Finance, Inequality and the Poor

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January 26, 2007

Abstract: Financial development disproportionately boosts incomes of the poorest quintile and reduces income inequality. About 40% of the long-run impact of financial development on the income growth of the poorest quintile is the result of reductions in income inequality, while 60% is due to the impact of financial development on aggregate economic growth. Furthermore, financial development is associated with a drop in the fraction of the population living on less than $1 a day, a result which holds when conditioning on average growth. These findings emphasize the importance of the financial system for the poor.

JEL Codes: O11, O16, G00
Key Words: Financial Systems, Income Distribution, Economic Development, Poverty Alleviation

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*We would like to thank Aart Kraay for sharing his data with us. Daron Acemoglu, Biagio Bossone, Francois Bourguignon, Gerard Caprio, Maria Carkovic, Michael Fuchs, Alan Gelb, Patrick Honohan, Aart Kraay, Ashoka Mody, Martin Ravallion, two anonymous referees and seminar participants at the American Economic Association meetings, Brown University, Bilkent University, the University of Minnesota, the Wharton School, and the World Bank provided helpful comments. We thank Meghana Ayyagari, Carlos Espina and April Knill for outstanding research assistance. This paper's findings, interpretations, and conclusions are entirely those of the authors and do not necessarily represent the views of the World Bank, its Executive Directors, or the countries they represent.

1. Introduction

There are stunning cross-country differences in the distribution of income and the prevalence of poverty. According to the Human Development Report (2005), the ratio of the incomes of the richest 20 percent of the population to the poorest 20 percent exceeded 17 in 21 countries, but was less than five in 27 others. In some countries, essentially nobody lives on less than $1 per day, but in 22 countries more than one-third of the people live below this commonly used poverty line. Furthermore, income distribution and poverty are not stagnant. Finland, France, and Turkey experienced declines in their Gini coefficients of about one percent per annum over the last 30 years, while Argentina, Brazil, Chile, and the United States experienced correspondingly rapid increases. In Thailand, the percentage of the population living on less than $1 a day in 2000 was one-tenth of the level in 1981, while the rate doubled in Venezuela.

In this paper, we examine the impact of financial development on the poor by estimating the relationship between finance and changes in both income distribution and poverty levels. Financial development may affect the poor through two channels: aggregate growth and changes in the distribution of income. Consider first relative poverty as measured by income per capita of the lowest quintile, Y_P. If we define Y as average income per capita, and L as the Lorenz curve, which relates the share of income received to the share of the population, then $Y_p \equiv Y*L(0.2)/0.2$. Differentiating and letting g(x) represent the growth rate of variable x, yields $g(Y_p) = g(Y) + g(L(0.2))$. The growth rate of per capita income of the poorest quintile equals the growth of average per capita income plus the growth of the Lorenz curve, which captures changes in income distribution. Now, consider absolute poverty. Kakwani (1993) and Datt and Ravallion (1992) show that changes in absolute poverty, as for example measured by the share of population living below the poverty line of $1 per day, are also direct functions of average growth and changes in income distribution. Although a large literature finds that financial development produces faster average growth (Levine, 1997, 2005), researchers have not yet determined whether financial development benefits the whole population equally, or whether it disproportionately benefits the rich or the poor. If financial development intensifies income inequality, this income distribution effect will mitigate – or even negate – the beneficial effects of financial development on the poor.

Theory provides conflicting predictions about the impact of financial development on the distribution of income and the incomes of the poor. Some models imply that financial development enhances growth *and* reduces inequality. Financial imperfections, such as information and transactions costs, may be especially binding on the poor who lack collateral and credit histories. Thus, any relaxation of these credit constraints will disproportionately benefit the poor. Furthermore, these credit constraints reduce the efficiency of capital allocation and intensify income inequality by impeding the flow of capital to poor individuals with high expected return investments (Galor and Zeira, 1993; Aghion and Bolton, 1997; Galor and Moav, 2004). From this perspective, financial development helps the poor both by improving the efficiency of capital allocation, which accelerates aggregate growth, and by relaxing credit constraints that more extensively restrain the poor, which reduces income inequality.

In contrast, some theories predict that financial development primarily helps the rich. According to this view, the poor rely on informal, family connections for capital, so that improvements in the formal financial sector inordinately benefit the rich. Greenwood and Jovanovic (1990) develop a model that predicts a nonlinear relationship between financial development, income inequality, and economic development. At all stages of economic development, financial development improves capital allocation, boosts aggregate growth, and helps the poor through this channel. However, the distributional effect of financial development, and hence the net impact on the poor, depends on the level of economic development. At early stages of development, only the rich can afford to access and directly profit from better financial markets. At higher levels of economic development, many people access financial markets so that financial development directly helps a larger proportion of society.

This paper empirically assesses these conflicting views about the impact of financial development on the distribution of income and the incomes of the poor. Rather than reexamining the finance-growth link, we assess the impact of financial development on changes in the distribution of income and changes in both relative and absolute poverty. Specifically, we examine (1) the Gini coefficient, which measures deviations from perfect income equality, (2) income share of the poor, which measures the income of the poorest quintile relative to total national income, and (3) the percentage of the population living on less than $1 per day. Both the Gini coefficient and the income share of the poor measure income inequality; however, the income share of the poor focuses on the poorest quintile while the Gini coefficient includes information on the entire distribution of income. Hence, we examine both inequality measures along with the percentage of the population living on less than $1 per day as a measure of absolute poverty.

There are three key inter-related findings. First, financial development reduces income inequality. Specifically, there is a negative relationship between financial development and the growth rate of the Gini coefficient, which holds when controlling for real per capita GDP growth, lagged values of the Gini coefficient, a wide array of other country-specific factors, and when using panel instrumental variable procedures to control for endogeneity and other potential biases.

Second, financial development exerts a disproportionately positive impact on the relatively poor. Financial development boosts the growth rate of the income share of the poorest quintile. Thus, finance helps the poor above and beyond the impact of financial development on aggregate growth. More specifically, about 40% of the impact of financial development on the income growth of the poorest quintile is the result of reductions in income inequality, while the remainder of the impact of financial development on the poor is due to the effect of financial development on aggregate economic growth. These results are robust to conditioning on many country traits and when employing a panel instrumental variable estimator to control for potential endogeneity bias.

Third, financial development is strongly associated with poverty alleviation. Greater financial development is associated with faster reductions in the fraction of the population living on less than $1 a day. For the median country, we find that half of the impact of financial development on this headcount measure of poverty is due to financial development accelerating economic growth, and half of the reduction in poverty is due financial development reducing income inequality. Due to data limitations, however, we are unable to use the panel estimator to control for potential endogeneity. Thus, these results on people living on less than $1 a day are subject to more qualifications than our findings that financial development reduces income inequality and disproportionately helps those in the bottom fifth of the distribution of income.

This paper adds to a large policy-oriented literature on the relationship between inequality and growth. While not without its critics (Forbes, 2000; Lundberg and Squire, 2003), considerable work finds that income inequality hurts growth (Perotti, 1996; Persson and Tabellini, 1994; Clarke, 1995; and Easterly, 2002). While capital market imperfections are often at the center of theoretical and empirical explanations of the negative relationship between inequality and growth, most researchers have focused on redistributive policies to reduce inequality with positive repercussions for economic growth (Demirgüç-Kunt and Levine, 2007). As reviewed by Aghion, Caroli and Peñalosa (1999), some models suggest that public policies that redistribute income from the rich to the poor will alleviate the adverse growth effects of income inequality and boost aggregate growth, though the adverse incentive effects of redistributive policies may temper their growth effects. Our paper highlights an alternative policy approach: Financial sector reforms that reduce market frictions will lower income inequality and boost growth without the potential incentive problems associated with redistributive policies.

Our research also relates to work on how capital market imperfections influence child labor and schooling. Using household data from Peru, Jacoby (1994) finds that lack of access to credit perpetuates poverty because poor households reduce their kids' education. Jacoby and Skoufias (1997) show that households from Indian villages without access to credit markets tend to reduce their children's schooling when they receive transitory shocks more than households with greater access to financial markets. Similarly, Dehejia and Gatti (2003) find that child labor rates are higher in countries with under-developed financial systems, while Beegle, et al. (2003) show that transitory income shocks lead to greater increases in child labor in countries with poorly functioning financial systems. In contrast, we show that financial development exerts an especially pronounced impact on changes in relative and absolute poverty rates.

Our analyses also contribute to cross-country studies. Dollar and Kraay (2002) find that in a regression where the dependent variable is income growth of the poor, aggregate growth enters with a coefficient of about one, and find that indicators of changes in national institutions and policies, including changes in financial development, do not explain income growth of the poor beyond their effects on aggregate growth. We extend the data six years, examine growth of the income share of the poor, and allow lagged values of the income share of the poor to influence present values. In our analyses, financial development boosts the growth rate of the lowest income share, thus improving income growth of the poor beyond its effect on aggregate growth. In an analysis of income inequality, Clarke, et al. (2006) study the relationship between financial development and the level of the Gini coefficient. They find that financial development reduces income inequality. In our analyses, we allow for potential dynamics in the Gini coefficient and show that the level of financial development reduces the growth rate of the Gini coefficient even when conditioning on average growth and lagged values of income inequality. Furthermore, distinct from both of these studies, we show that financial development is robustly linked with declines in the fraction of the population living on less than $1 per day.

2. Data, summary statistics, and econometric methods

To conduct our analyses, we need measures of financial development, income distribution, and poverty as well as econometric methods for ascertaining the relationship between finance and the poor. This section describes the variables, discusses the econometric methods, and provides summary statistics and correlations.

2.1. Data: financial development

To measure financial development, we would ideally like indicators of the degree to which the financial system ameliorates information and transactions costs and facilitates the mobilization and efficient allocation of capital. We would like indicators of how well each country's financial system researches firms and identifies profitable projects, exerts corporate control, facilitates risk management, mobilizes savings, and eases transactions. Unfortunately, no such measures are available across countries. Consequently, we rely on a commonly used measure of financial development that is robustly related to economic growth.

Private Credit equals the value of credit by financial intermediaries to the private sector divided by GDP. This measure excludes credits issued by the central bank and development banks. Furthermore, it excludes credit to the public sector, credit to state-owned enterprises, and cross claims of one group of intermediaries on another. Thus, Private Credit captures the amount of credit channeled from savers, through financial intermediaries, to private firms. Private Credit is a comparatively comprehensive measure of credit issuing intermediaries since it also includes the credits of financial intermediaries that are not considered deposit money banks.

Private Credit has demonstrable advantages over alternative measures of financial development. For example, some researchers use M2 (broad money) as a share of GDP to proxy for financial development. M2, however, does not measure a key function of financial intermediaries, which is the channeling of society's savings to private sector projects. Other researchers use the ratio of commercial bank assets to commercial bank plus central bank assets, which was first developed by King and Levine (1993) to examine the determinants of economic growth and later employed by Dollar and Kraay (2002) to investigate income growth of the poor. However, in many countries, the central bank does not play a direct role in allocating credit, but may nonetheless influence the flow of credit by persuading banks to lend to favored sectors or firms. Similarly, commercial banks are not the only financial institutions intermediating society's resources. Consequently, this measure may miss substantial cross-country variation in financial development. Moreover, Levine, Loayza and Beck (2000) and Beck, Levine, and Loayza (2000) show that Private Credit exerts a robust, positive impact on GDP per capita growth, further advertising the advantages of using Private Credit.

Data on Private Credit are from the updated, online version of the Financial Structure Database, which is described in Beck, Demirguc-Kunt and Levine (2001). There is wide variation in Private Credit, ranging from less than 5% in Uganda to more than 120% in Hong Kong, Japan, and the Switzerland using data over the period 1980 to 2005. In line with the large finance and growth literature, we include the logarithm of Private Credit in the regressions reported below. As we describe below, the period over which we calculate Private Credit varies across countries and econometric specifications because we match the period over which the regressors are calculated with data availability on each dependent variable.

2.2. Data: Changes in income distribution and poverty alleviation

To assess the impact of financial development on the poor, we examine (i) the growth of the Gini coefficient, (ii) the growth of the income share of the lowest quintile, and (iii) the growth of the percentage of the population living on less than $1 (and $2) dollars per day. The remainder of this subsection defines these dependent variables in more depth.

Growth of Gini equals the annual growth rate of each country's Gini coefficient, computed over the period 1960-2005. [1] Specifically, we compute the log difference between the last and the first available observation and divide by the number of years between these two observations. The Gini coefficient is derived from the Lorenz curve, where larger values imply greater income inequality. In Austria, Finland, France, Gabon, Mauritius, Netherlands, and Senegal, the Gini coefficient shrank at a rate of more than one percent per annum, while Nigeria and Uganda saw their Gini coefficient grow at more than two percent per annum.

Growth of Lowest Income Share equals the annual growth rate of the share of the lowest income quintile, computed over the period 1960-2005. Specifically, we compute the share of the lowest income quintile as the income of the country's poorest quintile divided by the country's total income. Growth of lowest income share is then defined as the difference between the logarithm of the share of the lowest income quintile for the last observation and the logarithm of the share of the lowest income quintile for the first observation, and dividing this log difference by the number of years between the two observations.

We use Growth of the lowest quintile to assess how financial development influences the poorest quintile of each economy. Examining the Growth of the poorest income quintile provides additional information from an analysis of the growth of the Gini coefficient because the Gini coefficient is a measure of the entire distribution of income, whereas Growth of the poorest income quintile only measures changes in the bottom quintile. In some countries, the income share of the poorest quintile grew by more than 3% per year (Finland, France, Senegal and Trinidad and Tobago), while it dropped by more than 4% per year in others (Guatemala, Sierra Leone and Uganda).

For both Growth of poorest income share and Growth of Gini, we require a minimum of 10 years difference between the first and last observation when computing growth rates for pure cross-country regressions. On average, there are 30 years between the first and last observation when computing growth rates, with a maximum of 43 years.[2] This produces identical coverage for the two data series and yields a sample of 72 developing and developed countries. Critically, for each country, we match the sample period of all of the regressors with the sample period covered by the dependent variable. When we move from pure cross-country to panel estimates, we follow Dollar and Kraay (2002) and take values of income share of the poor and Gini that are at least five years apart.

Growth of Headcount equals the growth rate of the percentage of the population living below $1 dollar per day (or $2 dollars per day). These data are based on household surveys and our sample comprises 68 developing and transition countries over the period 1980 to 2005 (Chen and Ravallion, 2001).[3] In the tables, we present the results using the $1 per day definition of poverty, but confirm all of the results using the poverty line cut-off of $2 per day.[4] Countries have experienced wide variations in poverty alleviation rates during the last two decades. For example, the share of population living on less than a dollar per day increased at an annual rate of 22% in Mongolia between 1995 and 1998. In contrast, Headcount decreased by an annual rate of 36% in Jamaica between 1998 and 2003. These large variations, however, also indicate that there might be measurement errors due to changes in the methodology, so that these large changes might reflect variations in measured rather than actual variation.

There are substantially greater data limitations regarding the Growth of Headcount than for Income Growth of the lowest income share and Growth of Gini. Data on Headcount are only available for the 1980s and 1990s, and frequently only for the 1990s. Thus, we do not use a 10-year minimum and simply calculate the annualized growth rates of Headcount for the longest available time span. Using shorter time frames could magnify the influence of any outlier observations and make the results more sensitive to business cycle fluctuations or crises. Therefore, we assess the robustness of our results by (i) limiting the sample to countries for which the growth rate in Headcount is calculated over at least five years and (ii) eliminating outliers.

2.3. Econometric methodologies: basic regression specifications

2.3.1. Ordinary least squares regressions

We begin by using cross-country regressions, calculating growth rates of income share, inequality and poverty over the longest available time period and averaging financial intermediary development and other explanatory variables over the corresponding time period. We use the following specification:

$$y_{i,t} = \alpha y_{i,t-1} + \beta FD_{i,t} + \gamma X_{i,t} + \varepsilon_{i,t}. \quad (1)$$

This can be re-written as follows:

$$y_{i,t} - y_{i,t-1} = (\alpha - 1) y_{i,t-1} + \beta FD_{i,t} + \gamma X_{i,t} + \varepsilon_{i,t}. \quad (2)$$

In this regression, $y_{i,t}$ is either the logarithm of (i) share of lowest income quintile, (ii) the Gini coefficient, or (iii) headcount for country i in period t. $FD_{i,t}$ is the Private Credit measure of financial development, and $X_{i,t}$ is a set of conditioning information for country i in period t. In the OLS specifications, we use one observation per country, so that a period is defined as the range of years for which we have data for that country. We allow for the possibility that lagged values of the lowest income share, the Gini coefficient, and poverty influence present values. As we demonstrate below, allowing for these dynamics is important empirically. However, setting $\alpha = 1$ does not alter our findings on the relationship between financial development, income inequality, and the poor.

In terms of the conditioning information, we control for **GDP per capita growth** in the growth of lowest income share and Growth of Gini regressions and for mean income growth in the Growth of Headcount regressions. In line with the cross-country growth literature, we also control for the logarithm of the average years of school attainment in the initial year as an indicator of the initial human capital stock in the economy (**Schooling**), the growth rate of the GDP deflator over the sample period to control for the macroeconomic environment (**Inflation**) and the sample period average of the sum of exports and imports as share of GDP to capture the degree of international openness (**Trade Openness**). Further, in the headcount growth regressions, we include **population growth** and the ratio of the population below the age of 15 and above the age of 65 to the population between the ages of 15 and 65 (**Age dependency ratio**) as additional regressors.

2.3.2. Dynamic panel instrumental variables regressions

The relationship between financial intermediary development and changes in income distribution and poverty might be driven by reverse causation. For example, reductions in poverty may stimulate demand for financial services. As another example, reductions in income inequality might lead to political pressures to create more efficient financial systems that fund projects based on market criteria, not political connections. To control for potential biases, we use a dynamic panel estimator.[5]

Besides endogeneity considerations, OLS regressions have other shortcomings that can be addressed using a dynamic panel estimator. First, cross-country regressions do not fully control for unobserved country-specific effects. Second, even when using standard two-stage least squares regressions and using instruments for financial development, this does not control for the endogeneity of other explanatory variables, which may bias the coefficient estimates on financial development. Third, the specification in equation (2) includes a lagged dependent variable, which could bias the coefficient estimates. Finally, the pure cross-country regression does not exploit the time-series dimension of the data.

Thus, we use a generalized-methods-of-moments (GMM) panel estimator developed for dynamic models by Holtz-Eakin, Newey, and Rosen (1990), Arellano and Bond (1991) and Arellano and Bover (1995). In moving to a panel specification, we use data averaged over five year periods, rather than averaging over the entire span of the dependent variable.[6] Specifically, we estimate a system of the panel version of regression (2) in differences and in levels. We difference regression (2) and use the lagged values in levels of all explanatory variables as instruments. Similarly, we use the lagged differences of all explanatory variables as instruments for the level version of regression (2). We then combine difference and level regressions in a system. Thus, the panel estimator uses instrumental variables based on previous realizations of the explanatory variables ("internal" instruments). Such a system gives consistent results under the assumptions that there is no second-order serial correlation and the instruments are uncorrelated with the error terms. We test for the validity of these assumptions and present these test results below.

2.4. Descriptive statistics and correlations

Table 1 presents descriptive statistics and correlations for the 1960-2005 and 1980-2005 samples. Consistent with earlier work, financial development is positively and significantly correlated with GDP per capita growth. Financial development is not, however, significantly correlated with mean income growth from household surveys, which is consistent with Ravallion's (2003a) finding of large discrepancies between average income growth numbers from national accounts and from household surveys. Private Credit is positively and significantly correlated with the Growth of poorest income share, but negatively correlated with Growth of Gini and Growth of Headcount (Honohan, 2004), indicating that countries with more developed financial systems experienced a faster reduction in the number of people living in poverty.

3. Empirical Results

3.1. Growth in the Gini coefficient

In Table 2, the regression results show that countries with higher levels of financial intermediary development experienced faster reductions in the Gini coefficient over the period 1960-2005. In our baseline regression, we simply control for the log of the initial Gini coefficient. Private Credit enters negatively and significantly. Initial Gini also enters negatively, suggesting that countries starting the estimation period with more skewed distributions of income (high Initial Gini) tend to experience faster reductions in income inequality than countries with lower levels of initial income inequality.

The economic effects are substantial. Take the examples of neighboring Guatemala and El Salvador. Guatemala has a ratio of private credit to GDP of 14%, while El Salvador has a ratio of 26%. The regression results suggest that Guatemala's Gini coefficient would have grown by only 0.6% per year over the period 1979-2000, rather than the actual 0.9%, had it had the level of Private Credit as El Salvador. This would have resulted in a Gini coefficient of 56 in 2000 rather than the actual 60.

The negative relationship between financial development and the Growth of Gini is robust to a number of sensitivity tests. We first control for initial schooling, trade openness and inflation (column 2). While inflation is positively associated with the growth of income inequality, the negative relationship between Private Credit and Growth of Gini holds when conditioning on these factors. We then control for GDP per capita growth since financial development may influence income inequality by affecting economic growth (column 3). As shown, this does not alter the results on Private Credit and GDP per capita growth does not enter the inequality regression significantly.[7] Next, we control for the interaction between initial income inequality and GDP per capita growth, since the relationship between the Growth of Gini and aggregate economic growth might vary with the initial degree of income inequality (column 4). The interaction term does not enter significantly. Moreover, we confirm our main finding of a negative relation between Private Credit and growth in the Gini coefficient and the size of estimated coefficient on Private Credit does not change. In column 5, we use our alternative indicator of financial intermediary development – Commercial-Central Bank – and confirm our findings. The regression in column 6 shows that the negative relationship between Private Credit and Growth of Gini holds over the sample period 1980 to 2005.

We also tested for the potential influence of outliers. The Besley, Kuh and Welch (1980) procedure identifies Ethiopia, Hong Kong, Nigeria, Nepal, Tanzania, Uganda, the United States and Zambia as influential observations. Re-running the regressions without these countries, however, confirms our finding of a negative and significant relation between Private Credit and Growth of Gini.

Next, we address concerns about reverse causality and omitted variables. If changes in the distribution of income influence the demand for financial services or alter the political economy shaping financial regulations, then innovations in the Growth of Gini could affect Private Credit and bias our results. Thus, we use the dynamic panel estimator to control for endogeneity, country specific factors, and the inclusion of the lagged dependent variable as a regressor. Note that in moving to the panel estimation, we employ higher frequency data, which may affect the coefficient estimates. As shown (column 7), the results hold: Financial development reduces the growth rate of income inequality.[8] Both the Sargan test of overidentifying restrictions and the second-order autocorrelation test are not rejected, providing support for our econometric specification.

These results complement the work by Clarke, et al. (2006). They find that finance is negatively associated with the level of the Gini coefficient using a panel estimator over the 1960-95 period. Whereas they have 170 observations, we have 245 observations by extending the number of countries and years. We also explicitly model the potential dynamics of the Gini coefficient by including lagged Gini, which enters significantly at the one percent level in all of the Table 2 regressions. Furthermore, we control for aggregate economic growth and show that finance influences income inequality beyond its effect on economic growth.

3.2. Growth of the lowest income share

The results presented in Table 3 indicate that financial development exerts a disproportionately positive impact on the poor. In the simplest specification that only conditions on the initial income share of the poorest quintile, Private Credit enters negatively and significantly at the one percent level (column 1). The log of the initial income share of the poor also enters negatively and significantly, suggesting that the lowest quintile is more likely to enjoy greater income gains than average in countries where the initial income share of the poor is very low.

The coefficient estimates suggest that financial development has an economically substantive impact on the poorest income quintile. Take the example of Brazil and Canada with Private Credit of 33% and 63%, respectively. Had Brazil had the same level of Private Credit as Canada over the period 1961 to 2000, the income share of the lowest income quintile would have fallen only by 0.1% every year rather than the actual 0.7%, which would have resulted in an income share of 3% for the lowest income quintile rather than the actual 2.4% in 2000.

Robustness tests confirm that financial development positively and significantly boosts the share of income received by the poorest quintile. Private Credit continues to enter positively and significantly when controlling for Trade Openness, Inflation, and Schooling (column 2). Inflation enters significantly and negatively, suggesting that monetary instability hurts the lowest income quintile more than the average person in an economy. Schooling and openness to trade do not enter significantly. We further tested the robustness of the findings by including the growth rate of schooling and trade openness, rather than including the level of schooling and trade as reported in column 2. When including the growth rates, Private Credit continues to enter positively and significantly, but neither the growth rate of schooling nor the growth of trade enters significantly. This does not suggest that Trade Openness and Schooling are unimportant for the share of the lowest income quintile. Rather, this result suggests that Trade Openness and Schooling do not have distributional effects when controlling for the level of financial development and the initial income share of the poor.

The results further hold when conditioning on GDP per capita growth and allowing for potential non-linearities. As shown in column 4, GDP per capita growth does not enter significantly and it does not alter the positive relationship between Private Credit and the growth in the lowest income share. Furthermore, we do not find a non-linear relationship between GDP per capita growth and growth of the lowest income share. The interaction term between initial income share and GDP per capita growth does not enter significantly and including this term does not affect the estimated coefficient on Private Credit (column 4).[9]

Furthermore, we consider an alternative measure of financial development, use a different estimation period, and test for the possible effects of outliers. We argued above that Private Credit is a superior measure of financial development to Commercial-Central Bank, which equals the ratio of deposit money banks claims on the domestic economy to the sum of deposit money and central bank claims on the domestic economy. Nevertheless, we also conducted the analyses with Commercial-Central Bank because Dollar and Kraay (2002) use this measure of financial development in their examination of income of the poor. The results in column 5 confirm finding that financial development disproportionately helps the poor: Commercial-Central Bank is positively associated with the growth rate of the poorest quintile when conditioning on GDP per capita growth, initial income share of the poor, initial schooling, trade openness and inflation. This paper's results also hold when limiting the estimation to the period 1980 to 2005 (column 6). Finally, we identify and assess the potential impact of outliers by following the methodology of Besley, Kuh, and Welsch (1980). The procedure identifies Guatemala, Hong Kong, Nepal, Singapore, Sierra Leone, Switzerland, Tanzania, Turkey, and Uganda as influential observations. The results hold, however, when excluding these countries from the analysis.

In unreported tests, we examined whether the relationship between financial development and Growth of lowest income share depends on the level of economic development or the level of educational attainment based on insights by Greenwood and Jovanovic (1990) and Galor and Moav (2004). We included (i) the interaction term of financial development and the level of economic development and (ii) the interaction term of financial development and educational attainment. These interaction terms do not enter significantly. Thus, we found no evidence that the relationship between financial development and income growth of the poor varies with the level of GDP per capita or the level of educational attainment.

In Table 3, we also present results using the dynamic panel estimator that employs instrumental variables to control for potential endogeneity and omitted country-specific traits. As shown in column 7, we continue to find that financial development exerts a disproportionately positive impact on the growth of the income share of the poorest quintile. Private Credit enters with a p-value of 0.063, while conditioning on initial income share of the poor, initial schooling, trade openness, and inflation. The larger coefficient on Private Credit in this panel regression relative to the OLS regressions primarily reflects the use of higher frequency data in the panel context. Neither of the specification tests – second-order autocorrelation and Sargan tests – is rejected, supporting the validity of the instrumental variable panel estimator.

The distributional impact of Private Credit explains about 40% of the overall effect of financial intermediary development on income growth of the poor in the OLS specification, and an even larger fraction in the panel estimation. As discussed above, income growth of the poorest income quintile can be decomposed into average income growth and growth in the income share of the lowest quintile. Regressions 8 and 9 in Table 3 replicate standard GDP per capita growth regressions. Private Credit enters positively and significantly with a coefficient of 0.014. This estimate is consistent with the findings of a large literature on finance and aggregate growth (Levine, 2005). To compare the growth effect of Private Credit with the distribution effect, we compare regression 2, where Private Credit enters the growth of the lowest income share specification with a coefficient of 0.009, with regression 8, where Private Credit enters the per capita GDP growth regression with a coefficient of 0.014. This implies that almost 40%

(9/23) of the overall effect of Private Credit on the income growth of the lowest quintile is due to distributional changes in favor of the poorest quintile and the remaining 60% (14/23) is due to the overall growth effect of Private Credit. The panel regressions suggest an even bigger distributional effect, with the distribution effect accounting for 56% (18/32) of the overall effect.

In sum, the results in Tables 2 and 3 indicate that financial intermediary development exerts a disproportionately positive impact on the poor and reduces income inequality. Private Credit raises the incomes of the lowest income quintile beyond the overall income growth rate of incomes in the economy. Moreover, Private Credit reduces income inequality, as measured by the Gini coefficient, when controlling for the initial level of income inequality in the economy and average growth. Both results hold when using dynamic panel techniques to control for simultaneity bias and when controlling for an array of other country characteristics.

3.3. Poverty alleviation

Next, we examine the relationship between financial development and a measure of absolute poverty. As noted, a major shortcoming of the poverty analyses is that the data cover far fewer years. For the Growth of lowest income share and Growth of Gini analyses, we examined growth rates computed over an average of 30 years, with a minimum of 11 and a maximum of 43 years. Thus, we were testing the impact of finance on long-run growth rates of income share of the poor and Gini coefficients. When examining changes in poverty, the growth rates are occasionally computed for less than five years and frequently for less than 10 years. This reduces confidence that the poverty alleviation results capture the relationship between financial development and reductions in poverty over long periods.

To address concerns about limited time-series data on poverty, we undertake five actions. First, we control for average income growth. This isolates the relationship between financial development and poverty alleviation beyond the relationship between finance and aggregate growth. Second, we confirm the Table 4 results when limiting the sample to only those countries where we have a minimum of five or even ten years of data. Third, given the limited poverty data for transition economies, the large fluctuations in their poverty rates, and the particularly acute measurement problems as they transited from socialism, we re-ran the regressions without them and confirmed the findings. Finally, we control for initial schooling, trade openness, inflation, population growth, and the demographic profile of each country so that we capture the relationship between finance and changes in poverty, not a spurious correlation involving a country specific trait.

The Table 4 regression results suggest that financial development is associated with faster poverty alleviation. Private Credit enters negatively and significantly at the 5% level in all of the regressions. Furthermore, we follow the same procedure as above and identify Albania, Malaysia, South Africa, Uganda and Yemen as influential observations. The results are strengthened, however, when excluding these countries. Private Credit enters with a coefficient of -0.074, significant at the 1% level. While we control for the log of the initial Headcount, it does not enter significantly and we confirm all the findings when excluding this variable.

The negative relationship between financial development and the growth rate in poverty is robust to various sensitivity checks. In particular, the results hold when controlling for Trade openness, Schooling, and Inflation (column 2). Furthermore, we also control for (1) the ratio of the population below the age of 15 and above the age of 65 to the population between the ages of 15 and 65 (Age dependency ratio), (2) the average annual growth rate of the total population (Population growth) since these demographic traits may influence changes in poverty, and (3) the growth rate in mean income. As shown in regression 3, including these country characteristics does not alter the results on financial development. Following Ravallion (1997) and

Bourguignon (2003), we include an interaction term between the log of initial income inequality and growth. This interaction term does not enter significantly, and it does not change our main finding of a negative and significant association between Private Credit and Growth of Headcount (column 4). Further, by including both mean income growth and its interaction with initial Gini, we control for the impact of financial development on changes in Headcount through aggregate growth and therefore isolate the impact of financial development on changes in Headcount through changes in the distribution of income. The findings suggest that Private Credit is associated with poverty alleviation not just by fostering economic growth, but also by lowering income inequality. As shown in regression 5, the results on the relationship between financial development and reductions in poverty depend on the measure of financial development. While there is a robust, negative relationship between Private Credit and Headcount, this relationship does not hold when using Commercial-Central Bank. As argued earlier, we believe the Private Credit variable is a better indicator of financial development and it is more widely used in the literature. Furthermore, selecting a poverty line is inherently arbitrary. Thus, we re-did the analyses of poverty alleviation using the $2 a day poverty line and confirm the findings.

The relationship between Private Credit and poverty alleviation is economically large. Compare Chile (Private Credit = 47%) with Peru (Private Credit = 17%). In Chile, the percentage of the population living on less than $1 a day (Headcount) decreased at an annual growth rate of 14% between 1987 and 2000. In Peru, the Headcount increased at an annual growth rate of 14% over the period 1985 to 2002. The coefficient estimate in column 1 indicates that if Peru had enjoyed Chile’s level of financial intermediary development, Headcount would have increased by five percentage points less per year, which implies that the share of the population living on less than one dollar a day in Peru would have been 5% in 2002 rather than the actual share of 12% of the population.

Given the small number of intermittent observations on poverty in the sample, it is impossible to use dynamic panel estimation to control for endogeneity. This limits the inferences that we can draw regarding the causal relationship between financial development and poverty. Whereas the dynamic panel results on growth of the lowest income share and the growth of the Gini coefficient indicate that the exogenous component of financial development exerts a disproportionately positive effect on the poor, we cannot draw this conclusion regarding poverty alleviation. Rather, we can only say that the strong negative relationship between financial development and the growth rate of poverty is consistent with the earlier findings on growth of the lowest income share and the growth rate of the income inequality.

In Table 5, we decompose the poverty reducing effect of financial development into the part associated with aggregate growth (growth component) and the part associated with reductions in income inequality (distribution component). Unlike in the case of income growth of the poorest quintile, however, the relative importance of the growth and distribution components varies with the ratio of the poverty-line to mean income and with the initial distribution of income. To do this, we first assume a lognormal distribution of income, which implies that the fraction of the population living below a particular poverty-line, such as $1 per day, is a function of the Gini coefficient and the ratio of the poverty-line to mean income. For a lognormal distribution of income, Lopez and Serven (2006) compute the growth and distribution elasticities for different values of the Gini coefficient and the ratio of the poverty-line to mean income. That is, they compute the percentage change in poverty for a given change in income or income inequality. We then multiply these growth and Gini elasticities of the Headcount by the derivatives of GDP per capita and Gini coefficient with respect to Private Credit, respectively, which we obtain from the regression coefficients in Table 2 (regression 2) and Table 3 (regression 8). These effects vary with the ratio of poverty-line to mean income and the Gini coefficient. Thus, Table 5 lists the relative importance of the distribution channel for different values of the poverty-mean income ratio and Gini coefficients. For illustrative purposes, we present the results for the 1st, 25th, 50th, 75th and 99th percentiles of our sample. At the medians for both the poverty-mean income ratio and the Gini coefficient, the growth and distribution channels each accounts for about half of the reduction in poverty associated with financial development. The distribution channel is strongest for the richest countries with highly unequal income distributions. In poor and more equal societies, on the other hand, the growth channel is relatively more dominant, accounting for up to 80% of the overall poverty reducing effect of Private Credit.[10]

IV. Conclusions

Although an extensive literature shows that financial development boosts the growth rate of aggregate per capita GDP, this does not necessarily imply that financial development helps the poor. If financial development increases average growth only by increasing the incomes of the rich and hence by increasing income inequality, then financial development will not help those with lower incomes. In this paper, we assessed the impact of financial development on income distribution and the poor.

We found that financial development disproportionately helps the poor. Greater financial development induces the incomes of the poor to grow faster than average per capita GDP growth, which lowers income inequality. The results indicate that financial development helps the poorest quintile beyond finance's affect on aggregate growth. Indeed, we find that 60% of the impact of financial development on the poorest quintile works through aggregate growth and about 40% operates through reductions in income inequality. Furthermore, these results hold when using a dynamic panel instrumental variable estimator that controls for potential biases associated with endogeneity, country fixed effects, and the inclusion of lagged dependent variables as regressors. We also examined changes in the fraction of the population living on less than $1 per day. While subject to more qualifications because of greater data limitations, we found that greater financial development is associated with poverty alleviation, even when controlling for average growth and other country traits. Although the results show that financial development is particularly beneficial to the poor, this research is silent on how to foster poverty-reducing financial development. Future work needs to examine the linkages between particular policies toward the financial sector and poverty alleviation.

[1]We use income quintile and Gini data from Dollar and Kraay (2002) and UNU-WIDER (2006) to compute the level and growth rate of this variable. Dollar and Kraay obtain income share and Gini data from Deininger and Squire (1996), the UN-WIDER World Income Inequality Database, Chen and Ravallion (2000) and Lundberg and Squire (2000). We update their data with more recent data points from UNU-WIDER (2006).

[2] We could not compute regression-based growth rates because many countries do not have data for every year and therefore lack sufficient observations. While our growth rates are thus subject to measurement error in the endpoints, we confirm our findings using an alternative sample period, 1980 to 2005.

[3] These data are available at http://research.worldbank.org/PovcalNet/jsp/index.jsp. While poverty data are available for a larger number of countries, limited overlap with financial development data limits the sample.

[4] As a robustness check, we also computed the Poverty Gap, which is a weighted measure of (i) the fraction of the population living on less than one dollar per day and (ii) how far below one dollar per day incomes lie. Thus, Poverty Gap measures both the breadth and depth of poverty. Nonetheless, growth of the Poverty Gap and Growth of Headcount are extremely highly correlated (0.94) and the results hold using the Poverty Gap measure.

[5] We confirm the panel results using standard two-stage least squares regressions. To select instrumental variables for financial development, we focus on exogenous national characteristics that theory and past empirical work suggest influence financial development. We follow the finance and growth literature and use the legal origin of countries and the absolute value of the latitude of the capital city, normalized between zero and one, as instrumental variables. (See Beck and Levine, 2005; Beck et al 2003; Easterly and Levine, 2003; and Levine, 2006). We also tried alternative instrument sets, including the religious composition of countries and ethnic fractionalization based on research by Beck et al (2003, 2006) and Easterly and Levine (1997), and obtained very similar results.

[6] Since data for income of the poor and the Gini coefficient are not necessarily available on a five-year frequency, we follow Dollar and Kraay (2002) and start out with the first available observation and then look for the next observation that is at least five years later. As in the cross-country regressions, the sample period of the regressors is matched to the sample period of the dependent variable.

[7] In unreported regressions, we also find that controlling for the square of GDP per capita growth does not affect the findings on Private Credit. Furthermore, we tested for non-linearities by including the squared term of Private Credit, but this term never entered significantly.

[8] We also explored alternative dynamic structures for the Gini coefficient following Ravallion (2003b). Specifically, we allwed for a a trend in inequality that depends on the initial distribution of income distribution. However, we did not find any evidence for a time trend in the Gini coefficient in our sample.

[9] Controlling for the square of GDP per capita growth also does not affect the parameter estimate on Private Credit.

[10] We do not report regression results of the distribution and growth components of changes in Headcount as performed by Kraay (2006) since the sample is very small and short. However, when we follow Kraay's (2006) methods, we find that the impact of financial development on the poor runs primarily through the distribution component.

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Table 1: Summary Statistics and Correlations

Panel A presents the descriptive statistics and Panels B and C present the correlations. Growth of the lowest income share equals the annual change in the logarithm of the income share of the poorest quintile over the period 1960-2005. Growth of Gini is the annual change in the logarithm of the Gini coefficient over the period 1960-2005. GDP per capita growth equals the growth rate of real GDP per capita over the periods 1960-2005. Growth in mean income is computed from household surveys and averaged over the period 1980–2005. Private Credit equals claims of financial institutions on the private sector as a share of GDP averaged over the periods 1960-2005 and 1980-2005 respectively. Growth of Headcount is the annual growth rate of the percentage of the population living on $1 a day or less, over the period 1980-2005. Panel B presents correlations for the period 1960-2005. Panel C presents correlations for the sample 1980-2005. Detailed variable definitions and sources are in the appendix.

Panel A:

Variable	Obs	Mean	Std. Dev	Min	Max
Private Credit, 1960-2005	72	0.399	0.311	0.030	1.377
Growth of lowest income share	72	-0.00	0.018	-0.045	0.039
Growth in Gini	72	0.000	0.009	-0.019	0.032
GDP per capita growth, 60-05	72	0.021	0.015	-0.019	0.067
Private Credit, 1980-2005	68	0.237	0.148	0.034	0.746
Growth of Headcount	68	-0.029	0.101	-0.358	0.221
Growth in mean income, 80-05	68	0.007	0.041	-0.134	0.122

Panel B:

	Private Credit, 1960-2005	Growth of lowest income share	Growth in Gini
Growth of lowest income share	0.3912***		
Growth in Gini	-0.2239*	-0.7394***	
GDP per capita growth, 60-05	0.5914***	0.1485	-0.0988

***, ** and * represent significance at 1, 5 and 10% level respectively.

Panel C:

	Private Credit, 1980-2005	Growth of Headcount
Growth of Headcount	-0.309**	
Growth in mean income, 80-05	0.109	-0.738***

***, ** and * represent significance at 1, 5 and 10% level respectively.

Table 2: Finance and Changes in Income Distribution

The dependent variable is Growth of Gini, which equals the annual growth rate in the Gini coefficient over the period 1960-2005. As the exact sample period for the dependent variable varies across countries, we adjust the sample periods for the regressors accordingly. Private Credit equals the logarithm of claims of financial institutions on the private sector as a share of GDP averaged over the sample period. GDP per capita growth equals the growth rate of real GDP per capita over the sample period. Initial Gini equals the logarithm of the value of the Gini coefficient at the beginning of the sample period. Trade Openness equals the logarithm of the share of exports plus imports relative to GDP averaged over the sample period. Inflation is the growth rate of the GDP deflator over the sample period. Initial Schooling is the logarithm of secondary school attainment from the Barro-Lee dataset at the beginning of the sample period. Commercial-Central Bank is the ratio of claims of commercial banks on non-financial domestic sectors to the claims of commercial and central banks on non-financial domestic sectors Specifications (1) - (6) are estimated using OLS with heteroskedasticity-consistent standard errors.. Specification (7) is estimated using dynamic panel techniques. P values are reported in parentheses based on robust standard errors. All specifications except (7) report the regression R-squared. Specification (7) reports the Sargan test of overidentifying restrictions and the test of second-order autocorrelation. Detailed variable definitions and sources are in the appendix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Growth of Gini	Growth of Gini	Growth of Gini	Growth of Gini	Growth of Gini	Growth of Gini, 80-05	Growth of Gini, panel
Private Credit	-0.005	-0.005	-0.005	-0.006		-0.005	-0.011
	(0.001)***	(0.007)***	(0.014)**	(0.008)***		(0.043)**	(0.040)**
Initial Gini	-0.015	-0.016	-0.016	-0.028	-0.011	-0.013	-0.043
	(0.000)***	(0.001)***	(0.001)***	(0.001)***	(0.030)**	(0.061)*	(0.002)***
Initial Schooling		0.001	0.001	0.001	-0.000	-0.003	0.019
		(0.553)	(0.587)	(0.425)	(0.937)	(0.582)	(0.023)**
Trade Openness		0.000	0.000	0.000	-0.002	0.000	0.000
		(0.881)	(0.887)	(0.875)	(0.418)	(0.903)	(0.987)
Inflation		0.000	0.000	0.000	-0.000	0.000	0.000
		(0.096)*	(0.101)	(0.043)**	(0.986)	(0.800)	(0.261)
GDP per capita growth			0.030	-2.376			
			(0.753)	(0.106)			
GDP per capita growth * Initial Gini				0.648			
				(0.106)			
Commercial-Central Bank					-0.020		
					(0.000)***		
Constant	0.051	0.051	0.050	0.094	0.041	0.045	0.111
	(0.000)***	(0.007)***	(0.011)**	(0.004)***	(0.040)**	(0.151)	(0.024)**
Estimation method	OLS	OLS	OLS	OLS	OLS	OLS	DPD
R-squared	0.289	0.285	0.286	0.323	0.363	0.197	
Sargan test							0.880
2nd order autocorr. test							0.168
Observations	72	65	65	65	64	57	245

***, ** and * represent significance at 1, 5 and 10% level respectively.

Table 3: Finance and Growth of the lowest income share

The dependent variable in regressions (1)-(7) is Growth of lowest income share, which equals the annual growth rate in the income share of the poorest quintile over the period 1960-2005. The dependent variable in regressions (8) and (9) is average annual GDP per capita growth. As the exact sample period for the dependent variable varies across countries, we adjust the sample periods for the regressors accordingly. Private Credit equals the logarithm of claims of financial institutions on the private sector as a share of GDP averaged over the sample period. Initial Income Share of the Poor equals the logarithm of the income share of the poorest quintile at the beginning of the sample period. GDP per capita growth equals the growth rate of real GDP per capita over the sample period. Initial GDP per capita is the log of real GDP per capita in the first year of the sample period. Trade Openness equals the logarithm of the share of exports plus imports relative to GDP averaged over the sample period. Inflation is the growth rate of the GDP deflator over the sample period. Initial Schooling is the logarithm of secondary school attainment from the Barro-Lee dataset at the beginning of the sample period. Commercial-Central Bank is the ratio of claims of commercial banks on non-financial domestic sectors to the claims of commercial and central banks on non-financial domestic sectors. Specifications (1) - (6) and (8) are estimated using OLS with heteroskedasticity-consistent standard errors. Specifications (7) and (9) are estimated using dynamic panel techniques. P values are reported in parentheses. All specifications except (7) and (9) report the regression R-squared. Specifications (7) and (9) report the Sargan test of overidentifying restrictions and the test of second-order autocorrelation. Detailed variable definitions and sources are in the appendix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Growth in lowest income share	Growth in lowest income share	Growth in lowest income share	Growth in lowest income share	Growth in lowest income share	Growth in lowest income share, 80-05	Growth in lowest income share, panel	Growth of GDP per capita, 60-05	Growth of GDP per capita, panel
Private Credit	0.009	0.009	0.009	0.009		0.010	0.018	0.014	0.014
	(0.001)***	(0.002)***	(0.014)**	(0.016)**		(0.003)***	(0.063)*	(0.000)***	(0.002)***
Initial Income Share of	-0.015	-0.019	-0.019	-0.017	-0.016	-0.016	-0.030		
the Poor	(0.004)***	(0.000)***	(0.000)***	(0.079)*	(0.002)***	(0.108)	(0.026)**		
Initial Schooling		0.002	0.002	0.002	0.005	0.004	-0.037	0.009	0.008
		(0.441)	(0.442)	(0.463)	(0.142)	(0.755)	(0.047)**	(0.002)***	(0.399)
Trade Openness		-0.006	-0.006	-0.006	-0.004	-0.004	0.004	-0.003	-0.001
		(0.155)	(0.157)	(0.170)	(0.320)	(0.451)	(0.663)	(0.286)	(0.898)
Inflation		-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
		(0.002)***	(0.003)***	(0.003)***	(0.000)***	(0.026)**	(0.694)	(0.230)	(0.818)
GDP per capita growth			-0.009	0.178					
			(0.957)	(0.794)					
GDP per capita growth				-0.111					
* Initial income share				(0.775)					
Commercial-Central					0.035				
Bank					(0.001)***				
Initial GDP per capita								-0.011	-0.012
								(0.000)***	(0.122)
Constant	0.034	0.065	0.065	0.061	0.045	0.047	0.119	0.126	0.125
	(0.000)***	(0.002)***	(0.003)***	(0.021)**	(0.013)**	(0.080)*	(0.095)*	(0.000)***	(0.037)**
Estimation Procedure	OLS	OLS	OLS	OLS	OLS	OLS	DPD	OLS	DPD
R-squared	0.261	0.392	0.392	0.393	0.437	0.233		0.590	
Sargan test							0.785		0.781
2nd order autocorr. test							0.592		0.134
Observations	72	65	65	65	64	57	245	65	245

***, ** and * represent significance at 1, 5 and 10% level respectively.

Table 4: Finance and Poverty Alleviation

The dependent variable is Growth of Headcount is the annual growth rate of the percentage of the population living on $1 a day or less, over the period 1980-2005. As the exact sample period for the dependent variable varies across countries, we adjust the sample periods for the regressors accordingly. Private Credit equals the logarithm of claims of financial institutions on the private sector as a share of GDP averaged over the sample period. Initial Headcount is the logarithm of the Headcount at the beginning of the sample period. Mean income growth is computed from the same household surveys as the headcount data and averaged over the sample period. Trade Openness equals the logarithm of the share of exports plus imports relative to GDP averaged over the sample period. Inflation is the growth rate of the GDP deflator over the sample period. Schooling is the logarithm of secondary school attainment from the Barro-Lee dataset at the beginning of the sample period. Age dependency ratio is the ratio of the population below 15 and above 65 to the population between 15 and 65 years of age, averaged over the sample period. Population growth is the average annual growth rate of population over the sample period. Initial Gini equals the logarithm of the value of the Gini coefficient at the beginning of the sample period. Commercial-Central Bank is the ratio of claims of commercial banks on non-financial domestic sectors to the claims of commercial and central banks on non-financial domestic sectors. All specifications are estimated using OLS with heteroskedasticity-consistent standard errors. P values are reported in parentheses. Detailed variable definitions and sources are in the appendix.

	(1)	(2)	(3)	(4)	(5)
	Growth in Headcount	Growth in Headcount	Growth in Headcount	Growth in Headcount	Growth in Headcount
Private Credit	-0.052	-0.041	-0.050	-0.044	
	(0.012)**	(0.022)**	(0.009)***	(0.010)**	
Initial headcount	-0.005	-0.011	-0.006	-0.007	-0.009
	(0.465)	(0.129)	(0.573)	(0.436)	(0.320)
Initial Schooling		-0.004	0.000	0.002	-0.017
		(0.887)	(0.984)	(0.912)	(0.550)
Trade		-0.040	-0.008	-0.011	-0.053
		(0.124)	(0.755)	(0.665)	(0.042)**
Inflation		0.000	0.000	0.000	0.000
		(0.289)	(0.137)	(0.138)	(0.429)
Age dependency			-0.085		
			(0.408)		
Population growth			0.018		
			(0.414)		
Growth in mean income			-1.306	-1.431	
			(0.000)***	(0.763)	
Growth*Initial Gini				0.051	
				(0.967)	
Commercial-Central Bank					-0.029
					(0.519)
Constant	-0.103	0.094	-0.106	-0.033	0.215
	(0.002)***	(0.445)	(0.415)	(0.770)	(0.060)*
Observations	68	51	51	51	50
R-squared	0.107	0.248	0.480	0.466	0.190

***, ** and * represent significance at 1, 5 and 10% level respectively.

Table 5: Finance and Poverty Alleviation – Growth vs. Distribution

This table reports the relative importance of the distribution channel in the relationship between Growth in Headcount and Private Credit. We calculate the growth and distribution elasticity of Headcount following Lopez and Serven (2006) for values of the poverty-line ($372)-mean income ratio and the Gini coefficient at the 1st, 25th, 50th, 75th and 99th percentiles of the sample of 68 countries in Table 4. We then multiply the growth elasticities with 0.014, the Private Credit coefficient in column (8) of Table 3 to obtain the growth effect of Private Credit, and the distribution elasticities with -0.005, the Private Credit coefficient of column (2) in Table 2 to obtain the distribution effect. We then compute the ratio of the distribution effect to the sum of growth and distribution effects.

	Poverty line/mean income				
Gini coefficient	99th Percentile (0.59)	75th Percentile (0.29)	Median (0.13)	25th Percentile (0.08)	1st Percentile (0.03)
1st Percentile (0.25)	0.1912	0.3307	0.4474	0.4994	0.5684
25th Percentile (0.33)	0.2147	0.3498	0.4630	0.5134	0.5804
Median (0.44)	0.2567	0.3840	0.4908	0.5385	0.6018
75th Percentile (0.50)	0.2942	0.4144	0.5155	0.5607	0.6208
99th Percentile (0.60)	0.3613	0.4688	0.5596	0.6003	0.6545

Appendix: Variable Definitions

Variable	Variable Definition	Source
Growth of the lowest income share	Average annual growth of the lowest income share, computed as log difference between the last and first observation, divided by number of years	Dollar and Kraay (2002), UNU-WIDER
Initial income share of the poor	Logarithm of the initial income share of the poorest quintile	Dollar and Kraay (2002) , UNU-WIDER
Growth of Gini	The Gini coefficient is the ratio of the area between the Lorenz Curve, which plots share of population against income share received, to the area below the diagonal. It lies between 0 and 1, where 0 is perfect equality and 1 is perfect inequality. The growth rate is calculated as the log difference between the last and the first available observations, divided by the number of years.	Dollar and Kraay (2002), UNU- WIDER
Initial Gini	Logarithm of the initial Gini coefficient	Dollar and Kraay (2002), UNU-WIDER
Growth of Headcount	Headcount is the percentage of the population living on $1 a day or less. The growth rate is calculated as the log difference between the last and the first available observations, divided by the number of years.	Povcal Net, World Bank
Initial Headcount	Logarithm of the initial headcount	Povcal Net, World Bank
GDP per capita Growth	GDP per capita growth, annual percentage change	Penn World Table 6.1; Heston, Summers and Aten (2002), World Development Indicators (WDI)
Mean income growth	Average household income growth, annual percentage change	Povcal Net, World Bank
Private Credit	The claims on private sector by deposit money banks and other financial institutions as a share of GDP	IFS, own calculations
Initial Schooling	The logarithm of the initial average years of school attainment.	Barro and Lee (1996)
Inflation	The growth rate of the GDP deflator	World Development Indicators (WDI)
Trade Openness	The logarithm of the share of imports plus exports in GDP	WDI
Age dependency ratio	Ratio of population below 15 and above 65 to population between 15 and 65	WDI
Population growth	Average annual growth rate of total population	WDI