)	351 ; 83.55%

Notes: Threshold selected via grid search minimizing SSR over 300 candidate FID values. Bootstrapped LR follows Seo & Shin (2016), 1000 replications. Threshold is considered significant at 1% level.

A grid search across 300 candidate values of financial institutional depth (lnFID) identifies a statistically significant threshold at $\gamma^* = 3.00812$. This value, equivalent to roughly 20.26 % of GDP in private sector domestic credit to private sector by banks (% of GDP), a level that marks the minimum financial capacity required to channel remittances toward productive ends. This value can be interpreted in real terms as the minimal financial capacity needed to absorb remittances productively. This level approximates the lower bound of financial deepening in emerging economies that have achieved stable access to formal credit for households and small enterprises. Below this point, banking systems are likely underdeveloped, credit rationing is widespread, and transaction costs inhibit the formal use of remittances. Above it, financial institutions typically reach a functional scale capable of reallocating remittance flows beyond immediate consumption. These implications, while suggestive, are examined more fully in the next subsection, which applies the identified threshold to regime-specific estimations.

Continuing, the bootstrap likelihood ratio test confirms the presence of a statistically significant threshold in financial institutional depth, with an LR statistic of 20.11 ($p < 0.002$), strongly rejecting the null hypothesis of linearity. While the full 95% confidence interval for the threshold (on the unlogged scale) spans a broad range, the consistent concentration of regime-specific effects around lnFID = 3.00812 supports the validity of the estimated inflection point.

The sample splits asymmetrically, with 83.55% of the observations falling above the threshold, while only 16.45% are below it. This reflects the reality that while most developing economies have crossed a basic financial depth threshold, a meaningful minority remain financially constrained.

4.4 Regime-Specific Results: Poverty Models across Financial Institutional Contexts

This section applies the observed threshold value by dividing the data into two regimes, Lower Regime (lnFID ≤ 3.00812) and Upper Regime (lnFID >3.00812), respectively. To enhance parsimony and interpretability, variables that were consistently insignificant across multiple specifications were removed. Even while doing so, coefficient magnitudes and statistical significance remained stable across nested models, confirming the robustness of the simplified specification. The results of the simplified model are shown in Table 4.4, while full results from extended specifications are presented in Appendix I for the readers' reference.

TABLE 4. 4
TWO-REGIME SPECIFIC RESULTS COMPLETE RESULTS

		Lower Regime lnFID ≤ 3.0081			**Upper Regime lnFID >3.00812**	
Variable	FE	FE (w/ int)	FE-IV(w/ int)	FE	FE (w/ int)	FE IV (w/ int)
ECM_L1_pov	**-0.808*** **	**-0.764*** **	**-0.745*** **	**-0.419*** **	**-0.411*** **	**-0.411*** **
	(0.149)	**(0.158)**	**(0.174)**	**(0.081)**	**(0.078)**	**(0.075)**
D_lnREM	-0.287	0.443	0.652	0.199	0.540	0.453
	(0.394)	(0.384)	(0.769)	(0.358)	(0.373)	(0.650)
D_lnFID	0.598	**1.111** **	**1.157*** **	0.302	0.503	0.497
	(0.462)	**(0.416)**	**(0.300)**	(0.458)	(0.575)	(0.528)
D_lnREM*		**-4.768*** **	**-5.329*** **		**-9.056*** **	**-8.814*** **
D_lnFID		**(1.396)**	**(1.736)**		**(2.921)**	**(2.682)**
D_lnGDP	**-4.963*** **	**-4.225*** **	**-4.006*** **	**-3.157** **	**-2.970** **	**-3.076*** **
	(0.800)	**(1.046)**	**(1.420)**	**(1.500)**	**(1.280)**	**(1.706)**
			Diagnostics			
R^2	0.629	0.627	0.627	0.258	0.321	0.325

Note: Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

In low financial institutional depth regimes (lnFID ≤ 3.00812), remittance inflows do not exhibit a statistically significant short-run effect on poverty reduction, regardless of estimation strategy. While the ECM terms across all three models are strongly significant and negative, ranging from -0.764 to -0.808, indicating a high speed of adjustment toward long-run equilibrium, the immediate poverty-alleviating effect of remittances remains statistically indistinguishable from zero. However, financial institutional development itself becomes significant under both FE and IV specifications, and its interaction with remittances is also consistently negative and strongly significant at 1%, ranging from -4.768 to -5.329. This implies that in low-FID contexts, remittances only begin to reduce poverty when combined

with improvements in financial depth. The GDP growth variable remains consistently negative and significant at 1%, with elasticities around -4.0 to -5.0.

In high financial institutional depth regimes (lnFID > 3.00812), the dynamic changes markedly. The ECM remains negative and significant at 1% (-0.411), indicating a stable long-run correction mechanism, though slower than in the low-FID regime. The faster ECM adjustment in low-FID regimes likely reflects a reactive, consumption-driven response to shocks, where households rapidly return to subsistence equilibrium due to a lack of alternative financial instruments. In contrast, high-FID regimes exhibit slower adjustment as remittance effects are mediated through savings and investment channels, which take longer to manifest in poverty outcomes. Again, the direct effect of remittances (D_lnREM) is insignificant, but its interaction with financial institutional development becomes even more pronounced, ranging from -8.814 to -9.056, and is highly significant at the 1% level. This confirms that financial maturity significantly amplifies the poverty-reducing power of remittance flows. GDP growth continues to play a robust role in poverty alleviation, albeit with slightly attenuated coefficients compared to the low-FID group.

Together, these findings reinforce the hypothesis that remittances are not inherently pro-poor but become effective when interacting with sufficient financial infrastructure. The stronger interaction effect in the high-FID regime compared to the low-FID regime (-5.329 vs. -9.056) illustrates how financial institutions serve as absorptive mechanisms that convert remittance inflows into structural poverty reduction. The R-squared values also reflect this shift in model explainability: while low-FID models show a higher R-squared (around 0.627), suggesting strong within-regime fit, high-FID models have lower R-squared values (0.258 to 0.325), which may indicate more complex or diffused transmission channels in developed financial systems.

4.5 Conditional Effects and Functional Channels of Remittance Use

The complementary diagnostics tests below were conducted to refine the interpretation of regime-specific remittance effects on poverty. The results clarify whether the remittance-poverty nexus reflects not just statistical breakpoints, but structural and behavioral inflection points. Two key diagnostics are presented: (1) joint significance of remittance terms by regime and (2) regime-based savings effects.

4.5.1 Joint Significance of Remittance Terms of Financial Regime

Table 4.5 shows Wald tests for the joint significance of remittance terms across regimes. In the low-FID regime, remittance terms are jointly significant at the 5% level ($F(2,13) = 3.96$, $p = 0.045$), while in the high-FID regime, significance strengthens to the 1% level ($F(2,28) = 7.62$, $p = 0.002$).

TABLE 4. 5
WALD TEST FOR JOINT SIGNIFICANCE OF REMITTANCE TERMS BY FINANCIAL REGIME

	Wald F-Statistic	Degrees of Freedom	p-value	Conclusion
Low-FID (lnFID < 3.00812)	F(2, 13) = 3.96	2, 13	0.045	significant at 5% level
High-FID (lnFID ≥ 3.00812)	F(2, 28) = 7.62	2, 28	0.002	significant at 1% level

Note: The Wald test jointly evaluates both linear and quadratic remittance terms (D_lnREM and D_lnREMsq), providing statistical confirmation that remittance effects are not only present but potentially nonlinear.

The stronger joint significance in high-FID regimes confirms that remittances carry greater explanatory power when financial institutional capacity is higher. This supports the hypothesis that financial institutions actively mediate remittance effectiveness rather than simply correlating with better outcomes.

4.5.2 Remittances and Financial Accumulation: Evidence from Gross Savings

The regime-specific regressions using the HIS-transformed gross savings (% of GNI) ratio (ΔIHSGSGNI) in Table 4.6 indicate that remittances contribute significantly to financial accumulation only in high-FID regimes. In the upper regime, both D_lnREM (0.14069) and D_lnREMsq (0.026) are positive and significant at 1%, suggesting a convex relationship. This implies that remittance-financed saving behavior is intensified as flows increase, but only under mature financial systems.

TABLE 4. 6
REMITTANCE EFFECTS ON GROSS SAVINGS BY FINANCIAL REGIME

D. Variable ΔIHS(GSGNI)	Lower Regime lnFID 3.00812	Upper Regime lnFID >3.00812
D_lnREM	0.070 (0.075)	0.141*** (0.047)
D_lnREMsq	0.012 (0.011)	0.026*** (0.010)
D_lnFID	-0.103 (0.132)	-0.584*** (0.248)
	DIAGNOSTICS	
Observations	619	1,049
Countries	62	76

Notes: Note: Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1 Full results with conrol variables are in Appendix J.

Interestingly, financial institutional depth (D_lnFID) is negative and significant at 1% (-0.584), indicating a possible shift in household financial behavior. In high-FID contexts, improved access to formal institutions may reduce reliance on precautionary savings. Alternatively, this pattern could reflect institutional saturation or macro-level dynamics not captured by gross savings metrics. One plausible interpretation is that households in financially mature environments diversify into illiquid or long-horizon investments outside the scope of national savings data. Regardless of the underlying mechanism, the strong remittance effects observed in this regime reaffirm the central role of financial institutional maturity in transforming the use of remittances.

By contrast, the lower regime exhibits no statistically significant relationship between remittances and savings accumulation, reinforcing the conclusion that financial institutional capacity is a necessary condition for channeling remittances toward productive financial uses.

4.6 Extended Indicators: Structural Poverty and Social Outcomes

To test whether the threshold effect extends beyond income poverty, this section applies the same estimation strategy to undernourishment (lnUNDER) and electricity access (lnELEC).

TABLE 4. 7
SENSITIVITY ANALYSIS THRESHOLD AND REGIME REGRESSION RESULTS

Specification	**lnUNDER**	**lnELEC**
Estimated threshold (γ*)	3.59854	2.97620
Threshold search range	10th-90th percentile	10th-90th percentile
Grid points tested	300	300
Minimum SSR	11.766182	17.0187
LR test statistic	37.94	38.97
95% conf. interval	[16.732, 59.154]	[18.778, 59.163]
Bootstrap replications	1000	1000
Bootstrap p-value	0.000***	0.000**
Regime 1 sample size (≤ γ*)	1090	222
Regime 2 sample size (> γ*)	580	1692
Regime-Specific Effects		
Regime 1 (≤ γ*): ECM	-0.057*** (0.014)	-0.266*** (0.061)
Regime 2 (> γ*): ECM	-0.053 (0.032)	-0.149*** (0.017)
Regime 1 (≤ γ*): D_lnREM	0.002 (0.004)	0.010 (0.007)
Regime 2 (> γ*): D_lnREM	0.034* (0.018)	0.010(0.007)
Regime 1 (≤ γ*): D_lnREMsq	0.001 (0.001)	-0.001 (0.001
Regime 2 (> γ*): D_lnREMsq	0.005* (0.003)	0.001(0.001)
Regime 1 (≤ γ*): D_lnFID	-0.027**(0.010)	0.069***(0.017)
Regime 2 (> γ*): D_lnFID	-0.049(0.058)	0.040***(0.013)

Note: Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Complete results with controls are in Appendix L and M.

Table 4.7 shows the results. Both indicators show statistically significant thresholds. Undernourishment yields a threshold at 36.5% of GDP (LR = 37.94, p<0.001), while electricity access shows a threshold at 19.6% of GDP (LR = 38.97, p<0.001). These values bracket the main poverty threshold of 20.26%, suggesting the financial institutional breakpoint is robust across welfare dimensions.

However, remittance effects differ markedly across indicators. For undernourishment, remittances show no significant effects in the lower regime and a counterintuitive positive coefficient (0.034) in the upper regime, suggesting that higher remittances are associated with more undernourishment. This likely reflects measurement issues or unobserved confounding

rather than genuine remittance harm given that the level of significance is at 10%. For electricity access, remittances show no significant direct effects in either regime, though financial institutional depth remains significant in both. The weaker remittance effects for structural indicators compared to income poverty likely reflect different transmission mechanisms. Income effects can respond quickly to household transfers, while infrastructure and nutrition outcomes require longer-term, coordinated investments beyond individual remittance flows. The error-correction terms also show slower adjustment for structural indicators, consistent with their more complex determinants.

These results confirm that financial institutional thresholds exist across welfare dimensions but caution against assuming uniform remittance effectiveness. The threshold represents a necessary but not sufficient condition for remittance-driven development outcomes. Future research should explore why remittances affect different welfare dimensions through distinct channels and timeframes.

While robustness was tested across alternative poverty indicators, this analysis lacks placebo tests using variables theoretically unrelated to remittances, which could strengthen confidence that observed thresholds reflect genuine structural breaks rather than statistical artifacts.

CHAPTER 5
SYNTHESIS

5.1 Overall Synthesis

This study finds that remittances reduce poverty only when financial institutional depth exceeds approximately 20.26% of domestic credit to the private sector by banks as a share of GDP. Below this threshold, remittances show no significant long-run poverty-reducing effects and do not translate into increased savings. Above the threshold, remittances demonstrate strong associations with savings accumulation, suggesting a shift from consumption smoothing to capital formation.

The threshold effect appears robust across multiple specifications and alternative poverty measures. In low-financial institutional contexts, remittances fail to reach statistical significance in poverty models, while GDP growth remains the dominant factor. In high-financial institutional contexts, remittances show significant interaction effects with financial depth, indicating increasing returns as institutions mature. The error-correction dynamics also differ between regimes, with faster adjustment in low-financial institutional settings suggesting reactive consumption responses, versus slower adjustment in high-financial institutional settings consistent with investment-mediated effects.

The savings channel provides the clearest evidence for institutional mediation. Remittances increase gross savings only in countries above the financial threshold, supporting the hypothesis that mature financial systems enable households to redirect inflows from immediate consumption toward future-oriented uses. This pattern holds across fixed-effects and instrumental variable specifications, though the IV strategy has limitations that prevent strong causal claims. This should be interpreted as partial empirical validation of the broader capacity framework, with the financial component serving as the binding constraint modeled here.

Institutional and social absorptive factors remain analytically relevant, and their exclusion reflects data availability rather than theoretical significance.

Several alternative explanations cannot be fully ruled out. Countries with stronger governance may simultaneously develop better institutions and attract more development-oriented remittances. Cultural factors affecting trust may influence both institutional quality and remittance utilization patterns. These limitations are inherent to cross-country panel analysis and suggest caution in causal interpretation. Furthermore, furture research may also explore behavioral constraints, such as trust gaps, social norms, or literacy deficits, that limit remittances transformation even in high-capacity environments.

The findings have direct implications for SDG 1 (No Poverty), SDG 10.c (Reduce remittance costs), and SDG 8.10 (Strengthen financial institutions). Policies focused solely on increasing remittance volumes or reducing transfer costs may yield limited poverty reduction benefits without concurrent financial sector development. The identified threshold provides a concrete benchmark for assessing when countries have sufficient financial capacity to transform remittances into development capital.

5.2 Policy Transition and Implications

This study identifies a critical threshold at 20.26% of domestic credit to the private sector by banks (% of GDP), suggesting differentiated policy approaches across three financial contexts.

For countries below this threshold (including Argentina, Azerbaijan, Mexico, Tajikistan, and others listed in Appendix H), remittances do not contribute meaningfully to long-term poverty reduction. In such contexts, policy must prioritize foundational reforms. Reducing remittance transfer costs, improving reliability, and promoting mobile or agent-based delivery mechanisms can enhance immediate welfare. Yet these efforts must be paired with deeper

institutional investments, expanding access to formal credit, increasing rural financial penetration, digitizing transactions, and improving regulatory frameworks, to enable remittances to move from cash inflows to capital formation. Financial literacy campaigns and formalization incentives are likewise essential to shift household behavior toward saving and investment.

For countries nearing the threshold (e.g., Armenia, Belarus, Dominican Republic, Ecuador, Georgia, and others with lnFID between 2.8 and 3.1), the return on financial reforms is highest. The 2.8 to 3.1 range is defined heuristically as a ±0.15 band around the estimated threshold ($\gamma = 3.00812$), intended to capture countries hovering near structural readiness. While not derived from formal statistical partitioning, this range reflects where marginal reforms are most likely to generate regime-shifting effects. These "transitional" economies face a pivotal opportunity: marginal improvements in financial depth can unlock the structural shift needed for remittances to become developmentally effective. Policymakers in this bracket should aggressively pursue interventions such as digital payment infrastructure, remittance-linked savings products, and supervised microcredit systems. These countries must be prioritized for financial innovation, institutional strengthening, and experimentation with scalable delivery models.

For countries above the threshold (including Albania, Brazil, China, Colombia, and others), the focus shifts to sustaining and leveraging financial maturity. In these settings, remittances are more likely to be absorbed through formal financial systems and channeled into productive use. Policies should aim to expand access to investment-grade instruments, promote diaspora engagement through remittance-backed bonds or infrastructure financing, and protect institutional integrity to avoid capture or misuse of increased flows. The slower adjustment speeds observed in these regimes suggest that long-term financial planning and patient financial institutional upgrading are more effective than short-term remittance-boosting campaigns.

The findings caution against the simplistic strategy of maximizing remittance inflows without concurrent financial institutional reform. Remittances are volatile, often dependent on migrant labor cycles, and can decline without notice. Countries that rely on them without building the financial institutional means to absorb and transform these flows risk long-term dependency. The consistent presence of the financial threshold across income, savings, and infrastructure-related outcomes demonstrates that financial institutional capacity is not peripheral; it is systemic.

Ultimately, the effectiveness of remittances is not a function of volume alone, but of the financial systems that receive them. Remittances cannot be treated as external development transfers. Their long-run developmental power depends entirely on domestic conditions: the depth of the banking sector, the availability of formal savings instruments, the reach of credit, and the strength of public trust in financial institutions. These domestic systems determine whether remittances will remain mere buffers or become engines of structural poverty reduction.

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APPENDIX A LIST OF DEVELOPING COUNTRIES INCLUDED IN THE STUDY

1	Albania	31	Egypt, Arab Rep.	61	Mongolia	91	Uganda
2	Algeria	32	El Salvador	62	Morocco	92	Ukraine
3	Angola	33	Fiji	63	Mozambique	93	Vanuatu
4	Argentina	34	Gabon	64	Namibia	94	Viet Nam
5	Armenia	35	Gambia, The	65	Nepal	95	Yemen, Rep.
6	Azerbaijan	36	Georgia	66	Nicaragua	96	Zambia
7	Bangladesh	37	Ghana	67	Niger		
8	Belarus	38	Guatemala	68	North Macedonia		
9	Benin	39	Guinea	69	Pakistan		
10	Bhutan	40	Guinea-Bissau	70	Paraguay		
11	Bolivia	41	Haiti	71	Peru		
12	Bosnia and Herzegovina	42	Honduras	72	Philippines		
13	Botswana	43	India	73	Rwanda		
14	Brazil	44	Indonesia	74	Samoa		
15	Burkina Faso	45	Iran, Islamic Rep.	75	Senegal		
16	Burundi	46	Jamaica	76	Serbia		
17	Cabo Verde	47	Jordan	77	Sierra Leone		
18	Cameroon	48	Kazakhstan	78	Solomon Islands		
19	Central African Republic	49	Kenya	79	South Africa		
20	Chad	50	Kyrgyz Republic	80	Sri Lanka		
21	China	51	Lao PDR	81	Sudan		
22	Colombia	52	Lebanon	82	Syrian Arab Republic		
23	Comoros	53	Lesotho	83	Tajikistan		
24	Congo, Dem. Rep.	54	Madagascar	84	Tanzania		
25	Congo, Rep.	55	Malaysia	85	Thailand		
26	Costa Rica	56	Maldives	86	Timor-Leste		
27	Cote d'Ivoire	57	Mali	87	Togo		
28	Djibouti	58	Mauritania	88	Tonga		
29	Dominican Republic	59	Mexico	89	Tunisia		
30	Ecuador	60	Moldova	90	Turkiye		

APPENDIX A ALL VARIABLES' DEFINITION, SOURCE, AND DESCRIPTIVE ANALYSIS

	Variable	Short Description	Sources	Mean	SD	Min	Max
1	ln(POV)	Poverty headcount ratio at $2.15 a day	WDI, WB	0.89	2.81	- 6.91	4.52
	ln(REM)	Remittance Inflows received (% of GDP)	WDI, WB	0.37	2.60	- 6.91	3.91
	ln(FID)	Domestic Credit to Private Sector by banks (% of GDP)	IMF	3.10	0.91	- 6.91	5.21
	ln(FMD)	Financial Market Depth Index	IMF	- 3.85	2.02	- 6.91	-0.05
	ln(GDP)	GDP per capita (constant 2015 US$)	WDI, WB	7.75	0.95	5.52	9.55
	ln(TRADE)	Trade (% of GDP)	WDI, WB	4.22	0.46	1.42	5.86
	ln(CC)	Control of Corruption: Estimate	WDI, WB	- 0.56	0.61	- 1.94	1.62
	ln(FDI)	Foreign direct investment Inflows(% of GDP)	WDI, WB	1.64	1.14	- 4.31	5.33
2	GSGNI	Gross savings (% of GNI)	WDI, WB	21.72	12.13	-29.26	75.76
	Ln(UNDER)	Prevalence of undernourishment (% of population)	WDI, WB	1.86	0.77	0.92	3.72
	Ln(ELEC)	Access to electricity (% of population)	WDI, WB	4.53	0.21	2.77	4.61
3	rempaid	Personal remittances, paid (current US$)	WDI, WB	1.88	5.85	0	7.36
	share	International Migrant Stock 1990 to 2024: Destination and origin	UNDESA	56283	604394	107.28	8718651
	Oil	Oil rents (% of GDP)	WDI, WB	3.70	9.40	0.00	65.16
	M2	Broad money (% of GDP)	WDI, WB	110.10	838.00	2.92	13866.92
	CPI	Consumer Price Index (CPI)	WDI, WB	159.50	810.72	15.35	22570.71
	unemp	Unemployment, total (% of total labor force)	WDI, WB	8.51	6.78	0.12	37.32

Note: WDI stands for World Development Indicator, WB stands for WorldBank, and UNDESA stands for The United Nations Department of Economic and Social Affairs. (1) are main variables, (2) are alternative variables used in the sensitivity analysis. (3) are variables used to construct the Bartik Style Instumental Variable.

APPENDIX B CORRELATION MATRIX OF ALL VARIABLES

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) lnPOV	1.000												
(2) lnUNDER	0.586	1.000											
(3) lnELEC	-0.432	-0.528	1.000										
(4) lnREM	0.025	0.111	0.180	1.000									
(5) lnREMsq	-0.013	0.077	-0.088	-0.380	1.000								
(6) lnFID	-0.324	-0.362	0.553	0.001	-0.027	1.000							
(7) lnFIDsq	0.008	0.028	-0.298	-0.034	-0.022	-0.411	1.000						
(8) lnFMD	-0.209	-0.233	0.350	-0.317	-0.141	0.493	-0.035	1.000					
(9) lnFMDsq	-0.133	-0.107	0.012	-0.246	-0.123	0.292	0.151	0.460	1.000				
(10) lnGDP	-0.449	-0.651	0.663	-0.253	-0.132	0.474	-0.069	0.475	0.135	1.000			
(11) lnTRADE	-0.276	-0.058	0.186	0.334	0.008	0.170	-0.028	-0.155	-0.135	-0.049	1.000		
(12) CC	-0.055	-0.269	0.131	-0.053	-0.178	0.371	-0.026	0.244	0.105	0.424	0.001	1.000	
(13) ihsFDI	-0.061	-0.057	0.058	0.172	-0.057	0.035	-0.038	-0.007	-0.080	0.032	0.313	0.141	1.000

Note: All squared terms (e.g., lnREMsq, lnFIDsq, lnFMDsq) are derived from their respective base variables. To mitigate multicollinearity in subsequent estimations, these components are mean-centered prior to inclusion in the correlation matrix and estimation models.

APPENDIX C VARIANCE INFLATION FACTOR (VIF)		
Variable	**VIF**	**1/VIF**
clnFID	2.69	0.371675
clnFMD	1.95	0.511937
lnREM	1.84	0.543271
lnGDP	1.75	0.571626
lnREMsq	1.51	0.661148
clnFIDsq	1.46	0.685539
clnFMDsq	1.46	0.68711
lnTRADE	1.35	0.740129
CC	1.35	0.743492
ihsFDI	1.16	0.86228
Mean VIF	**1.65**	

Note: *To mitigate multicollinearity in subsequent estimations, these components are mean-centered prior to inclusion*
VIF = 1 → No correlation with other predictors.
VIF > 5 → Moderate multicollinearity (watchlist).
VIF > 10 → Serious multicollinearity (potential problem).

APPENDIX D SIX MODEL SPECIFICATION		
Model	Equations	Details
1	$\ln POV_{it} = \alpha_i + \beta_1 \cdot \ln REM_{it} + \beta_2 \cdot \ln FID_{it} + \beta_3 \cdot \ln FMD_{it} + \beta_4 \cdot X_{it} + \varepsilon_{it}$.	the core model where lnPOV is poverty headcount at 2.15 a day, lnREM is remittances (% of GDP), lnFID and lnFMD capture financial institutional and market depth, respectively. X_{it} includes standard controls (GDP per capita, Trade Openness, Corruption Control, and Foreign Direct Investment Inflows). Country fixed effects α_i are included to absorb unobserved heterogeneity.
2	$\ln POV_{it} = \alpha_i + \beta_1 \cdot \ln REM_{it} + \beta_2 \cdot \ln FID_{it} + \beta_3 \cdot \ln REM_{it} * \ln FID_{it} + \beta_4 \cdot \ln FMD_{it} + \beta_5 \cdot X_{it} + \varepsilon_{it}$	adds an interaction term between remittances and financial development (lnREM* lnFID) to test for the marginal effects of remittances
3	$\ln POV_{it} = \alpha_i + \beta_1 \cdot \ln REM_{it} + \beta_2 \cdot \ln REMsq_{it} + \beta_3 \cdot \ln FID_{it} + \beta_4 \cdot \ln FMD_{it} + \beta_5 \cdot X_{it} + \varepsilon_{it}$	adds a quadratic remittance term (lnREMsq) to test for diminishing returns to poverty reduction.
4	$\ln POV_{it} = \alpha_i + \beta_1 \cdot \ln REM_{it} + \beta_2 \cdot \ln FMD_{it} + \beta_3 \cdot \ln FMDsq_{it} + \beta_4 \cdot X_{it} + \varepsilon_{it}$	introduces a quadratic term for financial institution depth (lnFIDsq) to explore nonlinearities in financial infrastructure.
5	$\ln POV_{it} = \alpha_i + \beta_1 \cdot \ln REM_{it} + \beta_2 \cdot \ln FMD_{it} + \beta_3 \cdot \ln FMDsq_{it} + \beta_4 \cdot X_{it} + \varepsilon_{it}$	replaces lnFIDsq with the squared term for financial market depth (lnFMDsq) to evaluate the market-based channel.
6	$\ln POV_{it} = \alpha_i + \beta_1 \cdot \ln REM_{it} + \beta_2 \cdot \ln REMsq_{it} + \beta_3 \cdot \ln FID_{it} + \beta_4 \cdot \ln FIDsq_{it} + \beta_5 \cdot X_{it} + \varepsilon_{it}$	a refined specification including lnREMsq and lnFIDsq. In effect, Model 6 is used to motivate the nonlinear strategy pursued in Section 3.3 (threshold modeling), without claiming finality or causality. A negative and statistically significant coefficient on remittance (lnREM) would indicate that greater remittance inflows are associated with lower poverty levels, consistent with a poverty-alleviating role. Same is true when lnFID and lnFIDsq are significant.

APPENDIX E FULL ESTIMATION RESULTS FOR 6 MODELS (FE AND FE-IV

Variables	Model1			Model 2		Model 3		Model 4		Model 5		Model 6	
	RE	FE	FE-IV	FE	FE-IV	FE	FE-IV	FE	FE-IV	FE	FE-IV	FE	FE-IV
lnREM	-0.198*	-0.202	-1.501*	-0.184	-1.536**	-0.383*	-1.468**	-0.184	-1.609*	-0.203	-1.495*	-0.371*	-1.622**
	(0.111)	(0.148)	(0.836)	(0.162)	(0.859)	(0.209)	(0.707)	(0.148)	(0.827)	(0.148)	(0.823)	(0.206)	(0.719)
lnREMsq						-0.057*	-0.184**					-0.059*	-0.204**
						(0.034)	(0.087)					(0.033)	(0.088)
clnFID	-0.055	0.312	0.356*	0.196	0.514	0.357	0.477*	0.774**	0.637*	0.310	0.353*	0.837**	0.901**
	(0.133)	(0.223)	(0.205)	(0.291)	(0.429)	(0.229)	(0.266)	(0.360)	(0.354)	(0.221)	(0.200)	(0.347)	(0.436)
lnREM*lnFID				(0.091)	-0.124								
				(0.146)	(0.292)								
clnFIDsq								0.068*	0.040			0.070**	0.059*
								(0.035)	(0.034)			(0.034)	(0.039)
clnFMD	0.118	0.131	0.111	0.133	0.107	0.087	-0.042	0.066	0.072	0.119	0.098	0.018	-0.116
	(0.081)	(0.107)	(0.204)	(0.106)	(0.203)	(0.105)	(0.154)	(0.115)	(0.209)	(0.117)	(0.195)	(0.100)	(0.165)
clnFMDsq										0.021	0.023		
										(0.064)	(0.060)		
lnGDP	-3.612***	-6.166***	-5.973***	-6.135***	-6.013***	-6.152***	-6.017***	-6.683***	-6.265***	-6.195***	-6.006***	-6.686***	-6.449***
	(0.539)	(0.879)	(0.834)	(0.876)	(0.835)	(0.880)	(0.848)	(0.979)	(0.932)	(0.913)	(0.862)	(0.987)	(0.967)
lnTRADE	1.390**	1.530**	2.328**	1.508**	2.367**	1.590**	2.177**	1.365**	2.297**	1.519**	2.310**	1.423**	2.114**
	(0.567)	(0.627)	(0.967)	(0.621)	(0.984)	(0.633)	(0.878)	(0.567)	(0.976)	(0.629)	(0.951)	(0.578)	(0.880)
CC	0.282	0.527	0.942	0.473	1.018	0.545	0.791	0.508	0.970	0.550	0.967	0.527	0.815
	(0.384)	(0.519)	(0.712)	(0.533)	(0.813)	(0.526)	(0.596)	(0.500)	(0.725)	(0.513)	(0.717)	(0.508)	(0.600)
ihsFDI	0.104	0.120	0.103	0.131	0.087	0.129	0.137	0.130	0.108	0.121	0.105	0.139	0.148
	(0.087)	(0.090)	(0.164)	(0.089)	(0.161)	(0.088)	(0.099)	(0.088)	(0.171)	(0.089)	(0.162)	(0.087)	(0.102)
DIAGNOSTICS													
Obs	485	485	467	485	467	485	467	485	467	485	467	485	467
Countries	33	33	33	33	33	33	33	33	33	33	33	33	33
R^2	0.4653	0.4768	0.2978	0.4780	0.4157	0.4832	0.4075	0.4841	0.2692	0.4771	0.1763	0.4909	0.3891
F-stat	94.10	8.23	67.17	7.40	7.04	7.56	8.76	8.80	8.76	7.93	8.88	8.98	7.32
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
UnderID			7.40		6.416		7.40		6.98		6.08		8.53
p-value			0.0065		0.0113		0.0065		0.0083		0.0137		0.0035
Weak (K-P F)			12.26		8.037		12.26		8.70		7.61		14.10
Hausman test		133.26***	1428***				2.998*		4.460**		3.740*		3.675*
Model		FE	FE-IV		FE-IV		FE-IV		FE-IV		FE-IV		FE-IV
SE type	Robust	Robust	Robust		Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust
Clustered by	country_id	country_id	country_id		country_id	country_id	country_id	country_id	country_id	country_id	country_id	country_id	country_id

Note: ***, **, * denote statistical significance at 1%, 5%, and 10% levels, respectively

APPENDIX F PANEL UNIT ROOT COINTEGRATION FOR EACH VARIABLE

Variable	Level				First Difference				
	IPS	ADF	PP	LLC	IPS	ADF	PP	LLC	
lnPOV	1.63	79.40**	51.08	-0.53		297.85***	569.44***	-5.29***	I(1)
lnREM	-3.41***	70.85***	96.84***	-3.53***	-6.44***	111.03***	140.39***	-6.43***	I(0)
lnREMsq	-2.46***	50.79***	48.52***	-4.05***	-6.31***	109.61***	173.23***	-6.12***	I(0)
lnFID	-1.96**	29.12**	18.60	-4.62***	-5.13***	91.74***	109.12***	-6.18***	I(0)
lnFMD	-0.88	23.81	34.15**	-1.80**	-6.11***	99.93***	238.36***	-5.37***	I(0)
lnGDP	-1.44*	26.03*	45.51***	-4.83***	-3.40***	52.96***	122.82***	-2.59***	I(0)
lnTRADE	-0.20	17.90	15.97	-1.88**	-5.73***	93.84***	171.88***	-3.61***	I(1)
ihsFDI	-2.70***	44.02***	29.09**	-0.27	-8.48***	150.39***	278.01***	-5.22***	I(0)
CC	0.98	13.31	552.92***	-0.27	-3.99***	61.74***	161.41***	-3.34***	I(0)
lnUNDER	-3.76***	57.53***	24.08	-6.31***	-2.87***	52.89***	24.60***	-3.54***	I(0)
lnELEC	-3.29***	52.32***	80.49***	-5.06***	-6.10***	104.29***	277.83***	-4.15***	I(0)

Note: ***, **, * denote statistical significance at 1%, 5%, and 10% levels, respectively
IPS: Im-Pesaran-Shin test; ADF: Augmented Dickey-Fuller test; PP: Phillips-Perron test; LLC: Levin-Lin-Chu test.
empty cells indicate test could not be computed or insufficient observations.
A variable is considered I(0) if at least two tests reject the null hypothesis of a unit root at level; otherwise, it is I(1).

APPENDIX G LIST OF COUNTRIES IN EACH REGIME

LOWER REGIME	TRANSITION REGIME	UPPER REGIME
1. Argentina	1. Armenia	1. Albania
2. Azerbaijan	2. Belarus	2. Brazil
3. Mexico	3. Dominican Republic	3. China
4. Tajikistan	4. Ecuador	4. Colombia
	5. Georgia	5. Costa Rica
	6. Kyrgyz Republic	6. El Salvador
	7. Moldova	7. Honduras
	8. Pakistan	8. India
	9. Paraguay	9. Indonesia
	10. Peru	10. Kazakhstan
		11. Kenya
		12. Mongolia
		13. North Macedonia
		14. Serbia
		15. Thailand
		16. Turkiye
		17. Ukraine
		18. The Philippines

Note: The **transition group** includes countries whose lnFID values crossed the identified threshold (**3.00812**) at some point during the panel period (2002-2021). These countries did not remain in a single regime throughout and therefore contribute observations to both lower and upper regime estimates depending on the year. This regime fluidity reflects financial institutional evolution over time.

APPENDIX H TWO - REGIME ESTIMATION RESULTS FOR LNPOV (FE AND FE-IV)

	Lower Regime lnFID ≤ 3.00812			Upper Regime lnFID >3.00812		
Variable	FE	FE (with interaction)	FE-IV(with interaction)	FE	FE (with interaction)	FE-IV(with interaction)
ECM_L1_pov	**-0.841*** (0.183)**	**-0.792***(0.196)**	**-0.773***(0.212)**	**-0.427*** (0.088)**	**-0.419***(0.085)**	**-0.419***(0.082)**
D_lnREM	-0.538 (0.412)	0.067(0.496)	0.276(0.881)	0.174 (0.363)	0.474(0.411)	0.387(0.688)
D_lnREMsq	-0.017 (0.079)	0.049(0.067)	0.041(0.051)	0.138 (0.128)	0.098(0.105)	0.096(0.089)
D_lnFID	0.536(0.579)	**0.991*(0.555)**	**1.037***(0.439)**	0.243 (0.423)	0.403(0.481)	0.397(0.434)
D_lnREM*D_lnFID		**-4.553***(0.678)**	**-5.114***(1.0182)**		**-8.241***(0.615)**	**-7.999***(0.376)**
D_lnFMD	-0.333 (0.350)	-0.332(0.359)	-0.331(0.3199)	0.206 (0.229)	0.188(0.204)	0.189(0.203)
D_lnGDP	**-5.869*** (1.185)**	**-5.328***(1.502)**	**-5.109***(1.876)**	**-3.700** (1.634)**	**-3.221**(1.435)**	**-3.327***(1.861)**
D_lnTRADE	1.034(1.050)	0.918(0.875)	0.775(0.989)	0.282 (0.488)	0.046(0.482)	0.089(0.478)
D_CC	0.859(0.922)	0.685(0.887)	0.670(0.784)	0.490 (0.390)	0.409(0.421)	0.422(0.356)
D_ihsFDI	0.056(0.060)	0.055(0.074)	0.053(0.068)	0.049 (0.065)	0.042(0.067)	0.042(0.067)
Diagnostics						
Observations	68	68	65	351	351	349
Countries	14	14	12	29	29	27
R^2	0.591	0.624	0.624	0.258	0.275	0.276
F-stat	54.3 (p = 0.0000)	2354.62 (p = 0.0000)	10492.89 (= 0.0000]	19.87 (p = 0.000)	25.86(p= 0.000)	35.13(p=0.000)
Under ID Test			4.287 (p = 0.038)			3.799(p= 0.056)
Weak (K-P F-stat)			9.233			12.127
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	By country	By country	By country	By country	By country	By country

Note: Standard errors in parentheses. ***, **, * denote statistical significance at 1%, 5%, and 10% levels, respectively
A new set of external IVs grounded in macroeconomic fundamentals are constructed in each regime. The rationale behind the use of a new set of IV is due to the potential for heterogeneous structural dynamics between low and high remittance environments. In particular, the variance structure and underlying determinants of remittance behavior are likely to differ between regimes. For instance, macroeconomic variables may affect remittance flows differently at lower versus higher intensity levels, invalidating pooled instruments such as the Bartik instrument when applied separately to each subsample. Moreover, splitting the sample reduces common support and alters covariate interactions, requiring tailored identification strategies. For the upper-remittance regime, the interaction between oil rents and broad money supply is used. This instrument captures the liquidity effects in remittance-origin countries that are heavily dependent on resource revenues, affecting remittance capacity through macroeconomic channels without a direct linkage to poverty in recipient economies. For the lower-remittance regime, the interaction between unemployment rate and consumer prices, capturing labor market slack and inflationary pressure in remittance-sending countries. These instruments are designed to reflect exogenous macroeconomic conditions in remittance-sending countries, affecting remittance supply but unlikely to correlate with unobserved shocks to poverty in recipient countries, thereby satisfying the exclusion restriction under standard assumptions.

APPENDIX I REMITTANCE EFFECTS ON GROSS SAVINGS BY FINANCIAL REGIME		
Dependent Variable: ΔIHS(GSGNI)	**(1) Low-FID Regime (lnFID < 3.00812)**	**(2) High-FID Regime (lnFID ≥ 3.00812)**
D_lnREM	0.06994 (0.07460)	**0.14069*** (0.04665)**
D_lnREMsq	0.01220 (0.01113)	**0.02612*** (0.01009)**
D_lnFID	-0.10325 (0.13205)	**-0.58379*** (0.24750)**
D_lnFMD	0.12782 (0.07817)	0.06292 (0.04442)
D_lnGDP	1.48203 (1.12048)	1.96321 (1.41760)
D_lnTRADE	-0.33330 (0.48639)	0.38590 (0.40815)
D_CC	0.09412 (0.41760)	0.05161 (0.11229)
D_ihsFDI	0.02945 (0.04640)	**-0.05859*** (0.02439)**
DIAGNOSTICS		
Observations	619	1,049
Number of Countries	62	76
R-squared (within)	0.0131	0.0722
F-statistic (8, N)	1.28	2.27
Prob > F	0.2706	**0.0313**
Fixed Effects Estimator	Yes	Yes
Robust Standard Errors (clustered)	Yes	Yes

Note: Robust standard errors in parentheses. ***, **, * denote statistical significance at 1%, 5%, and 10% levels, respectively

APPENDIX J PANEL COINTEGRATION TESTS FOR ALTERNATIVE POVERTY PROXIES

Test	lnUNDER - Statistic (p-value)	lnELEC - Statistic (p-value)
A. Kao Test for Cointegration		
Modified Dickey-Fuller t	3.1930 (0.0007)	1.9916 (0.0232)
Dickey-Fuller t	1.1044 (0.1347)	-0.5877 (0.2784)
Augmented Dickey-Fuller t	-2.1638 (0.0152)	4.0597 (0.0000)
Unadj. Modified DF t	4.8387 (0.0000)	-1.8735 (0.0305)
Unadj. Dickey-Fuller t	2.7965 (0.0026)	-3.5734 (0.0002)
B. Engel-Granger Panel Unit Root (ECT)		
Inverse Chi-squared (P)	ADF: 224.99 (0.0630)	ADF: 264.79 (0.0062)
	PP: 164.3247(0.9516)	PP: 335.87 (0.0000)
Inverse Normal (Z)	ADF: -0.5764 (0.2822)	ADF: -0.8134 (0.2080)
	PP: 3.0311(0.9988)	PP: -2.5788 (0.0050)
Inverse Logit t (L*)	ADF: -0.8126 (0.2084)	ADF: -1.3472 (0.0893)
	PP: 3.0010(0.9986)	PP: -3.2274 (0.0007)
Modified Inv. Chi-squared (Pm)	ADF: 1.5732 (0.0578)	ADF: 2.6736 (0.0038)
	PP: -1.5998(0.9452)	PP: 6.0158 (0.0000)

Note: Null Hypothesis: All panels contain unit roots (non-stationary); PP test strongly rejects the null → ECT is stationary (cointegration exists)

APPENDIX K TWO - REGIME ESTIMATION RESULTS FOR LNUNDER (FE AND FE-IV)		
Variable	**Lower Regime (lnFID ≤ 3.59854)**	**Upper Regime (lnFID > 3.59854)**
	FE	FE
ECM_L1_under	-0.057***(0.014)	-0.053(0.031)
D_lnREM	0.002(0.004)	0.034*(0.018)
D_lnREMsq	0.001(0.001)	0.005*(0.003)
D_lnFID	-0.027**(0.010)	-0.049(0.058)
D_lnFMD	-0.004(0.005)	-0.004(0.013)
D_lnGDP	-0.261*(0.134)	-0.390**(0.161)
D_lnTRADE	0.020(0.014)	0.060(0.042)
D_CC	0.003(0.022)	-0.004(0.022)
D_ihsFDI	-0.003(0.002)	0.001(0.004)
DIAGNOSTICS		
Observations	296	322
Countries	27	27
R^2	0.053	0.069
F-statistic	3.11 (p= 0.0028)	2.24 (p = 0.0351)
SE Type	Robust	Robust
Clustered By	country_id	country_id
Note: Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1		

APPENDIX L TWO - REGIME ESTIMATION RESULTS FOR LNELEC (FE AND FE-IV)		
Variable	**Lower Regime**	**Upper Regime**
	FE	**FE**
ECM_L1_under	-0.266***(0.061)	-0.149***(0.017)
D_lnREM	0.010(0.007)	0.011(0.007)
D_lnREMsq	-0.001(0.001)	0.001(0.001)
D_lnFID	0.069***(0.017)	0.040***(0.013)
D_lnFMD	-0.028(0.108)	0.113***(0.032)
D_lnGDP	-0.028(0.108)	0.113****(0.032)
D_lnTRADE	-0.084**(0.041)	0.007(0.170)
D_CC	0.093(0.065)	0.009(0.0111)
D_ihsFDI	-0.004(0.004)	-0.001(0.002)
DIAGNOSTICS		
Observations	61	378
Countries	11	30
R^2	0.45	0.27
F-statistic	8.36 (p = 0.0000)	14.03 (p = 0.0000)
SE Type	Robust	Robust
Clustered By	country_id	country_id
Note: Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1		