Are Financial Development and Financial Stability Complements or Substitutes in Poverty Reduction?

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Abstract: This paper studies the association between financial development, financial stability, and poverty for a sample of 136 developed and developing countries over the period 1995-2018. Most of the existing studies in this literature have focused on financial development. Few recent studies have looked at the effects of financial stability. However, none of the existing studies has looked at the interaction effect of the two on poverty. Our contribution to this literature is manifold. First and foremost, we investigate whether financial development and financial stability are substitutes or complement in reducing poverty and find evidence in favour of the former: financial development has greater effects on poverty alleviation in a more fragile financial system and vice-versa. Second, using two different measures of financial stability, we show that financial stability is associated with lower levels of poverty. And, finally, while previous studies have presumed that the effect of financial development on poverty is homogeneous at various levels of poverty, we show that financial development and financial stability both have heterogeneous effects on poverty depending on the level of poverty considered.

Keywords: financial development, financial stability, poverty, heterogeneous effects

JEL Codes: G20, I30, O11, O1

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1. Introduction

There are a number of studies, old and new, that have explored the relationship between financial development and economic growth.[1] The majority of the studies conclude that a financial system that effectively provides financial services, such as saving mobilization and better capital allocation, is crucial for the economic growth of a country. Whether a well-functioning financial system helps reduce the level of poverty and inequality has been the subject of a number of recent studies (see Beck et al., 2007; de Haan et al., 2021; Jalilian & Kirkpatrick, 2005; Zhang & Ben Naceur, 2019).

Theoretically, it's concluded by several studies that financial development affects poverty via several channels. First, financial development may have a direct impact on poverty. There are conflicting theories in this regard. On the one hand, financial development may reduce poverty as a number of credit market imperfections, such as information and transaction costs, maybe especially binding on the poor who lack collateral and credit histories. Relaxation of these constraints is going to benefit the poor (Beck et al., 2007). On the other hand, some theories suggest that financial development helps the rich. The reasoning behind such an argument is that the poor mainly rely on informal sources for their capital/credit requirements. Hence, development in the formal financial sector extremely benefits those already part of the formal financial system (Greenwood & Jovanovic, 1990). However, most empirical studies conclude that financial development leads to poverty reduction.

Second, rather than directly affecting poverty, financial development may indirectly affect poverty via various channels like economic growth, income inequality, and financial instability (de Haan et al., 2021).[2] The early literature on financial development and economic growth concludes that financial development promotes economic growth and development, which, in turn, may reduce poverty (King & Levine, 1993). The argument is that a well-developed financial system channelizes savings into productive investments, monitors borrowers to increase efficiency, facilitates pool, share and diversify risk, and enables trade, leading to

[1] See (Levine, 1997, 2005) for a detailed literature survey on financial development and economic growth.
[2] There could be other indirect benefits of financial development for poverty. For instance, the expansion of the banking system can benefit the poor through enhanced financial inclusion as the expansion of bank branches can reduce banks' market power and hence the cost of borrowing for the poor (Degl'Innocenti et al., 2018).

economic growth. However, some recent studies also suggest that the relationship between financial development and economic growth is nonlinear (Arcand et al., 2015; Botev et al., 2019; Law & Singh, 2014), and therefore, the impact of financial development on poverty may be different across regions, income levels, and whether the economy is developed or developing.

Another indirect channel is that financial development may affect the poor through its effect on income distribution. A more equal income distribution is generally associated with less poverty. Hence, depending on whether financial development increases or decreases income inequality, this income distribution effect will mitigate or enhance the potential beneficial direct effects of financial development on the poor (Beck et al., 2007). Finally, more developed financial systems also tend to be more financially stable, which, in turn, may affect poverty. Some recent studies report that financial instability leads to income inequality (de Haan & Sturm, 2017), which, in turn, may hurt the poor (Jeanneney & Kpodar, 2011; Nikoloski, 2011).

Empirically, the relationship between financial development and poverty has been explored in a direct, indirect, and interactive way. The direct and indirect effect of financial development on poverty has been well-documented in the literature (Boukhatem, 2016; Cepparulo et al., 2017; de Haan et al., 2021; Donou-Adonsou & Sylwester, 2016, 2016; Jalilian & Kirkpatrick, 2005; Jeanneney & Kpodar, 2011; Rashid & Intartaglia, 2017; Rewilak, 2017; Seven & Coskun, 2016; Zhang & Ben Naceur, 2019). The majority of the studies broadly provide evidence in favour of the positive impact of financial development on the poor, even after using different poverty and financial development measures and samples.

The interactive effect of financial development on poverty, using cross-section data, have not been explored comprehensively. There are few studies (de Haan et al., 2021; Jalilian & Kirkpatrick, 2005; Rashid & Intartaglia, 2017; Rewilak, 2018; R. Zhang & Ben Naceur, 2019) that have attempted to interact financial development with country-specific characteristics like economic growth, income level, quality of institutions, income inequality, and financial crisis and see its impact on the poverty.

In one of the early studies, (Jalilian & Kirkpatrick, 2005) examine the causal linkage between financial development, economic growth, inequality, and poverty reduction. While analyzing the link between poverty and financial development, they attempt to capture the effect of financial development on poverty indirectly via its impact on growth and find the effect to be positive. They conclude that *"there is no indication in our analysis that the growth* *effect of financial development is unequally shared; more specifically, as a result of financial development, the income of the poor changes as much as average income"*.

For a sample of developing countries, (Rashid & Intartaglia, 2017) assess the impact of financial development on the poor. They conclude that while financial development reduces poverty, it will have a larger impact on poverty reduction in the presence of sound institutions and higher economic growth. (R. Zhang & Ben Naceur, 2019) examine the impact of multidimensional measures of financial development like financial access, depth, stability, and liberalization on poverty and inequality for the sample of 143 countries from 1961-2011. They find that most of the measures of financial development are negatively associated with income inequality and poverty. Moreover, their findings indicate that finance is more effective in reducing poverty and income inequality in the presence of better institutions. A significant link between finance and income inequality is also confirmed in a recent study by (Agnello et al., 2012), who find that financial reforms are negatively associated with income inequality.

Another study by (Rewilak, 2018) investigates the impact of a banking crisis, a measure of financial development (private credit to GDP), and their interaction on the income of the poor. He concludes that while the banking crisis negatively and significantly impacts the income of the poor, the interaction term between banking crisis and financial development is insignificant. However, the interaction term is positive, which implies that the larger financial sector may reduce the negative impact of a banking crisis on the income of the poor.

More recently, studies have focused their attention on the effects of financial crises, which some also refer to as financial instability, on development outcomes such as poverty and income inequality. (Rewilak, 2018) investigates the impact of a banking crisis, a measure of financial development (private credit to GDP), and their interaction on the income of the poor. While the banking crisis is found to be negatively and significantly associated with the income of the poor, the interaction term between banking crisis and financial development is found to be positive but statistically insignificant. (de Haan et al., 2021) examine various channels such as income inequality, economic growth, and financial instability through which financial development can affect poverty. They find that while financial development does not directly impact poverty, it indirectly affects poverty through lower income inequality but not through economic growth and financial instability. Furthermore, while the effect of financial development on poverty declines with increases in income inequality, it increases with an increase in economic growth. Importantly, there is no significant interaction effect between financial development and financial crisis on poverty.

Against this background, our paper studies the association between financial development, financial stability, and poverty for a sample of 136 developed and developing countries over the period 1995-2018. We contribute to the existing literature in various ways. First, while the previous studies have investigated the effects of financial development on poverty, these studies have not considered the heterogeneous impact of financial development on poverty at different levels of poverty. As we will show later, the dependent variable used in the paper does not fulfil the normality and no-outlier assumptions suggesting the need for a quantile regression-based approach, which is generally true for earlier studies in this literature. Using quantile regression approach, our study is the first one that takes this heterogeneity into account and shows that it matters. Second, unlike previous studies that have primarily used the volatility of financial development or a dummy variable for financial crisis as a measure of financial stability to examine the relationship between financial stability and poverty (de Haan et al., 2021) (Rewilak, 2017), we utilize two different measures of financial stability – bank's Z-score and impaired loans – to examine the effects of financial development on poverty and whether the effects are heterogeneous across different poverty levels. Third, by combining these two strands of very similar literature, our study underscores the implications of quality-adjusted financial development for poverty and explores whether financial development and financial stability are substitutes or complements in poverty reduction.

The most important contribution of our study lies in our investigation of the effects of the interaction between financial development and financial stability on poverty, which, to the best of our knowledge, has not been studied. Studying whether financial development and financial stability are substitutes or complements has important implications in this context. If the two are substitutes, developing the financial system in countries with unstable financial systems will be more rewarding in terms of poverty reduction. Therefore, the aid targeted towards reducing poverty will be better spent in developing the financial system in countries where financial systems are unstable.

Moreover, the complementarity versus the substitutability between financial development and financial stability will also help determine how scarce development funds should be spent. If financial development and financial stability are substitutes in poverty reduction, it pays off to specialize in one or the other. The substitutability of the two will call for continuous improvements in either of the two depending on relative costs. The complementarity between the two, on the other hand, favours a balanced approach where both financial development and financial stability are promoted simultaneously. The complementarity would argue for an all-or-nothing approach that would either make substantial improvements in both or do little. The substitutability, in contrast, will rationalize moderate levels of investment in either of the two that are not heavily dependent on their costs. Therefore, it is important to learn, from the policy perspective, whether financial development and financial stability are substitutes or complements in poverty reduction.

We provide robust evidence of a significant link between financial development, financial stability, and poverty across countries. To the best of our knowledge, this is the first paper to document that the effects of financial development and financial stability on poverty are heterogeneous across the conditional distribution of poverty. Moreover, ours is the first study to show that financial development and financial stability are substitutes in poverty reduction. Thus, interventions that promote either of the two will result in a reduction in poverty, and hence policies should concentrate on continuously developing the financial system or improving its stability. Our findings thus suggest two important methodological improvements to this literature, which future studies should take into account. First, our results show that heterogeneity in poverty levels must be taken into account while exploring the effects of financial development and financial stability on poverty. And, second, a degree of substitutability between financial development and financial stability exists, and a correct empirical specification investigating the effects of either of the two variables must account for this.

The rest of the paper is organized as follows. Section 2 describes the data, empirical model and methodology. Section 4 presents the empirical results, and Section 5 concludes the study.

2. Data and Econometric Strategy

Model

To determine the relationship between financial development, financial stability and poverty, we develop the following model: -

$$Pov_{i,t} = \alpha_0 + \alpha_1 FinDev_{i,t} + \alpha_2 FinStab_{i,t} + \alpha_3 FinDev_{i,t} * FinStab_{i,t} + \sum_{k=1}^{K} \rho_k X_{k,i,t} + u_{i,t} \quad (1)$$

where Pov refers to measures of poverty; $FinDev$ refers to measures of financial development; $FinStab$ refers to various measures of financial stability; and X represents a set of control variables that are extensively used in the financial development-poverty and financial stability-poverty literature (Boukhatem, 2016; Cepparulo et al., 2017; de Haan et al., 2021; Donou-Adonsou & Sylwester, 2016, 2016; Jalilian & Kirkpatrick, 2005; Jeanneney & Kpodar, 2011; Rashid & Intartaglia, 2017; Rewilak, 2017; Seven & Coskun, 2016; Zhang & Ben Naceur, 2019). These variables are GDP growth, GDP per capita, inflation, government spending, education, and income inequality. Finally, u_i is the error term, which is assumed to have mean zero and variance equal to one.

Data

Our sample consists of 136 countries (91 developing countries and 45 developed countries) and covers the period 1995-2018.[3] We could not include the time period before 1995 in our study due to the unavailability of data related to financial stability measures. The sample period is divided into four non-overlapping averages of five-year, and the fifth panel consists of an average of three years. The reason for using periods average is to avoid annual fluctuations and to include as many data as possible. The list of sample countries is presented in Table A1.

Dependent Variable

Our dependent variable is poverty which has been defined in different ways. The two most popular measures used in most studies are the poverty headcount ratio and poverty gap ratio. According to the World Bank (2018), the poverty headcount ratio is defined as the percentage of the population living with an income below a threshold line based on a minimum amount of resources to maintain a basic standard of living, while the poverty gap is the mean shortfall in income or consumption from the poverty line. Recent empirical studies have preferred to use the poverty gap as a primary measure of poverty as it reflects the breadth and intensity of poverty. The World Bank provide data using three different poverty lines: \$ 1.90, \$ 3.20, and \$ 5.40 a day. People who live below the \$ 1.90 are considered to live in extreme poverty. We'll use the poverty headcount ratio (*HeadCount*) and poverty gap ratio (*PovGap*) definition based on the poverty line at \$ 1.90 in our study. The higher value of headcount ratio

[3] The classification is based on a report prepared by the Development Policy and Analysis Division of the Department of Economic and Social Affairs of the United Nations Secretariat. For more detail, see https://www.un.org/en/development/desa/policy/wesp/wesp_current/2014wesp_country_classification.pdf (accessed Auguest 22, 2021).

and poverty gap indicates higher poverty and vice-versa. The data on poverty comes from the Poverty and Equity Database, the World Bank.

Independent Variables

Our main independent variables are financial development and financial stability. We use private credit divided by GDP (*Credit*) as a proxy for financial development. This measure of financial development captures the amount of credit channelled from savers to borrowers via financial intermediaries and is a standard measure used in the related literature (Aghion et al., 2005; Ahlin & Pang, 2008). It is better than alternative measures of financial development, such as liquid liabilities (M3 divided by GDP), which focuses on the liabilities side of the financial system and not on the allocation of credit. As banks are the main providers of credit, especially in developing countries, the use of private credit to GDP seems appropriate in our study.

In line with (Demetriades & Rewilak, 2020; R. Zhang & Ben Naceur, 2019), we use two indicators of financial stability. The first indicator, Bank Z-score (*Z-Score*), captures the probability of default of a country's commercial banking system. Z-score compares the buffer of a country's banking system (capitalization and returns) with the volatility of those returns. A higher Z-score implies a lower probability of default and vice-versa. The second measure, impaired loan or non-performing loans (*ImpairedLoan*), is the ratio of defaulted loans (payments of interest and principal past due by 90 days or more) to total gross loans (total value of loan portfolio). A lower (higher) value of the impaired loan (higher inverse of the impaired loan) indicates a more (less) stable banking system.

The data on financial development and financial stability is taken from the Global financial development database, the World Bank.

Control Variables

Our control variable includes GDP growth (*GDPgrowth*), measured as annual percentage growth rate of GDP at market prices based on constant local currency; GDP per capita (*PCY*), measured as gross domestic product divided by midyear population at constant USD 2010; Inflation (*Inflation*), measured in terms of the annual percentage change in the consumer price index; Government Size (*GovExp*), measured as the ratio of general government final expenditure to GDP; Education (*Enrolment*), measured as the ratio of total enrolment in secondary school, regardless of age, to the population of the age group; Gini

(*Gini*), a measure of income inequality whose value lie between 0-100, 0 represent perfect equality while 100 implies perfect inequality. All the control variables except GDP growth rate and Gini have been converted into logarithmic form.

GDP growth seems to reduce poverty as high economic growth trickle down to the poor (Beck et al., 2007; de Haan et al., 2021; Inoue, 2018; Jalilian & Kirkpatrick, 2002; Seven & Coskun, 2016). As higher income is related to economic development and developed economies have lower poverty (e.g. de Haan et al., 2021; Donou-Adonsou & Sylwester, 2016; Inoue, 2018; Rashid & Intartaglia, 2017; Seven & Coskun, 2016; Zhang & Ben Naceur, 2019), an increase in GDP per capita should reduce poverty. Higher inflation is a sign of macroeconomic instability, and it has a negative impact on the poor (Boukhatem, 2016; de Haan et al., 2021; Inoue, 2018; Jalilian & Kirkpatrick, 2005; Rashid & Intartaglia, 2017; Seven & Coskun, 2016; R. Zhang & Ben Naceur, 2019). Higher government expenditure seems to reduce poverty, especially in developing countries (Boukhatem, 2016; de Haan et al., 2021; Jalilian & Kirkpatrick, 2005; Rashid & Intartaglia, 2017; Seven & Coskun, 2016; R. Zhang & Ben Naceur, 2019). According to Keynesian macroeconomics, higher government expenditure may increase the aggregate demand, which further stimulates economic growth, per capita income and employment. An increase in education, similar to investment in human capital, seems to reduce poverty (e.g. Beck et al., 2007; Rashid & Intartaglia, 2017; Seven & Coskun, 2016). A reduction in the Gini coefficient seems to reduce poverty (Beck et al., 2007; Cepparulo et al., 2017; de Haan et al., 2021; Donou-Adonsou & Sylwester, 2016; Rashid & Intartaglia, 2017). The data on control variables are taken from the World Development Indicator database, the World Bank.

Estimation Techniques

Our estimation technique consists of a three-step procedure. First, as a benchmark, we estimate equation (1) by applying pooled OLS regression and fixed effect panel regression estimation techniques. However, these mean-based regressions might have seriously under-or over-estimate effects in heterogeneous distribution.

Second, we also apply a panel quantile regression for estimating equation (1). The advantage of quantile regression techniques with respect to mean-based estimation procedures pooled OLS, or fixed effect regression is the following. First, quantile regression models are more robust to outliers and perform better in conditions of non-normality. Second, such models take into account the impact of covariates on the entire conditional distribution of the response variables and provide a more accurate description of the relationship (Koenker & Bassett, 1978). For instance, figure 1 shows the distributions of the poverty gap ratio via the histogram. We can conclude from the figure that it follows a long-tailed distribution, creating a significant problem in applying mean-based regression techniques. Therefore, the quantile regression is a robust technique to capture heterogeneity and assess how financial development and financial stability affect different countries according to their position along with the conditional poverty distribution.

<Figure 1 here>

As we know, in mean regression, the panel data allow for the inclusion of fixed effects to capture within-group variations. Many quantile regression methods for panel data use the same assumptions. However, the additive fixed effects alter the underlying model. In this study, we employ the quantile regression estimator for panel data with nonadditive fixed effects as proposed by (Powell, 2016)[4]. The main advantage of this method as compared to the existing panel quantile estimators with additive fixed effects is that it estimates the distribution of Y_{it} given X_{it} instead of $Y_{it} - \alpha_i$ given X_{it}. Powell (2016) method provides with point estimates that can be understood in a similar way to those originated from cross-sectional regressions. Additionally, Powell's approach is also consistent for the short panel.

Formally, following Powell's approach, the underlying model of this study is specified as follows:

$$Y_{it} = \sum_j X'_{it}\beta_j(U^*_{it}) \tag{2}$$

Where Y_{it} is the dependent variable, X'_{it} are our main independent variables, β_j is the parameter of interest, and U^*_{it} is the error terms, either time-varying or time-fixed. The model is assumed to be linear in parameter, and $X'_{it}\beta_j\ (\psi)$ is strictly rising in ψ. Generally, the ψ^{th} quantile of Y_{it}, quantile regression depends on the following conditional restriction:

$$P(Y_{it} \leq X'_{it}\beta_j(\psi)|X_{it}) = \psi, \psi\epsilon[0,1] \tag{3}$$

The above equation shows that the probability the outcome variables can be smaller than the quantile function is the same for all X_{it}; and identical to ψ. Powell's (2016) quantile regression for panel data permits this probability to fluctuate both by individual and even

[4] For robustness of our result, we have also used standard quantile regression estimator by Koenker and Basset (1978) which doesn't control for country level fixed effect. This approach is the most popular quantile regression technique and have been extensively used in the literature.

within-individuals, as long as fluctuation is orthogonal to the instrument. As a consequence, Powell's estimator, based on conditional and unconditional restriction, expressed as follows:

$$P(Y_{it} \leq X'_{it}\beta_j(\psi)|X_{it}) = P(Y_{is} \leq X'_{is}\beta_j(\psi)|X_{it}), X_i = (X_{i1}, \ldots\ldots, X_{iT}) \tag{4}$$

The quantile regression model for panel data, based on Powell (2016), is estimated by applying a numerical optimization based on the adaptive Markov Chain Monte Carlo (MCMC). This optimization approach relies on multivariate normal distribution proposed by (Baker, 2014).

Third, we also address the endogeneity issue, which is a common phenomenon in any cross-country analysis. Endogeneity may arise mainly from reverse causality and the presence of common unobserved factors affecting both dependent and independent variables. To address the endogeneity issue, we apply the generalized method of moments (GMM) (Arellano & Bond, 1991; Blundell & Bond, 1998). Under this estimation method, a lag of the dependent variable is incorporated into the set of independent variables. To avoid over-identification of variables, we rely on the Hansen test and perform the Arellano-Bond test to check for serial correlation (Arellano & Bond, 1991; Baltagi, 2008).

3. Empirical Results and Discussions

Preliminary Analysis

Table 1 provides the detailed descriptive statistics for the data used in this study. It shows that the 10^{th} and 90th quantile of our variables of interest vary significantly from lower to higher quantile. Similarly, the mean is significantly different from the median, implying that the distribution of our data is not normal. Generally, data is said to be normally distributed if the value of skewness is 0 and kurtosis is lower than 3. Table 1 shows that most of our variables are different from 0, suggesting that they are not distributed symmetrically. Further, the value of kurtosis for most of our variables is greater or different from 3, indicating the presence of extreme values. Finally, to conclude our observations statistically, we apply the Shapiro-Wilk test for univariate normality. As shown in the last column of Table 1, we conclude that our variables do not fulfil the normality and no-outlier assumptions, further reinforcing the need for a quantile regression-based approach.

<Table 1 here>

Table 2 presents the pairwise correlation matrix. The correlation among most of the explanatory variables is not too high that lead to serious multicollinearity issues.

<Table 2 here>

Further, figure 2 shows a scatter plot of poverty with financial development and financial stability measures. The figure suggests a weak but positive relationship between poverty and financial development, poverty and Z-score, and poverty and inverse of impaired loan.

<Figure 2 here>

Conditional Mean Regression

Though mean-based regressions are likely to produce inconsistent estimates in the presence of a heterogeneous distribution of our dependent variable, we present pooled and fixed effects regression estimates as benchmark specifications to compare our results from those of the previous studies. The results based on pooled and fixed effects regression are presented in Table 3.

<Table 3 here>

Columns 1-3 in Table 3 present the relationship between financial development, measures of financial stability, and poverty using the pooled OLS in the presence of all the controls. We start by estimating the relationship between financial development, measured as private credit to GDP, and poverty, measured as poverty gap ratio in column 1. In subsequent columns, we add two financial stability measures along with the financial development variable. In all three columns, the coefficient of the financial development variable is negative and statistically significant at conventional levels suggesting that financial development is negatively associated with poverty. Similarly, the coefficients of Z-score and the inverse of impaired loan ratio are statistically significant in columns 2 and 3, respectively and appear with the expected negative sign. These estimates indicate that financial stability is associated with lower poverty.

Next, the coefficient of the interaction term between financial development and financial stability measures is found to be statistically significant and positive. The significant positive coefficient estimates indicate that financial development and financial stability are substitutes in reducing poverty. Therefore, improving financial development has greater effects on poverty reduction when the financial system is more unstable and vice-versa. In other words, we can say that a financial institution that focuses on sound lending practices may not be engaged in providing excessive credit to risky borrowers, particularly the poor. Of the controls, most of them are significant with the expected sign on the coefficients.

In Columns 4–6 in Table 3, we present the estimates of the same specifications as in columns 1–3 using the fixed effects regression. All key variables, *i.e.*, financial development, financial stability, and their interaction, are now statistically insignificant at conventional levels.

However, as argued earlier, neither the pooled OLS nor the fixed effects estimates are reliable. While the former suffers from the potential omitted country-specific fixed factors, both pooled OLS and fixed effects regression methods concentrate only on the mean of the distributions, which doesn't allow the impact of financial development and financial stability on poverty to differ across quantiles. A failure to take the heterogeneity of impact across different quantiles of the dependent variable will result in misspecification and might cause the coefficient estimates to be insignificant even though the true effect is present. The quantile regression addresses this issue by taking the heterogeneity into account. Hence, next, we present the estimates from the quantile regression.

Panel Quantile Regression with nonadditive fixed effect by Powell (2016)

Columns 1–5 in Table 4(a) presents the relationship between financial development and poverty by applying panel quantile regression based on Powell (2016). We present the regression results for the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} quantiles in columns 1–5 to explore whether the impacts of financial development are different at different levels of poverty distribution. The coefficient estimates are statistically significant for the 10^{th}, 25^{th}, and 50^{th} quantile, while they are statistically insignificant for 75^{th} and 90^{th} quantiles. These estimates are consistent with the hypothesis that the effects of financial development on poverty are not homogeneous across different levels of poverty, suggesting that it is important to use quantile regression to look at the effects of financial development on poverty. These specifications, however, do not include financial stability measures and their interaction with financial development. If the inclusion of the financial development variable and the interaction term between financial development and financial stability belongs to the model, then their omission will likely result in biased estimates. To investigate this, we incorporate the financial stability and the interaction term in empirical specifications and report the results in Table 4b.

<Table 4(a) here >

<Table 4(b) here >

The measure of financial stability is Z-score in the first five columns, while it is the inverse of impaired loans in the last five columns of Table 4b. The main conclusions that can be derived from the estimates presented in these columns are consistent with our expectations and are as follows. First, although financial development reduces poverty at all levels of poverty distribution, the effect gets larger as the poverty levels get worse. Second, the same is true for financial stability: a more stable financial system leads to a reduction in poverty at all levels of poverty distribution, but the effects are stronger for higher levels of poverty. Note that the coefficient on the financial stability measure is statistically significant in all but the last column. Finally, in all but one quantile for each of the financial stability measures, the interaction term between financial development and financial stability measures is positive and statistically significant. These results, therefore, confirm that financial development and financial stability are substitutes in their effects on poverty reduction.

Robustness Analysis

We test for the robustness of our results in four ways: first, we apply a standard and the most popular quantile regression estimator by Koenker and Basset (1978); secondly, we estimate our model using alternative measures of poverty; thirdly, we evaluate our model for the sample of developing countries; finally, we estimate our model using system GMM to address endogeneity issue.

Pooled Quantile Regression and Interquantile Regression by Koenker and Basset (1978)

In Table 5, we present the results of our first robustness check that explores the relationship between financial development, financial stability, and poverty using pooled quantile regression technique developed by Koenker and Basset (1978). The main conclusions derived from Table 4 remain unchanged. Both financial development and financial stability variables remain significantly, negatively associated with poverty, with the effects being larger for the set of countries that fall under higher quantiles of poverty. And, the interaction term between the two variables remains positive and statistically significant for most quantiles. Overall, these results support the main conclusions that (1) financial development and financial stability reduce poverty across all quantiles of poverty distribution and that the effects become stronger as we move from lower quantiles (low poverty) to higher quantiles (high poverty), and (2) financial development and financial stability are substitutes in poverty reduction.

<Table 5 here >

Results obtained using quantile regressions show that the impact of financial development and financial stability on poverty is heterogeneous across different quantiles. Next, we test whether differences in the impact of financial development and financial stability on poverty at different quantiles are statistically significant. To do so, we perform the inter-quantile regressions that allow for the testing of equality of coefficients across quantiles (Koenker and Basset, 1978). The estimated coefficients of inter-quantile regressions are exactly the difference in coefficients of two quantiles regressions estimated separately. We run the inter-quartile regressions for upper quantiles (the 90^{th} and 80^{th} quantile) and the lower quantiles (the 10^{th} and 20^{th} quantile), *i.e.*, q(90/10) and q(80/20). Results presented in Table 6 show that the differences in the coefficients of key variables (i.e., financial development and financial stability) for 90^{th} and 10^{th} percentiles are statistically significant and have the correct signs. Although the differences in the coefficient estimate key variables for 80^{th} and 20^{th} percentiles have the correct sign, these are statistically significant only for one of the two measures of financial stability, namely, impaired loan. Overall, these results provide robust evidence that the impact of financial development and financial stability is heterogeneous across the poverty distribution.

<Table 6 here >

Alternative Poverty Measures – Poverty Headcount Ratio

We test the sensitivity of our results using an alternative measure of poverty, *i.e.,* poverty headcount ratio. The panel quantile regression estimates presented in Table 7 show that our main findings remain unchanged when the poverty headcount ratio is used as an alternative measure of poverty.

<Table 7 here >

Addressing Endogeneity Issue - System GMM

Our final robustness exercise is targeted at addressing endogeneity concerns and uses a two-step system GMM estimation technique. The system GMM estimation includes a lag of the dependent variable to account for the persistence of the dependent variable, and the lags of the independent variables are used as their instruments. Results are presented in Table 8. As we can see, the lag of the poverty gap is positive and statistically significant, indicating the poverty tends to be persistent. The relevant statistics reported in the Table indicate a proper specification. To check for over-identification, we rely on the Hansen J-test and perform the Arellano-Bond test to check for serial correlation (Arellano & Bond, 1991; Baltagi, 2008). While AR(1) statistics show that there is a significant first-order correlation, there is no evidence of significant second-order correlation as indicated by AR(2) statistics in all three columns. Moreover, p-values for the Hansen-J statistics indicate that the validity of the overidentification test cannot be rejected. The system GMM estimates confirm that both financial development and financial stability are significantly associated with lower poverty. Moreover, the interaction terms between the financial development and financial stability variables are positive and significant, indicating that the two are substitutes in poverty reduction.

<Table 8 here >

Overall, we can conclude that our main results for the whole sample are robust to using alternative methodologies like pooled quantile regression technique and system GMM, an alternative measure of poverty, and developing countries sample.

4. Conclusion

This paper studies the inter-relationship between financial development, financial stability, and poverty. We have two important findings with important implications. First, we show that the effects of financial development and financial stability are heterogeneous across the conditional distribution of poverty. Importantly, both financial development and financial stability has the greatest gains in reducing poverty in the poorest countries – where it is needed the most. These findings are consistent with the existing theoretical and empirical evidence that the poor benefit more from financial inclusion (Kling et al., 2020; Zhang and Posso, 2019). Second, we find that financial development and financial stability are substitutes in poverty reduction: when one is weaker, the marginal effect from improving the other on poverty is greater. To the extent that financial inclusion promotes financial stability (Danisman & Tarazi, 2020; Kling et al., 2020; Q. Zhang & Posso, 2019), developing a more inclusive financial system by uplifting the poor will promote financial stability, further reducing poverty over time.

What can explain the substitutability between financial development and financial stability in reducing poverty? Clearly, financial development, in terms of credit disbursement, is good for poverty reduction in every country regardless of the stability of their financial system. However, this effect will be more pronounced in countries with unstable financial systems where the banks would be reluctant to provide credit to the poor to keep the Z-score high and impaired loans at low levels. Conversely, the financial institutions' reluctance to provide credit to poor, risky borrowers in countries with less developed financial systems (where the poor already have limited access to finance) places a greater weight on financial stability and increases the gains from improving it.

Our findings have important implications for future studies as well as policymaking. First, the substitutability between financial development and financial stability must be taken into account in order to assess the true effect of either of the two variables on poverty. Second, a little push in improving either of the two will result in poverty reduction, suggesting that policies can be implemented, resulting in gains even when resources are limited. Third, promoting financial development and financial stability results in greater gains in poorer countries, suggesting that these countries have a strong incentive to adopt policies that promote either. Finally, our results highlight the need for taking the heterogeneity of effects across the different distribution of the dependent variable while exploring the effects of financial development and financial stability on poverty.

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Figure 1: Histogram – Poverty Gap Ratio

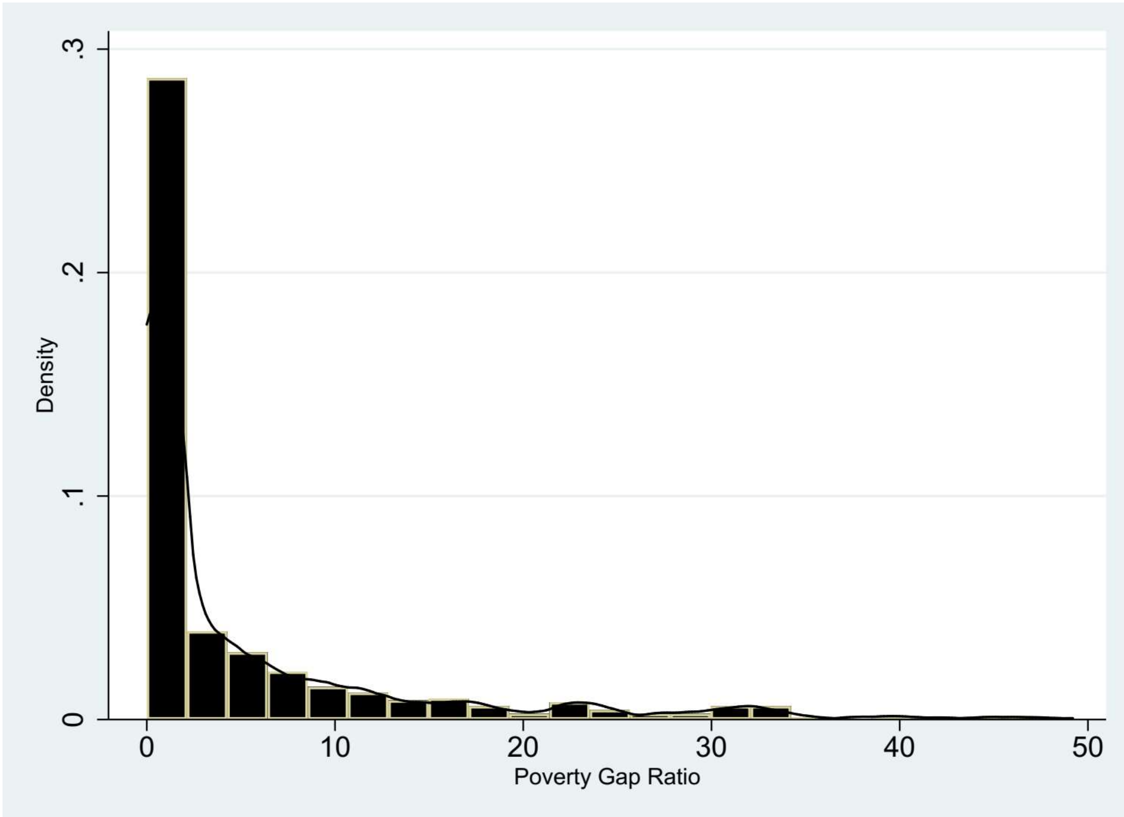
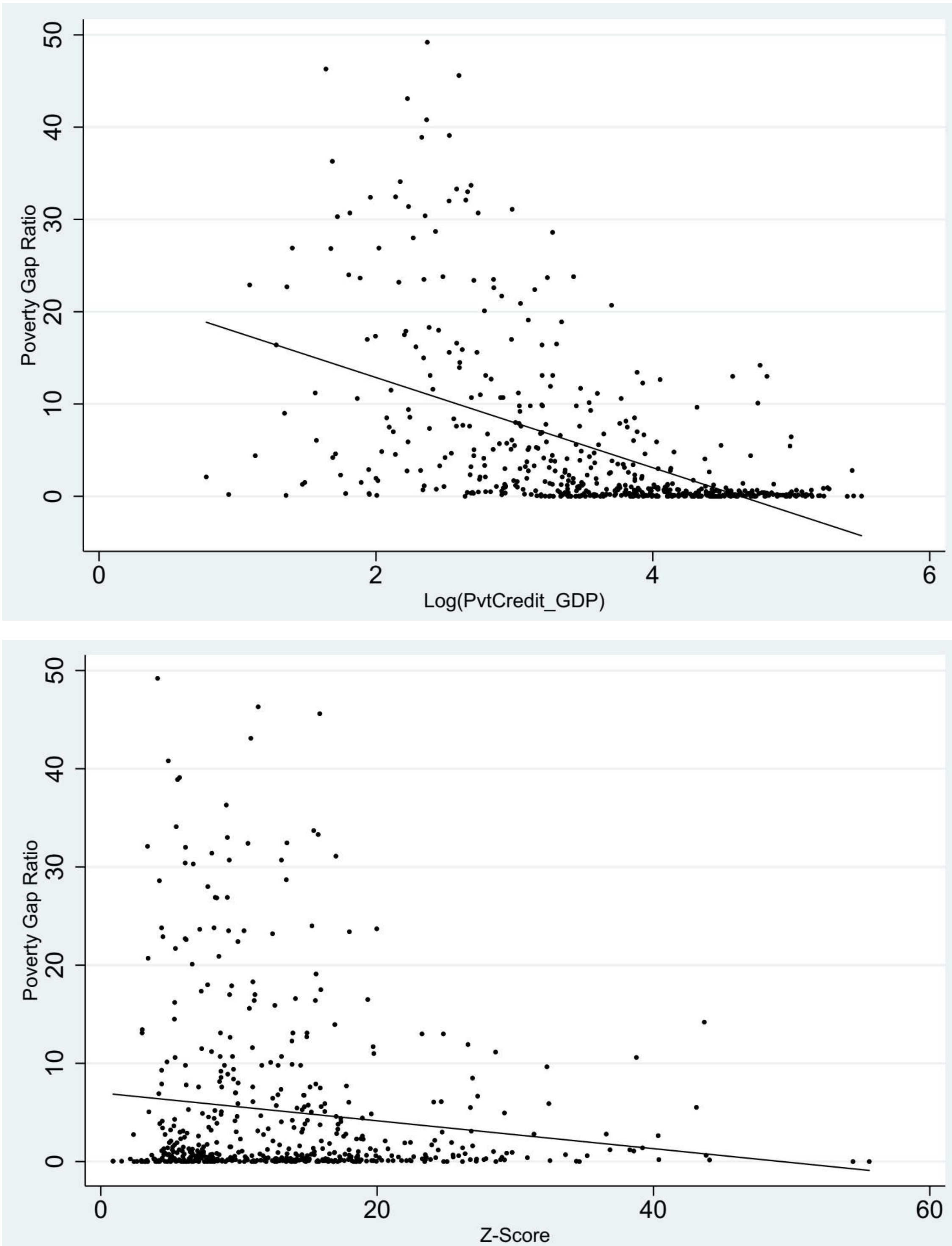
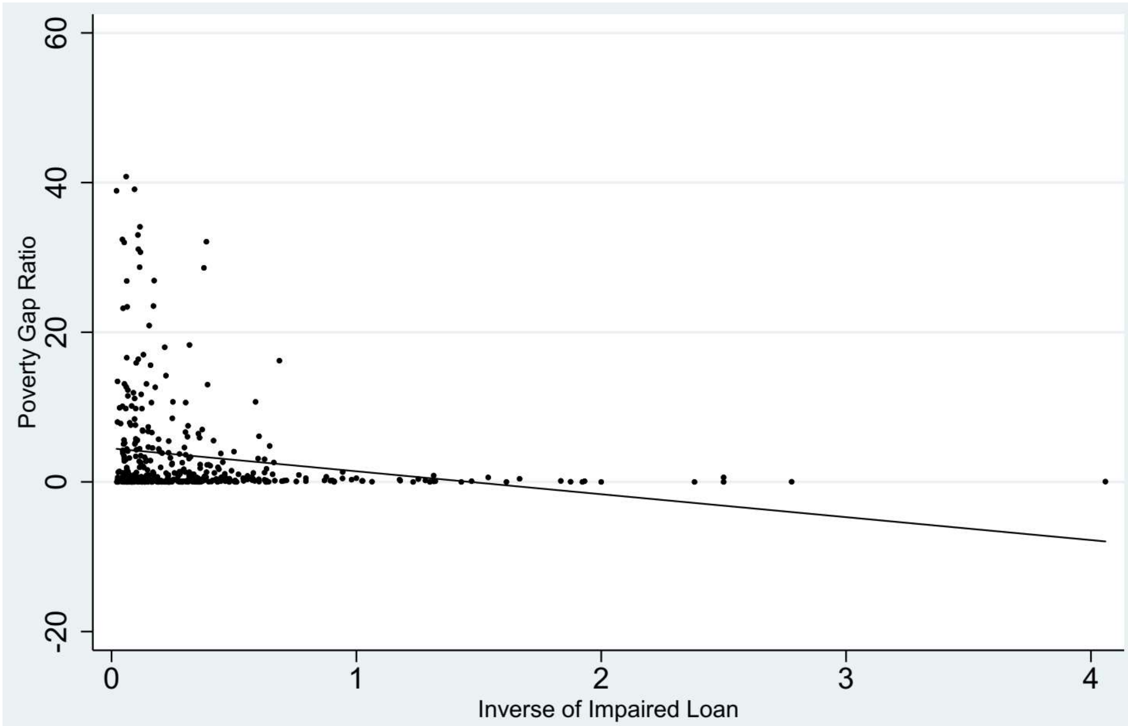


Figure 2: Scatterplots - Poverty, Financial Development, and Financial Stability





Poverty Gap Ratio
60
40
20
0
-20
0
1
2
3
4
Inverse of Impaired Loan

Table 1: Summary Statistics

Variables	Obs	Mean	Std_Dev	Min	p10	p50	p90	Max	Skew	Kurt	S-W Test
PovGap	544	5.089	8.755	0.000	0.020	0.900	16.600	49.200	2.408	8.780	11.714***
HeadCount	544	13.697	20.303	0.000	0.100	3.213	49.400	86.200	1.706	4.954	11.189***
Credit	666	3.507	0.963	0.237	2.216	3.517	4.741	5.508	-0.329	2.708	4.129***
Z-score	645	13.278	8.377	0.612	4.962	11.581	24.419	55.620	1.535	6.414	9.441***
ImpairedLoan	475	0.333	0.424	0.021	0.055	0.197	0.686	4.059	3.686	22.471	11.469***
GDPgrowth	672	3.939	2.986	-14.147	1.096	3.816	6.912	33.869	1.594	21.831	9.822***
PCY	671	8.418	1.447	5.260	6.524	8.274	10.626	11.600	0.183	2.209	5.609***
Inflation	620	1.499	1.159	-4.534	0.207	1.486	2.848	7.298	-0.020	6.003	6.039***
GovExp	634	16.290	7.712	1.150	9.648	16.057	22.602	119.497	6.487	76.124	12.316***
Enrolment	598	4.008	0.778	0.672	2.832	4.339	4.672	5.082	-1.371	4.451	9.864***
Gini	543	38.716	8.660	23.000	28.367	37.100	51.900	65.800	0.665	2.886	6.442***

Table 2: Correlation Matrix

	1	2	3	4	5	7	8	9	10	11	12
PovGap	1										
HeadCount	0.975	1									
Credit	-0.496	-0.535	1								
Z-score	-0.063	-0.050	0.192	1							
ImpairedLoan	-0.167	-0.194	0.322	0.134	1						
GDPgrowth	0.206	0.262	-0.330	0.092	-0.010	1					
PCY	-0.567	-0.639	0.705	-0.002	0.466	-0.410	1				
Inflation	0.307	0.331	-0.525	-0.167	-0.203	0.098	-0.515	1			
GovExp	-0.234	-0.294	0.468	0.021	0.145	-0.396	0.554	-0.340	1		
Enrolment	-0.657	-0.699	0.513	-0.032	0.198	-0.315	0.647	-0.363	0.419	1	
Gini	0.414	0.409	-0.266	0.174	-0.126	0.159	-0.412	0.328	-0.381	-0.346	1

Table 3: Pooled OLS and Fixed Effect Regression

Dependent Variable - Poverty Gap Ratio						
	Pooled OLS			Fixed Effect		
	1	2	3	4	5	6
Credit	-1.119**	-2.196***	-2.384***	-0.423	-0.431	0.00232
	[-2.39]	[-2.74]	[-3.60]	[-0.58]	[-0.40]	[0.00]
Z-Score		-0.421**			0.0646	
		[-2.02]			[0.29]	
Credit*Z-Score		0.0823*			0.00227	
		[1.68]			[0.05]	
ImpairedLoan			-12.36**			-3.600
			[-2.18]			[-1.08]
Credit*ImpairedLoan			3.050**			0.776
			[2.42]			[1.05]
GDPgrowth	-0.315**	-0.199	-0.0498	-0.164**	-0.180**	-0.139***
	[-2.37]	[-1.43]	[-0.33]	[-2.10]	[-2.23]	[-2.81]
PCY	-1.457***	-1.837***	-1.002*	-2.303	-2.028	-3.509***
	[-3.93]	[-4.54]	[-1.94]	[-0.91]	[-0.74]	[-2.64]
Inflation	-1.135***	-1.246***	-0.472*	-0.492**	-0.553**	-0.266
	[-3.90]	[-4.09]	[-1.77]	[-2.09]	[-2.28]	[-1.42]
GovExp	0.0556	0.277***	0.299***	0.0111	-0.00592	-0.151
	[1.51]	[3.26]	[3.00]	[0.13]	[-0.03]	[-1.39]
Enrolment	-4.930***	-4.598***	-4.367***	-1.242	-1.251	-0.495
	[-7.05]	[-6.67]	[-5.70]	[-1.59]	[-1.54]	[-1.26]
Gini	0.145***	0.174***	0.165***	0.241*	0.251*	0.156*
	[5.11]	[6.12]	[6.71]	[1.96]	[1.96]	[1.90]
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-FE	No	No	No	Yes	Yes	Yes
adj. R-sq	0.558	0.583	0.533	0.310	0.314	0.428
No. of Groups				121	119	99
N	423	416	340	423	416	340

Notes: *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Figures in parentheses are their respective t-statistics with robust standard errors.

Table 4 (a): Full Sample - Panel Quantile Regression with nonadditive fixed effect by Powell (2016)

	Dependent Variable - Poverty Gap Ratio				
	q10	q25	q50	q75	q90
	1	2	3	4	5
Credit	-0.172***	-0.262*	-0.409**	147.5	125.5
	[-3.65]	[-1.76]	[-2.48]	[0.28]	[0.27]
GDPgrowth	-0.0289***	-0.0787***	-0.0904***	1.62	-36.9
	[-3.40]	[-3.29]	[-4.37]	[0.28]	[-0.27]
PCY	-0.108***	-0.574**	-0.147	-226.9	-818.6
	[-3.19]	[-2.52]	[-1.54]	[-0.28]	[-0.27]
Inflation	-0.0178	-0.0547	0.0726	199.3	139.3
	[-0.75]	[-0.34]	[1.20]	[0.28]	[0.27]
GovExp	0.00491	-0.0156	0.0281***	15.6	56.6
	[0.76]	[-1.10]	[7.10]	[0.28]	[0.27]
Enrolment	-0.0605	-0.113	-4.795***	142.6	-720.8
	[-1.37]	[-0.63]	[-22.44]	[0.28]	[-0.27]
Gini	0.0348***	0.0754***	0.0980***	50.1	-126.5
	[12.15]	[4.02]	[4.64]	[0.28]	[-0.27]
Group	121	121	121	121	121
N	423	423	423	423	423

Notes: The model is estimated using QREGPD command in STATA 15. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Figures in parentheses are their respective t-statistics with robust standard errors.

Table 4 (b): Full Sample - Panel Quantile Regression with nonadditive fixed effect by Powell (2016)

	Dependent Variable - Poverty Gap Ratio									
	q10	q25	q50	q75	q90	q10	q25	q50	q75	q90
	1	2	3	4	5	6	7	8	9	10
Credit	-0.376***	-1.753***	-2.059***	-1.058**	-2.497***	-0.432***	-0.742***	-2.064***	-1.997***	-2.046***
	[-4.25]	[-6.65]	[-6.29]	[-2.18]	[-8.01]	[-9.27]	[-27.91]	[-5.62]	[-17.29]	[-4.79]
Z-Score	-0.0449***	-0.432***	-0.526***	-0.277**	-1.023***					
	[-4.05]	[-4.31]	[-6.77]	[-1.99]	[-6.88]					
Credit*Z-Score	0.00897**	0.0850***	0.124***	0.0533	0.224***					
	[2.29]	[4.91]	[6.30]	[1.52]	[7.03]					
ImpairedLoan						-1.457***	-2.686***	-9.077***	-14.23***	-4.103
						[-4.03]	[-10.29]	[-7.46]	[-15.88]	[-0.93]
Credit*ImpairedLoan						0.329***	0.626***	1.468***	3.215***	1.158
						[4.00]	[10.65]	[7.97]	[16.07]	[1.25]
GDPgrowth	-0.0241***	-0.181***	-0.307***	0.0131	-0.0785	-0.0166***	-0.0511***	-0.208***	0.0676***	-0.0185
	[-3.65]	[-6.12]	[-4.96]	[0.47]	[-1.12]	[-3.09]	[-7.21]	[-2.85]	[10.93]	[-0.35]
PCY	0.00518	-0.346***	-0.401***	-1.123***	-3.989**	-0.0289	-0.0264	-1.005***	-0.255***	-1.097***
	[0.30]	[-6.27]	[-7.41]	[-3.90]	[-2.32]	[-0.72]	[-1.23]	[-2.64]	[-4.29]	[-5.29]
Inflation	-0.0836***	-0.150**	-0.216**	-0.496***	-1.322**	-0.0535***	-0.133***	-0.455***	-0.212***	-0.0999
	[-6.64]	[-2.50]	[-2.36]	[-3.44]	[-2.41]	[-3.77]	[-4.77]	[-3.71]	[-3.59]	[-0.51]
GovExp	-0.000433	0.0192	0.0789**	0.330***	0.652***	0.0133***	0.0280***	0.0284	0.319***	0.439***
	[-0.06]	[1.40]	[2.56]	[8.84]	[4.38]	[6.16]	[4.12]	[0.75]	[62.14]	[14.81]
Enrolment	-0.171***	-0.746*	-5.006***	-7.457***	-8.917***	-0.0542	-0.679***	-1.414**	-6.316***	-8.722***
	[-4.05]	[-1.91]	[-19.63]	[-15.25]	[-5.15]	[-1.62]	[-26.97]	[-2.55]	[-47.43]	[-47.00]
Gini	0.0371***	0.146**	0.141***	0.199***	0.0741***	0.0328***	0.0611***	0.154***	0.157***	0.126***
	[13.36]	[2.30]	[8.90]	[3.93]	[3.53]	[25.96]	[24.48]	[7.48]	[54.94]	[9.11]
Group	119	119	119	119	119	99	99	99	99	99
N	416	416	416	416	416	340	340	340	340	340

Notes: The model is estimated using QREGPD command in STATA 15. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Figures in parentheses are their respective t-statistics with robust standard errors.

Table 5 (a): Robustness – Pooled Quantile Regression by Koenker and Basset (1978) – Full Sample

	Dependent Variable - Poverty Gap Ratio				
	q10	q25	q50	q75	q90
	1	2	3	4	5
Credit	-0.274***	-0.479***	-0.582**	-0.292	-1.494*
	[-2.73]	[-3.73]	[-2.50]	[-0.70]	[-1.78]
GDPgrowth	-0.0395*	-0.0888***	-0.0910**	-0.0830	-0.107
	[-1.86]	[-2.65]	[-2.09]	[-0.82]	[-0.51]
PCY	-0.0280	-0.252**	-0.290*	-0.838**	-0.859
	[-0.42]	[-2.19]	[-1.66]	[-2.51]	[-1.59]
Inflation	-0.170**	-0.373***	-0.496***	-0.694***	-0.613
	[-2.48]	[-3.94]	[-4.32]	[-2.83]	[-0.92]
GovExp	0.0110	0.0440	0.0417	0.198***	0.316**
	[0.68]	[1.44]	[1.45]	[2.72]	[2.12]
Enrolment	-0.447***	-1.202***	-5.243***	-7.536***	-11.19***
	[-2.84]	[-2.79]	[-5.99]	[-6.67]	[-7.02]
Gini	0.0365***	0.0622***	0.0769***	0.116***	0.0880
	[4.35]	[5.27]	[4.89]	[3.56]	[1.37]
Constant	Yes	Yes	Yes	Yes	Yes
N	423	423	423	423	423

Notes: The model is estimated using QREG command in STATA 15. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Figures in parentheses are their respective t-statistics with robust standard errors.

Table 5 (b): Robustness – Pooled Quantile Regression by Koenker and Basset (1978) – Full Sample

	Dependent Variable - Poverty Gap Ratio									
	q10	q25	q50	q75	q90	q10	q25	q50	q75	q90
	1	2	3	4	5	6	7	8	9	10
Credit	-0.431**	-0.783***	-1.473***	-1.219*	-3.389***	-0.365***	-0.602***	-0.918**	-1.369***	-2.742**
	[-2.30]	[-3.16]	[-4.59]	[-1.80]	[-3.22]	[-5.79]	[-4.28]	[-2.59]	[-3.60]	[-1.97]
Z-Score	-0.0571	-0.141***	-0.341***	-0.324	-0.698*					
	[-1.42]	[-2.94]	[-4.66]	[-1.51]	[-1.82]					
Credit*Z-Score	0.0133	0.0303***	0.0697***	0.0659	0.146*					
	[1.39]	[2.76]	[4.17]	[1.39]	[1.75]					
ImpairedLoan						-1.569**	-2.087	-5.159**	-9.224***	-12.27
						[-2.49]	[-1.26]	[-2.43]	[-4.36]	[-1.08]
Credit*ImpairedLoan						0.365***	0.491	1.197**	2.078***	2.697
						[2.60]	[1.40]	[2.56]	[4.44]	[1.07]
GDPgrowth	-0.0254	-0.0888**	-0.0699	-0.0150	-0.108	-0.0145	-0.0792***	-0.0174	0.0504	0.0395
	[-1.48]	[-1.98]	[-1.37]	[-0.13]	[-0.43]	[-1.18]	[-2.95]	[-0.37]	[0.88]	[0.15]
PCY	-0.0129	-0.248**	-0.434***	-0.806**	-0.989	-0.0468	-0.115	-0.284	-0.278	-0.328
	[-0.16]	[-2.46]	[-2.65]	[-2.33]	[-1.50]	[-1.42]	[-1.62]	[-1.36]	[-1.03]	[-0.46]
Inflation	-0.113*	-0.377***	-0.755***	-0.712***	-0.889	-0.111***	-0.232***	-0.263	-0.0675	-0.230
	[-1.70]	[-3.11]	[-5.57]	[-2.74]	[-1.35]	[-4.96]	[-3.85]	[-1.57]	[-0.46]	[-0.38]
GovExp	0.00103	0.0223	0.122***	0.304***	0.460***	0.0162**	0.0215	0.178***	0.279***	0.412***
	[0.10]	[0.95]	[3.46]	[6.74]	[4.03]	[2.36]	[1.41]	[4.03]	[10.32]	[2.61]
Enrolment	-0.236	-1.179**	-5.177***	-8.211***	-11.53***	-0.201*	-0.630***	-2.688**	-6.270***	-9.229***
	[-1.36]	[-2.41]	[-7.00]	[-6.69]	[-6.29]	[-1.74]	[-2.64]	[-2.55]	[-8.63]	[-3.31]
Gini	0.0321***	0.0694***	0.103***	0.136***	0.0938	0.0321***	0.0610***	0.111***	0.137***	0.167**
	[3.19]	[5.24]	[5.56]	[4.50]	[1.61]	[8.58]	[6.63]	[5.50]	[6.97]	[2.53]
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	416	416	416	416	416	340	340	340	340	340

Notes: The model is estimated using QREG command in STATA 15. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Figures in parentheses are their respective t-statistics with robust standard errors.

Table 6 – Robustness – Interquartile Regression by Koenker and Basset (1978)

	Dependent Variable - Poverty Gap Ratio					
	q(90/10)	q(90/10)	q(90/10)	q(80/20)	q(80/20)	q(80/20)
	(1)	(2)	(3)	(4)	(5)	(6)
Credit	-1.219*	-2.958***	-2.377***	0.186	-0.436	-0.767**
	[-1.92]	[-2.92]	[-2.60]	[0.49]	[-0.69]	[-1.98]
Z-Score		-0.641*			-0.183	
		[-1.80]			[-1.22]	
Credit*Z-Score		0.133*			0.0356	
		[1.80]			[1.05]	
ImpairedLoan			-10.70*			-7.136**
			[-1.74]			[-2.15]
Credit*ImpairedLoan			2.332			1.587**
			[1.57]			[2.18]
GDPgrowth	-0.0674	-0.0822	0.0540	0.00582	0.0738	0.130
	[-0.45]	[-0.46]	[0.36]	[0.04]	[0.98]	[1.48]
PCY	-0.831	-0.976*	-0.281	-0.586	-0.558	-0.164
	[-1.60]	[-1.88]	[-0.36]	[-1.56]	[-1.42]	[-0.44]
Inflation	-0.443	-0.777	-0.119	-0.322	-0.335	0.164
	[-0.93]	[-1.19]	[-0.31]	[-1.31]	[-1.13]	[0.98]
GovExp	0.305***	0.459***	0.396**	0.154*	0.282***	0.258***
	[4.56]	[4.25]	[2.50]	[1.66]	[5.27]	[6.72]
Enrolment	-10.75***	-11.29***	-9.028***	-6.334***	-7.032***	-5.640***
	[-9.56]	[-8.30]	[-4.59]	[-5.09]	[-5.43]	[-7.75]
Gini	0.0515	0.0617	0.135***	0.0534	0.0665*	0.0760***
	[0.94]	[1.30]	[2.80]	[1.50]	[1.75]	[3.44]
Constant	Yes	Yes	Yes	Yes	Yes	Yes
N	423	416	340	423	416	340

Notes: The model is estimated using IQREG command in STATA 15. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Figures in parentheses are their respective t-statistics.

Table 7 (a) – Robustness – Alternative Poverty Measures – Panel Quantile Regression with nonadditive fixed effect by Powell (2016)

	Dependent Variable - Poverty Headcount Ratio				
	q10	q25	q50	q75	q90
	1	2	3	4	5
Credit	-1.287***	-1.254	-0.523	-1.814	-1.832**
	[-11.53]	[-1.17]	[-1.01]	[-0.93]	[-2.45]
GDPgrowth	-0.232***	-0.195*	-0.210***	-0.412	-0.356**
	[-8.74]	[-1.93]	[-6.00]	[-0.81]	[-2.27]
PCY	-0.406***	-2.642***	-1.759***	-9.846**	-6.866***
	[-5.31]	[-3.21]	[-37.66]	[-2.01]	[-12.09]
Inflation	-0.411***	-0.349	-0.588**	-1.718*	-1.734***
	[-4.77]	[-1.25]	[-2.12]	[-1.69]	[-8.01]
GovExp	-0.0100**	0.168***	0.193***	0.680***	0.731***
	[-2.02]	[6.14]	[19.05]	[3.98]	[26.11]
Enrolment	-0.669***	-0.658	-12.96***	-9.112	-19.30***
	[-5.58]	[-0.71]	[-16.97]	[-1.40]	[-12.67]
Gini	0.146***	0.0796	0.189***	0.325**	0.0430
	[18.50]	[0.89]	[6.48]	[2.09]	[0.90]
N	423	423	423	423	423
Group	121	121	121	121	121

Notes: The model is estimated using QREGPD command in STATA 15. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Figures in parentheses are their respective t-statistics with robust standard errors.

Table 7 (b) – Robustness – Alternative Poverty Measures – Panel Quantile Regression with nonadditive fixed effect by Powell (2016)

	Dependent Variable - Povert Headcount Ratio									
	q10	q25	q50	q75	q90	q10	q25	q50	q75	q90
	6	7	8	9	10	11	12	13	14	15
Credit	-1.707***	-1.865***	-2.058***	-4.674***	-2.610***	-1.520***	-2.315***	-1.704***	-4.363***	-5.218***
	[-16.38]	[-7.49]	[-4.62]	[-2.83]	[-3.97]	[-4.57]	[-2.60]	[-11.79]	[-6.95]	[-3.83]
Z-Score	-0.235***	-0.269***	-0.627**	-1.383***	-0.577***					
	[-10.07]	[-5.75]	[-2.57]	[-3.63]	[-2.65]					
Credit*Z-Score	0.0502***	0.0541***	0.140**	0.297***	0.127**					
	[9.71]	[4.58]	[2.19]	[3.40]	[2.34]					
ImpairedLoan						-4.667**	-10.71*	-11.83***	-21.78***	-69.78*
						[-2.01]	[-1.72]	[-10.07]	[-5.81]	[-1.69]
Credit*ImpairedLoan						1.010*	1.838	2.437***	4.323***	15.05*
						[1.93]	[1.39]	[8.75]	[5.09]	[1.76]
GDPgrowth	-0.163***	-0.201***	-0.255***	-0.0930	-0.154	-0.143***	-0.126***	-0.112***	0.147	0.224
	[-4.59]	[-11.68]	[-3.71]	[-0.68]	[-1.17]	[-3.74]	[-2.78]	[-4.44]	[1.17]	[0.71]
PCY	-0.253***	-0.923***	-1.176***	-4.027***	-5.542***	-0.266***	-0.314	-0.907***	-0.735	-3.879***
	[-7.99]	[-8.52]	[-2.98]	[-8.86]	[-28.71]	[-3.54]	[-0.75]	[-15.79]	[-1.28]	[-5.28]
Inflation	-0.297***	-0.658***	-0.409	-1.765***	-1.870***	-0.273***	-0.173	-0.699***	-0.210	-1.836***
	[-19.12]	[-5.30]	[-0.64]	[-8.91]	[-12.20]	[-4.67]	[-0.55]	[-10.26]	[-0.55]	[-3.23]
GovExp	0.0406***	0.142***	0.0528	0.548***	0.828***	0.0257	0.0562	0.323***	0.650***	0.613**
	[4.08]	[3.93]	[0.35]	[5.44]	[13.58]	[1.00]	[1.11]	[28.99]	[11.36]	[2.43]
Enrolement	-0.571***	-5.224***	-12.96***	-17.59***	-23.97***	-0.267	-3.167***	-10.14***	-13.70***	-18.61***
	[-7.94]	[-40.19]	[-22.68]	[-14.65]	[-64.67]	[-1.14]	[-13.24]	[-90.59]	[-43.07]	[-9.91]
Gini	0.142***	0.211***	0.284***	0.244***	0.146***	0.121***	0.199***	0.240***	0.357***	0.244
	[23.99]	[18.51]	[7.14]	[7.89]	[7.71]	[21.66]	[6.35]	[33.76]	[8.49]	[1.36]
N	416	416	416	416	416	340	340	340	340	340
Group	119	119	119	119	119	99	99	99	99	99

Notes: The model is estimated using QREGPD command in STATA 15. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Figures in parentheses are their respective t-statistics with robust standard errors.

Table 8: Robustness - System GMM

Dependent Variable - Poverty Gap Ratio			
	1	2	3
L.PovGap	0.548***	0.545***	0.684***
	[4.13]	[4.22]	[5.63]
Credit	-0.407	-1.371**	-0.460**
	[-1.34]	[-2.46]	[-2.06]
Z-Score		-0.338**	
		[-2.46]	
Credit*Z-Score		0.0738**	
		[2.40]	
ImpairedLoan			-3.738*
			[-1.94]
Credit*ImpairedLoan			0.862**
			[2.04]
GDPgrowth	-0.268***	-0.245***	-0.107**
	[-4.24]	[-3.59]	[-2.27]
PCY	-0.423	-0.528*	-0.221
	[-1.64]	[-1.73]	[-1.03]
Inflation	-0.320	-0.300	-0.134
	[-1.52]	[-1.34]	[-1.35]
GovExp	0.0134	0.0739	0.0411
	[0.62]	[1.36]	[0.98]
Enrolment	-1.325**	-1.067**	-0.540**
	[-2.45]	[-2.11]	[-2.21]
Gini	0.0363	0.0487*	0.0147
	[1.60]	[1.84]	[0.66]
Constant	Yes	Yes	Yes
Year-FE	Yes	Yes	Yes
Country-FE	Yes	Yes	Yes
Hansen Test (p-value)	0.8	0.79	0.25
AR(1) (p-value)	0.05	0.05	0.08
AR(2) (p-value)	0.57	0.33	0.19
No. of Instruments	20	22	22
No. of Groups	112	111	95
N	310	307	269

Notes: The model is estimated using XTABOND2 command in STATA 15. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Figures in parentheses are their respective t-statistics with Windmeijer-corrected cluster-robust standard errors. The row for the Hansen test reports the *p*-values for the null hypothesis of instrument validity. The values reported for AR(2) are the *p*-values for second order autocorrelated disturbances in the first differences equations.

Appendix A1 – List of Sample Countries

Developing Countries					
Angola	Colombia	Guatemala	Liberia	Niger	Tajikistan
Argentina	Congo, Rep.	Guinea	Madagascar	Nigeria	Tanzania
Armenia	Costa Rica	Honduras	Malawi	Pakistan	Thailand
Azerbaijan	Cote d'Ivoire	India	Malaysia	Panama	Timor-Leste
Bangladesh	Djibouti	Indonesia	Maldives	Paraguay	Togo
Benin	Dominican Republic	Iran, Islamic Rep.	Mauritania	Peru	Tonga
Bhutan	Ecuador	Iraq	Mauritius	Philippines	Tunisia
Bolivia	Egypt, Arab Rep.	Jamaica	Mexico	Rwanda	Turkey
Botswana	El Salvador	Jordan	Micronesia, Fed. Sts.	Samoa	Uganda
Brazil	Eswatini	Kazakhstan	Mongolia	Sao Tome and Principe	Uruguay
Burkina Faso	Ethiopia	Kenya	Morocco	Senegal	Venezuela, RB
Burundi	Fiji	Korea, Rep.	Mozambique	Solomon Islands	Vietnam
Cabo Verde	Gambia, The	Kosovo	Namibia	South Africa	West Bank and Gaza
Cameroon	Georgia	Kyrgyz Republic	Nepal	Sri Lanka	Yemen, Rep.
Chile	Ghana	Lao PDR	Nicaragua	Sudan	Zambia
China					
Developed Countries					
Albania	Croatia	Greece	Lithuania	Poland	Sweden
Australia	Cyprus	Hungary	Luxembourg	Portugal	Switzerland
Austria	Czech Republic	Iceland	Malta	Romania	Ukraine
Belarus	Denmark	Ireland	Moldova	Russian Federation	United Kingdom
Belgium	Estonia	Israel	Montenegro	Serbia	United States
Bosnia and Herzegovina	Finland	Italy	Netherlands	Slovak Republic	
Bulgaria	France	Japan	North Macedonia	Slovenia	
Canada	Germany	Latvia	Norway	Spain	