Finance, Growth, and Inequality: Channels and Outcomes

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Abstract

Identifying the specific channels through which financial development impacts inequality via growth is important both for research and policy prescriptions. Only if the specific channels are identified researchers can study endogenous evolution of finance, growth, and inequality. This knowledge is also important for prescribing sensible policy guidelines that typically have large macroeconomic implications. The existing literature on the subject has not yet attempted this important task. In the present study we consider three sets of possible channels: (1) human capital development (specifically UNDP human development index (HDI), adult literacy rate, and level and years of schooling); (2) institutional environment (creditor rights); (3) industrial composition (share of labor-intensive industries in total industrial output, value added and employment). For the most part, we find that the channels impact inequality significantly, but not always beneficially for the poor. We also find that broadening financial access may work faster than merely deepening credit availability.

Keywords: financial systems, income distribution, economic development, poverty alleviation

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I. Introduction

There is a large literature on the relation between growth and inequality (Dollar and Kraay, 2002; Gine and Townsend, 2004; Burgess and Pandey, 2005; Beck et al, 2009) , and another large literature on financial development and growth (Rajan and Zingales, 1998; Levine, 2005). But the existing literature on the effect of financial development on inequality is sparse. The general finding is that growth increases inequality in the earlier stages of development and then reduces it. But the process through which growth affects inequality is important for researchers in growth economics because the knowledge helps them focus their research agenda on critical issues. Understanding the process is, of course, very important for policy purposes. In this context, examining the role of financial development in growth may help. If financial development aids growth primarily by benefitting the incumbents then inequality will increase. On the other hand, if financial development aids growth by relaxing financial constraints of the poor and small firms, inequality will decrease. Thus, looking at the process of how financial development aids growth will unify the literature on finance, inequality and growth. Further, identifying the specific channels through which financial development impacts inequality via growth is important both for research and policy prescriptions. Only if the specific channels are identified researchers can study endogenous evolution of finance, growth, and inequality. This knowledge is also important for prescribing sensible policy guidelines that typically will have large macroeconomic implications. The existing literature on the subject has not yet attempted this important task. These are the two main motivations of the present study.

The dataset used in the present cross-country study includes more countries and more observations than all existing studies. We consider the two most widely used measures of economic inequality in a country: Gini coefficient of the country and the income share of the poorest 20% of the population of the country (Q1). We also use the most common measure of financial development: ratio of private credit to GDP for the country. We examine the direct effect of financial development on inequality and find it to be beneficial (Gini coefficient declines and Q1 improves). However, the unique contribution of the paper lies in examining channels through which financial development impacts inequality. We consider three sets of possible channels: (1) human capital development (specifically UNDP human development index (HDI), adult literacy rate, and level and years of schooling); (2) institutional environment (creditor rights); (3) industrial composition (share of labor-intensive industries in total industrial output, value added, wages paid, employment and number of establishments). In the next section of the paper, the data and the variables are discussed in detail. We find that human capital development is a beneficial channel and reduces inequality, though schooling does not seem to add value. Institutional environment and industrial composition appear to *increase* inequality. However, we find explanations for the apparently counter-intuitive results.

Though we primarily use private credit to GDP as a proxy for financial development, we recognize that this measures the only the depth of financial development. Financial access measures like branch and ATM density allow us to proxy for the breadth of financial development. We find that broadening is not only useful in reducing inequality, it might even work faster than merely deepening credit.

To the best of our knowledge, the existing literature includes only one study (Beck et al , 2007) that produces cross-country evidence directly linking financial development to inequality. The study finds that financial development disproportionately boosts incomes of the poorest quintile and reduces income inequality in terms of Gini coefficient and *headcount* (percentage of population living below $1 per day). However, the study does not examine any specific channels through which financial development impacts inequality. Claessens and Perotti (2007) discuss the importance of channels, but do not offer any empirical evidence.

The rest of the paper is organized as follows. In Section II we discuss the data and the variables used in the present study. Section III and IV respectively present the methodology and the results. Section V discusses the role of financial access. Section VI presents the conclusions. Appendix I at the end lists the variables and the data sources.

II. Data and Variables

A) Inequality

The source of our data on inequality is the World Income Inequality Database (WIID) of the United Nations University World Institute of Development Economics Research (UNU-WIDER). The data contains 4981 overlapping country-year observations on the gini coefficient and 2945 observations on quintiles and deciles for 157 countries spanning from before 1960 to 2006.

As suggested by Kuznets (1955), an ideal database on inequality should measure inequality on the basis of gross (rather than net) incomes (rather than consumption expenditures) of family units (rather than individuals) covering all the segments (rather than a particular upper or lower tail), all the regions (rather than underdeveloped regions) for the income earners (excluding those in the age of learning and already retired).

While selecting the observations from WIID we have kept this preference ordering. For a given country-year we preferred to choose high quality household level income-based gini coefficients/Q1 calculated for all the regions in the country and for all the age groups. For instance, if for a given country-year we have two high quality data points at household level for gini, one based on income and another based on consumption, we include the data point based on income. In addition, we adjust for different survey methodologies and measurements across countries by regressing both the gini coefficient and the first quintile share on a constant, a set of country dummies, and dummy variables indicating whether the measure is income (D_i=1) or consumption (D_i=0), whether the income measure is gross (D_g=1) or net (D_g=0) and whether the unit of analysis is household (D_h=1) or individual (D_h=0). We add back the coefficients on D_i ,D_g and D_h for the sample points wherever inequality is defined on the basis of consumption, net income and at an individual level respectively.

This process leaves us with 2302 country-year observations covering 157 countries with the median number of observations per country being 12. As can be seen in Table 1, the dataset has substantial coverage of all geographic regions and income groups[1]. Since our interest is in the impact of financial development on inequality over the medium to long run, we need to filter our inequality data so it is suitable for this purpose. To do that, we employ the approach of Dollar and Kraay (2002). We start with the first observation for a particular country and then pick observations for that country so that there are at least five years between two consecutive observations. This leaves us with spaced data of 829 country-year observations covering 157 countries with median number of observations per country of 5. This is more than double the size

[1] The income groups are as per the World Bank definitions

of the data set used in the study done by Dollar and Kraay (2002). The summary statistics in Table 2 show that the median value of the gini coefficient (on a scale of 100) is 39.10 while the share of a country's income accruing to the poorest 20% of the population is 6% in the median country year. Further restricting our sample to those countries for which we have at least three spaced observations and also removing those observations where the adjusted inequality variables are negative leaves us with a total of 655 country-year observations to use in our regressions. The number of countries in the sample is 123 with the median country having 5 spaced observations. The summary statistics in Table 2 show that the median value of the gini coefficient (on a scale of 100) is 39.10 while the share of a country's income accruing to the poorest 20% of the population is 6% in the median country year.

B) Financial Development

A financial system is more developed compared to another if that system brings borrowers and savers together at lower cost thus enabling a more efficient allocation of capital. Indicators of financial development would thus measure the ease with which borrowers can access capital markets, the extent to which loan providers are able to identify profitable projects, and how well a country's savings are channeled to their most efficient use. Though we do not have perfect indicators for all these aspects of financial development, the ratio of private credit given by deposit money banks and other financial institutions to a country's GDP is a broadly representative measure of the development of a financial system. This is the measure we choose as our proxy of financial development. Since government entities are excluded, private credit captures the amount of credit channeled by financial intermediaries from savers to private firms. As pointed out by Beck et al (2007), this measure is a better proxy for financial development than measures like the ratio of M2 (broad money) to GDP and the ratio of commercial bank assets to commercial and central bank assets.

The source for our data on Private Credit/GDP is the World Bank Financial Structure Dataset which has data from 1960-2007 for 160 countries. The dataset uses raw data from the International Monetary Fund's International Finance Statistics and then suitably deflates the nominal values.

C) Channels

i). Human Capital

Intuitively, the clearest way for an individual to raise her income level would be by acquiring the skills that would allow her to command a higher wage. Hence, the development of human capital at the lower ends of the income distribution can be thought of as a means to reduce inequality. Ideally, if we want to see how human capital functions as a channel through which finance affects inequality, we would like a variable like the amount of educational loans given by the financial sector. However, such data are very hard to come by. Hence, we are forced to rely on broad measures of a country's human capital.

We use two such measures, the first of which is the United Nations Development Programme's (UNDP) Human Development Indicator (HDI). The HDI value for a country is a composite measure which captures information on a country's achievements along the triple dimensions of health, education and economic well-being. From the same data source, we also use the adult literacy rate which is a purely educational metric.

ii). Institutional Environment

Claessens and Perotti (2007) argue that a country's institutional framework would play an important role in how the benefits of financial development are distributed throughout the economy, hence having an impact on inequality. In countries with weak institutional oversight, the major benefits of financial inequality might be captured by a small group of elites at the expense of the poor, leading to a widening in inequality.

La Porta et al (1998) show that a country's legal origins are related to the development of the financial sector. We use the same legal origin variable to see whether finance has a differential impact on inequality in countries with differing legal origins. We also use the index of creditor rights developed by La Porta et al (1998) with an updated time series obtained from Djankov et al (2007). The index aggregates four different creditor rights and scores each country based on how many of those rights it has enshrined in law.

iii). Labour Intensity of Industries

If finance, through the allocation of credit, promotes the growth of industries which are labour intensive it would lead to higher employment and a subsequent reduction in inequality.

The source of the data we use to study this channel is the United Nations Industrial Development Organization's (UNIDO) Industrial Statistics Database (INDSTAT2 2010) which has data for the period from 1963 to 2007 for 162 countries. The data are arranged at the 2-digit level of the International Standard Industrial Classification of All Economic Activities (ISIC) Revision 3 pertaining to the manufacturing sector, which comprises 23 industries. In order to use the data, we need to ensure that, for a particular country, the set of industries (be some combined or all separate) remain the same throughout the period of analysis. The variables we use from the UNIDO dataset are (i) the number of establishments, (ii) wages and salaries, (iii) total number of employees, (iv) value added and, (v) value of output.

Our data is at the industry level for each country-year. We need to find a representative number for each country-year which we can use in our regressions. This number should capture the difference between industries which are more labour intensive and those which are less labour intensive. To do this, we first find the share of each industry for each of the 5 variables mentioned above for each year. For instance, we find the wage share for food and beverages in USA in 1985 by dividing the wages in 1985 in the food and beverage industry in the US by the total wages for all industries in the US in 1985.

Our measure of the labour intensity of an industry is the ratio of the wage share to the value added share (we also use ratio of employment share to output share to cross check. Results are qualitatively similar). Industries with a high relative wage share compared to their value added share are the ones with high labour intensity. We sort the industries by this measure for every country-year and pick the industries at the 25th percentile and 75th percentile of the distribution as our representative low labour intensive and high labour intensive industries.

Having got these two industries for each country-year, we find the difference between share of value added of the high labour intensive industry and share of value added of the low labour intensive industry (We also repeat the same process using output share and wage share for robustness). This gives us a unique country-year observation which we use in our regressions.

D) Controls

In our estimation, we also control for some of the important factors mentioned in the cross-country growth literature. The ones we need to control for are mean income, inflation and trade openness. Real GDP per capita allows us to control for changes in the income of the entire population. The growth in the value of the GDP deflator controls for changes in a country's macroeconomic environment and the ratio of the sum of exports and imports to a country's GDP proxies for trade openness. The data source for these controls is the updated version 6.3 of the Penn World Tables.

Details on all variables and their sources can be found in Appendix I.

III. Methodology

As discussed before, our interest is in estimating the effect of financial development on inequality and in identifying the channels through which financial development, measured by *Pvt. Credit to GDP (PVTCRED)* affects the *income distribution,* measured by *GINI,* and income of the poorest quintile, measured by *Q1*.

The first equation we estimate is:

$$IQ_{ct} = \beta_0 + \beta_1 FD_{c,t-s} + \gamma' Z_{ct} + \eta_t + \epsilon_{ct} \quad (1)$$

In the above equation, IQ_{ct}, refers to measure of inequality in country *c,* year *t* . In our case, we use *GINI* and *Q1*, as two measures of inequality. $FD_{c,t-s}$ refers to financial development (measured by *PVTCRED*) in country *c,* year *t-s*, where *s* refers to last spaced year. Taking lag of financial development by spaced year solves the possible problem of reverse causality between financial development and inequality as is well documented in the literature (Dollar and Kraay (2002), Beck et al (2007)). We use a bunch of controls, Z_{ct}, as noted in the literature (Beck et al (2007)), like inflation, growth in trade openness, and growth in real GDP per capita. η_t refers to year fixed effects to control for macro-economic shocks. Here the hypothesis is $\beta_1 < 0$ in case of *GINI* and $\beta_1 > 0$ in case of *Q1*.

The second equation we estimate is:

$$IQ_{ct} = \beta_0 + \beta_1 FD_{c,t-s} + \beta_2 FD_{c,t-s} * Channels_{c,t-s} + \gamma' Z_{ct} + \eta_t + \epsilon_{ct} \quad (2)$$

We use the above equation to identify the channels through which financial development affects inequality. The possible channels through which financial development can affect inequality are: (i) Human Capital, (ii) Institutional Environment and (iii) Labour Intensity of Industries. The other controls and fixed affects are the same as in equation (1).

i). <u>Human Capital:</u> Better financial development which reduces the transaction cost and increases access of credit to poor for education can help increase the literacy rate. Also, access of credit can help in access to better healthcare. Both education and health increase the ability to earn and dampen inequality. We hypothesize that higher financial development along with increased investment in human capital can reduce inequality much faster than otherwise ($\beta_2 < 0$, in case of *GINI* and $\beta_2 > 0$, in case of *Q1*). As data for investment in human capital by private sector is difficult to obtain, we use two proxies for human capital, (a) Human Development Index (*HDI*, a composite score of education, income and health, with equal weights). (b) Adult Literacy rate (*ADLRT*)

ii). <u>Institutional/Legal Environment:</u> The effect of legal environment on financial development is widely documented in literature (LaPorta et al, 1998). Through this channel we would like to identify how the effect of financial development on inequality varies with creditor-friendly and debtor-friendly institutional environments. We hypothesize that the countries with stronger creditor rights and, in equilibrium, more financial development, help reduce the transaction cost and provide access to credit to the poor ($\beta_2 < 0$, in case of *GINI* and $\beta_2 > 0$, in case of *Q1*).

iii). <u>Labour Intensity of Industries:</u> Another channel through which financial development can affect inequality is through more credit to labor-intensive industries, which in turn increases employment opportunities and helps the poor get out of poverty. For this we identify labor intensive industries by ranking the industries on the basis of (1) Wage share /Share of Value Added and (2) Employment Share/Share of value of output in a given country-year. We calculate the 75th percentile and 25th percentile of the ratios. Here, 75th percentile industry is more labor intensive compared to 25th percentile. We calculate the difference between the Share of a) Value added, b) Value of output, c) Wages paid, d) Employees and, e) Establishments between the 75th percentile and 25th percentile industries. We denote this variable as *DSHLII* (disproportionately higher share of labor intensive industries in GDP). We hypothesize that higher *DSHLII* along with higher financial development can help generate more employment and hence reduce inequality faster, than other wise ($\beta_2 < 0$, in case of *GINI* and $\beta_2 > 0$, in case of *Q1*).

This approach of identifying channels works as a difference-in-difference. For a given level of financial development, for example, how better creditor rights affects the relationship between financial development and inequality.

The OLS estimates, with year fixed-effects, are likely to be biased owing to endogeneity caused by omitted variables. There could be many country-specific factors which can impact income inequality and financial development. In our case, we cannot use country fixed-effects owing to the small number of observations per country. As mentioned before, the median country in our spaced data has only 5 observations. Given this issue, we re-estimate equations (1) and (2) using the System Generalised Method of Moments (GMM) approach developed by Arellano and Bover (1995) and Blundell and Bond (1998). This approach combines the first-difference estimator (which takes care of country fixed-effects) with the estimator in levels to create a more efficient 'system' estimator. This methodology involves generation of internal instruments. However, as noted by Roodman (2008), this process might generate internal instruments which are numerous and also suspect.

IV. Results

Table 3 reports the results from the estimation of equation (1) using OLS. We separately report results for gini and Q1 in different panels. In our regressions, we use the logarithms of our inequality variables, *GINI* and *Q1*, as well as our measure of financial development, *PVTCRED*. Column 1 of Panels A and B in Table 3 reports the results from a regression of inequality on contemporaneous financial development. We see that financial development is negatively associated with the overall income distribution (*GINI*) and positively associated with the income share of the poorest quintile (*Q1*).

The above results might be biased due to reverse causality as inequality itself could have an impact on how a country's financial system develops. If a country's income distribution is highly unequal, it might be in the interest of those who command a disproportionate share to suppress policies, like increased financial development, which have the potential to reduce the skew in the distribution of income. Hence, to get around this issue we take a spaced lag of *PVTCRED* as our independent variable. Column 2 of each panel reports the results of this regression. The results are very similar to the ones obtained in column 1. The use of the lagged value of *PVTCRED* confirms the causal relationship between financial development and inequality.

In columns 3-4, we introduce a series of controls used in the literature in our regression. In column 3, we observe that real GDP growth is negatively associated with inequality while the effect of inflation and growth in trade openness is insignificant. The coefficient on financial development remains highly significant. In column 4, we drop real GDP growth and introduce dummies for legal origin. As suggested by La Porta et al (1998), a country's financial development is related to its legal origins. Rajan and Zingales (1998) argue that in turn financial development promotes economic growth. We find that countries with French legal origin have higher inequality than those of English origin while German and Scandinavian countries see less inequality than the English origin countries. These results indicate that creditor-friendly countries may face higher inequality. In columns 5 and 6, we estimate the specifications of columns 3 and 4 with the addition of year fixed effects to control for worldwide macroeconomic shocks. The causal relationship between financial development and inequality remains negative and significant. The result in column 5 indicates that a one standard deviation increase in private credit to GDP for the median country-year observation would reduce the gini coefficient from 41.05 to 36.93 (10.0% reduction) and increase the income share of the lowest quintile from 0.052 to 0.058 (12.8% increase). In column 7 of each panel, we report the estimates obtained by using System GMM. The results are comparable to those in column 5. We see that there is no qualitative change in the coefficient for financial development.

Channels

We estimate Equation (2) with different channels through which financial development could affect inequality. The detailed results for the three channels, i) Human Capital, ii) Institutional Framework, and iii) Labour Intensity of Industries follow.

i) Human Capital

As discussed earlier, we use *HDI* and Adult Literacy Rate (*ADLRT)* as proxies for the channel of human capital. Table 4 reports the OLS estimates of equation (2). Column 1 repeats the results from column 4 of table 3. Column 2 in each panel reports the interactive effect of lagged *PVTCRED* and lagged *HDI*. The results suggest that countries with higher financial development and a high value of human capital as measured by *HDI* see a faster decline in inequality than other countries. Results from panel B show that in countries with high human capital, the effect of financial development on raising income shares of the poorest is greater. We get similar results when we use the adult literacy rate as a proxy for human capital as shown in column 3. Column 4-6 in each panel reports the results when we include year fixed effects. All the results reported above remain significantly unaltered. The results support the alternate hypothesis ($\beta_2 < 0$, in case of *GINI* and $\beta_2 > 0$, in case of *Q1)*. We also tried using another proxy for human capital, namely the percentage of the population above 25 years of age to have completed secondary schooling from the Barro-Lee (2010) dataset. We do not find the interaction effect to be significant with this proxy.

ii) Institutional Environment

Through this channel we would like to identify how the effect of financial development on inequality varies with the creditor-friendly and debtor-friendly institutional environments. Table 5 reports the results of an OLS estimation of equation (2) with creditor rights (*CR*) acting as a proxy for the institutional environment channel. In column 2, we observe the coefficient of the interaction term to be positive in panel A with significance at the 10% level and negative but insignificant in panel B. This is consistent with the results we obtained in Table 3 when we used legal origin to proxy institutional environment. This suggests that, in equilibrium, strengthening legal enforcement of lender rights does not necessarily mean more access to credit for the poor and the resulting fall in inequality. Our results are similar to a study on India by Lilienfeld-Toal, Mookherjee and Visaria (2009). They find that with inelastic supply, strengthening enforcement generates general equilibrium effects which reduce credit access for small borrowers while expanding it for wealthy borrowers. Column 4 in each panel reports the results when we include year-fixed effects. Though the results in panel A are similar, we see that the coefficient of the interaction term in panel is now negative and significant at the 10% level. The results do not support the alternate hypothesis ($\beta_2 < 0$, in case of *GINI* and $\beta_2 > 0$, in case of *Q1)*. In fact, we observe weak evidence of the opposite effect.

iii) Labour Intensity of Industries

High labour intensive industries differ from low labour intensive industries in the proportionate share of (i) value added (*VA*), (ii) value of output (*VO*), and (iii) wages paid (*W*) that they command in a given country-year. We interact this difference with financial development and obtain the results shown in Table 6. We observe the coefficient of the interaction term to be positive and significant in all specifications in panel A and negative and significant in panel B. We also interacted the differences in employment share and share of establishments in a similar manner and found them to be insignificant. We note from the summary statistics in Table 2 that the median country-year value for *DSHLII* is negative for value added and value of output, zero for wages and number of employees while it is positive for the number of establishments. This suggests that less labour intensive industries contribute a higher share to total value added and value of output. Our results suggest that as the dominance of less labour intensive industries increases, the negative impact of financial development on inequality rises. The reasons for this phenomenon deserve further examination.

Here too we find results that are counter to our initial hypothesis ($\beta_2 < 0$, in case of *GINI* and $\beta_2 > 0$, in case of *Q1*).

We also attempted to estimate equation (2) using System GMM. We find that many of the coefficients either become insignificant or change sign. We believe that these results are driven by the proliferation of internal instruments. The number of instruments is far greater than the number of countries, which is considered a minimal rule of thumb on instrument count.

Robustness

All the above results are based on spaced data as described in the data section. To ensure that these results are robust even when data is constructed in alternate ways, we run our regressions on two more data sets. Our original methodology maximizes the number of spaced observations while ensuring that there is a gap of at least 5 years between two observations for a given country. In our first robustness check, we fix the gap at 5 years for all countries. This leads to the creation of five series of spaced data. Series 1 has data for 1955, 1960, 1965 and so on. Series 2 has data for years 1956, 1961, 1966 and so on. Similarly we create three more series. From these series, we pick the series with the maximum number of observations. This happens to be Series 1. We then run equation (1) and (2) on this data. Most of our results (not reported here) are similar to the ones obtained previously. However, the coefficients for human capital as a channel become insignificant which is probably due to lack of sufficient observations.

As a second robustness check, we abandon the idea of spacing the data and instead run equations (1) and (2) on the entire data set of 2302 observations. The results are similar to the ones obtained in the original spaced data.

V. Access to Finance

In the preceding analysis, the measure of financial development we have used is the ratio of private credit to GDP. As described earlier, this measure serves as the best proxy for the development of a financial system. However, private credit to GDP only measures the 'depth' of financial development. It is not able to adequately capture the 'breadth' of financial development or in other words, the access to financial services that the population has. As described in Beck et al (2007b), broad financial access is likely to be most beneficial to poor families and small entrepreneurs as they are most likely to suffer from credit constraints. These constraints could be in the form of lack of credit history, information asymmetries and even geographical distance from banking service providers. Hence, examining the role played by access to financial services in reducing inequality, if any, as well as comparing the impact of developing 'financial breadth' with 'financial depth' is bound to be interesting. We hypothesize that countries with higher financial access have lower growth in inequality. Unfortunately, the cross-country data on financial access is sparse. The source of our data is the financial access data set presented in Beck et al (2007b). They present data for 99 countries for the year 2003-04 for a host of banking sector outreach indicators. The ones we use in our study are the geographic and demographic penetration of bank branches and Automated Teller Machines (ATMs). Data on branches is available for 98 countries and on ATMs for 89 countries. Since there is only one observation for each country, we are able to test only for the cross-sectional variation.

We estimate the effect of financial access using the following specification:

$$GRWIQ_c = \beta_0 + \beta_1 Breadth_c + \beta_2 Depth_c + \gamma' Z_c + \epsilon_c \quad (3)$$

Since the 'breadth' data is only for 2003-04, we are restricted to studying the impact of 'breadth' only on those countries for which inequality data is available for at least two years post

2002. Our ‘depth’ measure is the log of private credit to GDP in 2003. Our dependent variable in this specification is the growth in inequality from 2003 onwards, the year for which we have access data. Our inequality data ends in 2006. We control for the initial value of inequality which can affect the rate of growth. We also have our usual controls like growth in trade openness and growth of real GDP per capita during the period.

As per our hypothesis, β_1 should be negative in case of gini and positive in case of Q1. Panel A of Table 7 reports the regression results when the measure of inequality is the growth in the value of the gini coefficient while Panel B has the corresponding results for growth in Q1. Columns 1-4 in each panel report the results with only the ‘breadth’ measure along with controls while columns 5-8 have ‘depth’ included. We find geographic branch penetration and demographic penetration to be statistically significant with the signs that we hypothesized. This is true both when the depth measure is included and excluded, except for the impact of demographic branch penetration on growth of Q1 when private credit is excluded. The other two access proxies, relating to ATM penetration, are insignificant in all cases. Interestingly, the ‘depth’ measure becomes insignificant in the presence of a ‘breadth’ measure in all cases in Panel A. In columns 5 and 6 of panel B, private credit is weakly significant but with an opposite sign to that of the ‘breadth’ variables. We observe that a one standard deviation increase in geographic (demographic) branch penetration for the median country reduces the growth rate of the gini coefficient by 4.0% (2.9%) and increases the growth rate of Q1 by 11.1% (5.4%). In unreported results, we observe that on including only depth and excluding all the breadth measures, for this data set, the coefficient on the depth measure in statistically insignificant. Given the limited number of observations, we hesitate to draw any concrete conclusions from these results. However, we can say that financial access does play a role in reducing income inequality and that broadening access to financial services is likely to work faster than merely deepening credit availability in the system.

VI. Conclusion

We find that financial development reduces income inequality in a large data set spanning more than 45 years and over 150 countries. A one standard deviation increase in financial development (private credit to GDP) reduces the gini coefficient by 10% and increases the income share of the lowest quintile by 12.8%. We also find that human capital development is a beneficial channel and reduces inequality. Institutional environment and industrial composition in favour of labour intense industries appear to increase inequality. Broadening access is useful and may work faster than deepening credit. Our results are robust to various data constructions.

We would like to further explore some of the results which we have obtained so far, preferably with more direct measures of the channels than we have used currently. The effect of financial development on income inequality as well as the channels through which it operates may vary across income groups, level of economic development of the countries studied. We would also like to study whether this differential impact exists and what is its magnitude.

APPENDIX I – Variables and Data Sources

Variable	***Variable Description***	***Source***	***Coverage***
GINI	The gini co-efficient is the ratio of the area between the Lorenz Curve, which plots cumulative population against cumulative income share, and the diagonal to the area below the diagonal, multiplied by 100. A value of 100 indicates perfect inequality while a value of 0 means no inequality.	UNU-WIDER WIID (V2.0c May 2008)	From before 1960 to 2006 covering 159 countries
Q1	Q1 refers to the income share of the poorest 20% of a country's population. In cases where deciles, and not quintiles, are available, Q1 is calculated as D1+D2. If no data on either quintiles or deciles are available, Q1 is calculated using gini by assuming a lognormal income distribution as per Dollar and Kraay (2002).	UNU-WIDER WIID (V2.0c May 2008)	From before 1960 to 2006 covering 159 countries
Private Credit to GDP (*PVTCRED*)	Ratio of Private credit by deposit money banks and other financial institutions to GDP	World Bank Financial Structure Dataset (rev. April 2010)	1960-2007, covering 160 countries
Growth in Real GDP per Capita (*RGDPGRW*)	Growth rate of Real GDP per capita (Constant Prices: Laspeyres), derived from growth rates of c, g, i, unit: I$	Penn World Table 6.3, August 2009	1950-2007, covering 189 countries
Growth in Trade Openness (*TOGRW*)	Growth in Trade Openness where Trade openness is defined as exports plus imports divided by GDP (at contant prices)	Penn World Table 6.3, August 2009	1950-2007, covering 189 countries
Inflation (*INFL*)	Our measure of inflation is the GDP deflator which we calculate using the values of GDP at current and constant prices as per the Penn World Table	Penn World Table 6.3, August 2009	1950-2007, covering 189 countries
Legal Origin	Identifies the legal origin of the Company law or Commercial Code of a country. The five origins are English, French, German, Nordic and Socialist.	Djankov, McLiesh and Shleifer (2007)	129 countries

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Variable	***Variable Description***	***Source***	***Coverage***
HDI	Human Development Index values	UNDP's annual Human Development Reports	Reports from 1990 onwards
ADLRT	Adult Literacy Rate (%)	UNDP's annual Human Development Reports	Reports from 1990 onwards
Creditor Rights (CR)	An index aggregating creditor rights in a country in a year. The index ranges from 0 (weak) to 4 (strong).	Djankov, McLiesh and Shleifer (2007)	1978-2002, covering 129 countries
Number of establishments (ESTB)	Number of establishments of given industry in given country-year.	UNIDO Industrial Statistics Database (INDSTAT2 2010 ISIC Rev.3)	1963-2007, covering 162 countries
Wages and Salaries (W)	Total wages of all employees working in given industry in given country-year in local currency and USD	UNIDO Industrial Statistics Database (INDSTAT2 2010 ISIC Rev.3)	1963-2007, covering 162 countries
Number of employees (EMP)	Number of employees working in given industry in given country-year	UNIDO Industrial Statistics Database (INDSTAT2 2010 ISIC Rev.3)	1963-2007, covering 162 countries
Value Added (VA)	Value added by the industry in given country-year	UNIDO Industrial Statistics Database (INDSTAT2 2010 ISIC Rev.3)	1963-2007, covering 162 countries
Vale of Output (VO)	Output of the industry in given country-year	UNIDO Industrial Statistics Database (INDSTAT2 2010 ISIC Rev.3)	1963-2007, covering 162 countries
DSHLII	Disproportionately higher share of Labour Intensive Industries is the difference in the values for the industries at the 75th percentile and 25th percentile of our measure of labour intensity	Calculated from data in UNIDO Industrial Statistics Database (INDSTAT2 2010 ISIC Rev.3)	1963-2007, covering 162 countries
Geographic Branch Penetration (GBP)	Number of Bank branches per 1000 km^2	Beck, Demirguc-Kunt and Peria (2007)	2003-04, covering 98 countries
Demographic Branch Penetration (DBP)	Number of Bank branches per 100,000 people	Beck, Demirguc-Kunt and Peria (2007)	2003-04, covering 98 countries
Geographic ATM Penetration (GATMP)	Number of ATMs per 1000 km^2	Beck, Demirguc-Kunt and Peria (2007)	2003-04, covering 89 countries
Demographic ATM Penetration (DATMP)	Number of ATMs per 100,000 people	Beck, Demirguc-Kunt and Peria (2007)	2003-04, covering 89 countries

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Table 1A: Inequality by Geographic Region

The table reports means of inequality variables, *GINI* and *Q1*, by geographic region for all and the spaced sample.

	All			*Spaced*		
Geographic Region	***N***	***GINI***	***Q1***	***N***	***GINI***	***Q1***
East Asia & Pacific	121	39.29	0.063	54	40.41	0.061
Europe & Central Asia	431	31.37	0.077	131	31.33	0.078
High income: OECD	807	32.79	0.073	225	33.38	0.070
High income: non OECD	187	37.89	0.060	69	39.31	0.058
Latin America & Caribbean	407	49.64	0.038	143	49.34	0.040
Middle East & North Africa	49	41.25	0.056	36	40.82	0.057
South Asia	100	36.12	0.071	37	37.67	0.068
Sub-Saharan Africa	200	49.99	0.043	134	49.43	0.044
Total	2302	38.08	0.06	829	39.87	0.06

Table 1B: Inequality by Income Group

The table reports means of inequality variables, *GINI* and *Q1*, by income group for all and the spaced sample.

	All			*Spaced*		
Income Group	***N***	***GINI***	***Q1***	***N***	***GINI***	***Q1***
High income: OECD	782	33.18	0.072	217	33.72	0.069
High income: non OECD	187	37.89	0.060	69	39.31	0.057
Low income	249	44.27	0.054	137	44.52	0.055
Lower middle income	514	40.70	0.058	204	41.95	0.056
Upper middle income	521	40.85	0.057	179	42.27	0.054
No group	49	28.65	0.090	23	34.75	0.078
Total	2302	38.08	0.06	829	39.87	0.06

Table 2: Summary Statistics

The table reports the summary statistics of the variables we used in our regression models. The description of the variables is available in Appendix 1.

Variables	N	Mean	SD	Min	P25	Median	P75	Max
INEQUALITY								
GINI	655	39.52	11.32	16.90	30.90	39.10	47.40	76.50
Q1	655	0.06	0.03	0.00	0.04	0.06	0.08	0.12
FINANCIAL DEVELOPMENT								
PVTCRED	480	0.46	0.37	0.02	0.19	0.32	0.66	1.80
CHANNELS								
Human Capital								
Adult Literacy Rate *(ADLRT)*	285	0.85	0.18	0.26	0.79	0.93	0.99	1.00
Human Development Index*(HDI)*	286	0.73	0.20	0.09	0.64	0.77	0.90	0.98
Institutional Environment								
Creditor Rights (*CR*)	358	1.96	1.11	0.00	1.00	2.00	3.00	4.00
Disproportionately Higher Share of Labour-Intensive industries (DSHLII) in								
Value Added (*VA*)	376	-0.04	0.10	-0.59	-0.06	-0.02	0.01	0.24
Value of Output (*VO*)	368	-0.04	0.12	-0.75	-0.07	-0.02	0.01	0.51
Wages (*W*)	376	-0.01	0.11	-0.69	-0.04	0.00	0.03	0.42
Number of Establishments (*ESTB*)	213	0.01	0.09	-0.41	-0.02	0.02	0.06	0.24
Number of Employees (*EMP*)	367	-0.01	0.10	-0.53	-0.03	0.00	0.04	0.38
CONTROLS								
Real GDP Growth (*RGDPGRW*)	560	0.02	0.03	-0.12	0.01	0.02	0.04	0.10
Inflation (*INFL*)	492	0.04	0.02	-0.02	0.02	0.03	0.05	0.15
Growth in Trade Openness (*TOGRW*)	560	0.02	0.04	-0.14	0.00	0.02	0.04	0.14
ACCESS								
Geographic Branch Penetration *(GBP)*	47	32.38	65.55	0.14	2.14	9.10	31.04	375.00
Demographic Branch Penetration *(DBP)*	47	19.41	19.61	0.73	4.73	11.15	30.08	95.87
Geographic ATM Penetration *(GATMP)*	45	50.62	83.86	0.09	3.72	21.72	64.56	462.50
Demographic ATM Penetration *(DATMP)*	45	35.41	32.75	0.53	11.07	28.78	52.39	126.60

Table 3: Inequality and Financial Development

The table reports the OLS regression results of the following model : $IQ_{ct} = \beta_0 + \beta_1 FD_{c,t-s} + \gamma^{'} Z_{ct} + \eta_t + \epsilon_{ct}$ (1).

In the equation (1), IQ_{ct}, refers to measure of inequality in country *c,* year *t* . In our case, we use *GINI* and *Q1*, as two measures of inequality. $FD_{c,t-s}$ refers to financial development (measured by *PVTCRED*) in country *c,* year *t-s*, where *s* refers to last spaced year. Taking lag of financial development by spaced year solves the possible problem of reverse causality between financial development and inequality as is well documented in the literature (Dollar and Kraay (2002), Beck et al (2007)). We use a bunch of controls, Z_{ct}, as noted in the literature (Beck et al (2007)), like inflation, growth in trade openness, and growth in real GDP per capita. η_t refers to year fixed effects to control for macro-economic shocks.

	Panel A: *Log GINI*							Panel B: *Log Q1*						
	1	2	3	4	5	6	7	1	2	3	4	5	6	7
Financial Development														
Log *PVTCRED*$_{ct}$	-0.087***							0.121***						
	[0.013]							[0.027]						
Log *PVTCRED*$_{c,t-s}$		-0.089***	-0.091***	-0.042**	-0.091***	-0.047***	-0.091***		0.121***	0.116***	0.048	0.116***	0.056*	0.129**
		[0.014]	[0.016]	[0.016]	[0.016]	[0.016]	[0.028]		[0.028]	[0.031]	[0.033]	[0.031]	[0.032]	[0.054]
Legal Origin(English=0)														
French				0.094***		0.088***					-0.148**		-0.146**	
				[0.028]		[0.027]					[0.057]		[0.057]	
German				-0.175***		-0.199***					0.273***		0.312***	
				[0.045]		[0.044]					[0.071]		[0.089]	
Scandinavian				-0.256***		-0.227***					0.315***		0.270***	
				[0.050]		[0.053]					[0.083]		[0.092]	
Controls														
RGDPGRW$_{ct}$			-1.015**		-1.147**		0.411			2.503**		2.779***		0.525
			[0.489]		[0.529]		[1.011]			[0.983]		[1.032]		[1.458]
INFL$_{ct}$			-0.384	-0.228	1.590*	1.563	1.444*			-0.365	-0.247	-4.105**	-3.901	-2.192
			[0.518]	[0.538]	[0.930]	[1.130]	[0.824]			[1.018]	[1.065]	[2.051]	[2.462]	[2.475]
TOGRW$_{ct}$			-0.522	-0.535	-1.178***	-1.206***	-1.267***			1.168	1.263	2.330**	2.509**	2.516***
			[0.390]	[0.364]	[0.399]	[0.392]	[0.276]			[0.913]	[0.900]	[0.959]	[0.972]	[0.660]
Constant	3.577***	3.562***	3.629***	3.647***	2.992***	3.715***	3.441***	-2.849***	-2.828***	-2.930***	-2.932***	-2.126***	-2.960***	-2.693***
	[0.019]	[0.021]	[0.031]	[0.034]	[0.035]	[0.096]	[0.139]	[0.033]	[0.036]	[0.061]	[0.066]	[0.069]	[0.068]	[0.201]
Year Fixed Effects	**No**	**No**	**No**	**No**	**Yes**	**Yes**	**Yes**	**No**	**No**	**No**	**No**	**Yes**	**Yes**	**Yes**
Observations	**480**	**405**	**362**	**338**	**362**	**338**	**362**	**480**	**405**	**362**	**338**	**362**	**338**	**362**
R-squared	**0.08**	**0.08**	**0.11**	**0.25**	**0.24**	**0.35**		**0.04**	**0.04**	**0.07**	**0.13**	**0.19**	**0.25**	

Robust standard errors in brackets, * significant at 10%; ** significant at 5%; *** significant at 1%

Table 4: Inequality and Financial Development: Human Capital

The table reports the OLS regression results of the following model : $IQ_{ct} = \beta_0 + \beta_1 FD_{c,t-s} + \beta_2 FD_{c,t-s} * Channels_{c,t-s} + \gamma^{'} Z_{ct} + \eta_t + \epsilon_{ct}$ (2)

We use the above equation to identify the channels through which financial development affects inequality. Here we use *Human Capital* as a channel.

	Panel A: *Log GINI*						**Panel B: *Log Q1***					
	1	2	3	4	5	6	1	2	3	4	5	6
Financial Development												
Log $PVTCRED_{c,t-s}$	-0.091***	0.013	0.104**	-0.091***	0.005	0.105**	0.116***	-0.121**	-0.316***	0.116***	-0.104	-0.304***
	[0.016]	[0.031]	[0.040]	[0.016]	[0.037]	[0.045]	[0.031]	[0.059]	[0.067]	[0.031]	[0.067]	[0.075]
Channels: Human Capital												
Log $PVTCRED_{c,t-s}$* $HDI_{c,t-s}$		-0.237***			-0.227***			0.473***			0.455***	
		[0.048]			[0.056]			[0.091]			[0.104]	
Log $PVTCRED_{c,t-s}$ * $ADLRT_{c,t-s}$			-0.003***			-0.003***			0.006***			0.006***
			[0.001]			[0.001]			[0.001]			[0.001]
Controls												
$RGDPGRW_{ct}$	-1.015**	-2.340**	-2.019**	-1.147**	-2.323**	-1.937**	2.503**	5.270**	4.624**	2.779***	5.069**	4.297**
	[0.489]	[1.002]	[0.990]	[0.529]	[0.987]	[0.956]	[0.983]	[2.099]	[2.030]	[1.032]	[2.010]	[1.943]
$INFL_{ct}$	-0.384	-2.964	-2.138	1.590*	-2.845	-2.161	-0.365	7.040*	5.361	-4.105**	6.028	4.661
	[0.518]	[1.991]	[1.890]	[0.930]	[2.541]	[2.483]	[1.018]	[3.806]	[3.472]	[2.051]	[4.995]	[4.835]
$TOGRW_{ct}$	-0.522	-0.645	-0.756	-1.178***	-1.358**	-1.436**	1.168	0.935	1.164	2.330**	2.329	2.486*
	[0.390]	[0.583]	[0.620]	[0.399]	[0.684]	[0.696]	[0.913]	[1.176]	[1.220]	[0.959]	[1.408]	[1.401]
Constant	3.629***	3.663***	3.649***	2.992***	3.501***	3.464***	-2.930***	-3.041***	-3.012***	-2.126***	-2.866***	-2.792***
	[0.031]	[0.054]	[0.053]	[0.035]	[0.187]	[0.181]	[0.061]	[0.107]	[0.102]	[0.069]	[0.245]	[0.233]
Year Fixed Effects	**No**	**No**	**No**	**Yes**	**Yes**	**Yes**	**No**	**No**	**No**	**Yes**	**Yes**	**Yes**
Observations	**362**	**128**	**128**	**362**	**128**	**128**	**362**	**128**	**128**	**362**	**128**	**128**
R-squared	**0.11**	**0.3**	**0.32**	**0.24**	**0.35**	**0.39**	**0.07**	**0.24**	**0.28**	**0.19**	**0.28**	**0.33**

Robust standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: Inequality and Financial Development: Institutional Environment

The table reports the OLS regression results of the following model : $IQ_{ct} = \beta_0 + \beta_1 FD_{c,t-s} + \beta_2 FD_{c,t-s} * Channels_{c,t-s} + \gamma' Z_{ct} + \eta_t + \epsilon_{ct}$ (2)

We use the above equation to identify the channels through which financial development affects inequality. Here we use *Institutional Enviroment* as a channel.

	Panel A: *Log GINI*				Panel B: *Log Q1*			
	1	2	3	4	1	2	3	4
Financial Development								
Log $PVTCRED_{c,t-s}$	-0.091***	-0.127***	-0.091***	-0.138***	0.116***	0.156***	0.116***	0.182***
	[0.016]	[0.026]	[0.016]	[0.027]	[0.031]	[0.052]	[0.031]	[0.053]
Channels: Institutional Enviroment								
Log $PVTCRED_{c,t-s} * CR_{c,t-s}$		0.017*		0.021*		-0.028		-0.036*
		[0.010]		[0.011]		[0.020]		[0.021]
Controls								
$RGDPGRW_{ct}$	-1.015**	-0.958	-1.147**	-1.135	2.503**	2.621**	2.779***	2.738**
	[0.489]	[0.660]	[0.529]	[0.715]	[0.983]	[1.259]	[1.032]	[1.312]
$INFL_{ct}$	-0.384	-1.618	1.590*	-1.361	-0.365	2.177	-4.105**	1.37
	[0.518]	[1.134]	[0.930]	[1.741]	[1.018]	[2.213]	[2.051]	[3.585]
$TOGRW_{ct}$	-0.522	-0.265	-1.178***	-1.026*	1.168	0.484	2.330**	1.639
	[0.390]	[0.476]	[0.399]	[0.522]	[0.913]	[0.955]	[0.959]	[1.058]
Constant	3.629***	3.648***	2.992***	3.643***	-2.930***	-2.978***	-2.126***	-2.871***
	[0.031]	[0.043]	[0.035]	[0.127]	[0.061]	[0.084]	[0.069]	[0.254]
Year Fixed Effects	**No**	**No**	**Yes**	**Yes**	**No**	**No**	**Yes**	**Yes**
Observations	**362**	**214**	**362**	**214**	**362**	**214**	**362**	**214**
R-squared	**0.11**	**0.16**	**0.24**	**0.27**	**0.07**	**0.09**	**0.19**	**0.19**

Robust standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6: Inequality and Financial Development: Labour-Intensity of Industries

The table reports the OLS regression results of the following model : $IQ_{ct} = \beta_0 + \beta_1 FD_{c,t-s} + \beta_2 FD_{c,t-s} * Channels_{c,t-s} + \gamma' Z_{ct} + \eta_t + \epsilon_{ct}$ (2)

We use the above equation to identify the channels through which financial development affects inequality. Here we use *Labour intensity of Industries* as a channel.

	Panel A: *Log GINI*						Panel B: *Log Q1*					
	1	2	3	4	5	6	1	2	3	4	5	6
Financial Development												
Log $PVTCRED_{c,t-s}$	-0.103***	-0.106***	-0.110***	-0.104***	-0.108***	-0.112***	0.111***	0.114***	0.123***	0.103***	0.110***	0.120***
	[0.020]	[0.020]	[0.019]	[0.020]	[0.020]	[0.020]	[0.038]	[0.037]	[0.036]	[0.036]	[0.036]	[0.035]
Channels: DSHLII												
Log $PVTCRED_{c,t-s} * VA_{c,t-s}$	0.189**			0.242***			-0.356**			-0.473***		
	[0.079]			[0.087]			[0.165]			[0.179]		
Log $PVTCRED_{c,t-s} * VO_{c,t-s}$		0.137**			0.180***			-0.291**			-0.374***	
		[0.057]			[0.065]			[0.126]			[0.138]	
Log $PVTCRED_{c,t-s} * W_{c,t-s}$			0.150**			0.184**			-0.301**			-0.366**
			[0.065]			[0.074]			[0.139]			[0.156]
Controls												
$RGDPGRW_{ct}$	-0.803	-0.814	-0.816	-0.998	-1.026	-1.02	2.465**	2.463**	2.479**	3.059***	3.101***	3.099***
	[0.561]	[0.566]	[0.566]	[0.614]	[0.622]	[0.619]	[1.132]	[1.135]	[1.143]	[1.166]	[1.171]	[1.177]
$INFL_{ct}$	-0.783	-0.841	-0.842	1.14	1.335	1.085	0.736	0.825	0.838	-1.567	-1.806	-1.463
	[0.625]	[0.627]	[0.625]	[1.118]	[1.156]	[1.122]	[1.123]	[1.117]	[1.113]	[1.946]	[2.017]	[1.957]
$TOGRW_{ct}$	0.225	0.215	0.234	-0.572	-0.638	-0.564	-0.475	-0.454	-0.494	0.876	0.97	0.859
	[0.413]	[0.418]	[0.414]	[0.472]	[0.482]	[0.474]	[0.802]	[0.808]	[0.803]	[0.867]	[0.886]	[0.869]
Constant	3.591***	3.593***	3.592***	3.748***	3.066***	3.757***	-2.893***	-2.895***	-2.895***	-3.023***	-2.305***	-3.040***
	[0.038]	[0.038]	[0.038]	[0.072]	[0.038]	[0.072]	[0.070]	[0.070]	[0.070]	[0.120]	[0.064]	[0.120]
Year Fixed Effects	**No**	**No**	**No**	**Yes**	**Yes**	**Yes**	**No**	**No**	**No**	**Yes**	**Yes**	**Yes**
Observations	**251**	**250**	**251**	**251**	**250**	**251**	**251**	**250**	**251**	**251**	**250**	**251**
R-squared	**0.13**	**0.13**	**0.13**	**0.29**	**0.29**	**0.29**	**0.09**	**0.09**	**0.09**	**0.24**	**0.24**	**0.23**

Robust standard errors in brackets, * significant at 10%; ** significant at 5%; *** significant at 1%

Table 7: Inequality and Financial Development: Breadth v/s Depth

The table reports the OLS regression results of the following model : $GRWIQ_c = \beta_0 + \beta_1 Breadth_c + \beta_2 Depth_c + \gamma' Z_c + \epsilon_c$ (3)

We use the above equation to compare different affect of indicators of financial development, *Financial Depth* and *Financial Breadth*, on inequality.

	Panel A: Growth in GINI								***Panel B: Growth in Q1***							
	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
Financial Breadth																
Log GBP_c	-0.007**				-0.009*				0.012*				0.025***			
	[0.003]				[0.005]				[0.007]				[0.009]			
Log DBP_c		-0.013***				-0.017**				0.01				0.034**		
		[0.004]				[0.006]				[0.015]				[0.014]		
Log $GATMP_c$			-0.005				-0.005				-0.001				0.017	
			[0.005]				[0.008]				[0.012]				[0.014]	
Log $DATMP_c$				-0.006				-0.006				-0.017				-0.004
				[0.005]				[0.012]				[0.016]				[0.034]
Financial Depth																
Log $PVTCRED_{2003}$					0.002	0.006	-0.006	-0.006					-0.042*	-0.045*	-0.045	-0.033
					[0.008]	[0.008]	[0.011]	[0.011]					[0.024]	[0.025]	[0.034]	[0.031]
Controls																
Initial GINI/Q1	-0.056***	-0.057***	-0.048*	-0.045**	-0.063***	-0.061***	-0.063*	-0.060**	-0.061**	-0.052*	-0.036	-0.02	-0.048	-0.044	-0.048	-0.023
	[0.019]	[0.017]	[0.024]	[0.019]	[0.021]	[0.021]	[0.031]	[0.029]	[0.026]	[0.030]	[0.038]	[0.032]	[0.031]	[0.035]	[0.043]	[0.053]
$TOGRW_c$	0.168***	0.170***	0.169**	0.167**	0.146**	0.140**	0.174*	0.167	-0.43***	-0.41***	-0.40**	-0.34**	-0.36***	-0.34***	-0.31*	-0.291
	[0.053]	[0.056]	[0.074]	[0.075]	[0.055]	[0.059]	[0.092]	[0.101]	[0.120]	[0.132]	[0.171]	[0.156]	[0.095]	[0.123]	[0.183]	[0.201]
$RGDPGRW_c$	-0.094	-0.105	-0.091	-0.071	-0.03	0.007	-0.145	-0.102	0.158	0.045	-0.084	-0.4	-0.181	-0.295	-0.371	-0.648
	[0.181]	[0.183]	[0.276]	[0.256]	[0.182]	[0.185]	[0.339]	[0.335]	[0.419]	[0.445]	[0.639]	[0.553]	[0.310]	[0.399]	[0.711]	[0.742]
Constant	0.203**	0.226***	0.171	0.164*	0.228***	0.246***	0.223	0.215	-0.173**	-0.143	-0.065	0.044	-0.186**	-0.210**	-0.177	-0.02
	[0.077]	[0.068]	[0.105]	[0.082]	[0.081]	[0.077]	[0.138]	[0.136]	[0.082]	[0.112]	[0.146]	[0.132]	[0.076]	[0.100]	[0.149]	[0.249]
Observations	46	46	44	44	38	38	35	35	46	46	44	44	38	38	35	35
R-squared	0.57	0.6	0.54	0.54	0.62	0.63	0.59	0.59	0.63	0.62	0.61	0.63	0.74	0.72	0.7	0.68

Robust standard errors in brackets * significant at 10%; ** significant at 5%; *** significant at 1%