The long-run relationship between finance and income inequality: evidence from panel data

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ABSTRACT

We use heterogeneous panel cointegration techniques to examine the long-run effect of financial development on income inequality in a panel of 119 countries from 1980 to 2015. We include real GDP per capita in the cointegration relation and explicitly deal with cross-sectional dependence in the data that arises due to unobserved common factors. On average, financial development reduces income inequality in the long-run, with the result robust to different measures of finance and across country income groups.

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1. Introduction

The impact of financial development on income inequality has received a lot of attention, reflecting conflicting theoretical predictions and empirical findings. One set of theoretical models implies that financial development enhances economic growth and reduces income inequality. In these models, financial imperfections (e.g., information and transactions costs) are especially binding on low-income individuals who lack collateral and credit histories and any improvement on the imperfections (reflecting financial deepening) disproportionately benefits them. Furthermore, the financial imperfections reduce the efficiency of capital allocation and intensify income inequality by impeding the flow of capital to low-income individuals with high expected return investments (Aghion and Bolton, 1997; Galor and Zeira, 1993; Galor and Moav, 2004). From this perspective, financial development helps low-income individuals both by improving the efficiency of capital allocation, which accelerates economic growth, and by relaxing credit constraints on the poor, which reduces income inequality. In the same vein, Braun, et al. (2019) develop a model in which broader access to finance as a result of financial deepening moves resources from highly endowed to poorly endowed individuals such that financial deepening reduces the ex post level of income inequality. In contrast, other models predict that financial development primarily helps high income individuals. According to this view, low income individuals rely mainly on informal connections for capital, so that improvements in the

[1] We are grateful to an anonymous referee for comments that improved the paper.

formal financial sector mainly benefits those on high incomes. For example, Greenwood and Jovanovic (1990) argue that financial and economic development interact to produce an inverted u-shaped relationship between income inequality and financial development. In their model, financial development improves capital allocation at all stages of development, boosts aggregate growth, and helps the low-income individuals through this channel. However, the distributional effect of financial development depends on the level of economic development. At early stages of development, only the high-income individuals can afford to access and benefit from financial markets, whereas at higher levels of economic development, many more people access financial markets so that financial development directly helps a larger proportion of society and the distribution of income stabilizes.

The empirical evidence on the impact of financial development on income inequality is also inconclusive. For example, Li et al. (1998), Clarke et al. (2006), Beck et al. (2007), Hamori and Hashiguchi (2012) and Naceur and Zhang (2016) report that countries with higher levels of financial development have less income inequality. Kim and Lin (2011) and Law et al. (2014) report a non-linear relationship, Jaumotte et al. (2013), de Haan and Sturm (2017), and Dabla-Norris et al. (2015) report a positive relationship between finance and income equality, and Bahmani-Oskooee and Zhang (2015) find mixed results.[2]

In this paper, we revisit the empirical relationship between finance and income inequality making several contributions to the empirical literature. First, we measure financial development

[2] See Claessens and Perotti (2007), Demirgüç-Kunt and Levine (2009), de Haan and Sturm (2017) for more detailed reviews of the relevant empirical literature.

employing an index of financial development developed recently by IMF staff, which is designed to capture the depth, access and efficiency dimensions of financial institutions and financial markets (see Sahay et al., 2015; Svirydzenka, 2016), This contrasts with most other studies that have relied on the ratio to GDP of bank credit or broad money supply as a measure of financial development, both of which reflect narrow banking sector-oriented measures of financial development. For completeness, however, we also report results using the bank credit-to-GDP ratio as a measure of financial development. Second, the mixed results from other studies partly reflects differences in sample size and estimation methodologies that are subject to a variety of estimation problems, including omitted variables, slope heterogeneity, and endogenous regressors. In contrast, we employ a much larger number of countries in our data panel than is typical of other studies, which allows us to examine the effects of finance on income inequality generally as well as across country income groups to shed light on whether the impact of finance depends upon income levels. Third, we employ heterogeneous panel cointegration techniques that are robust to many problems common to standard cross-country and panel regressions (Pedroni, 2007) to examine the long-run effect of financial development on income inequality. We deal with unobserved common factors by incorporating cross sectional averages in the panel data (Pesaran, 2006). Despite the robustness of this cointegration methodology to endogenous regressors and omitted variables, we also include per capita real GDP in the cointegration relation due to its possible importance as a determinant of income inequality in the long-run (see most notably, Kuznets, 1955).

2. Model and data

We employ a trivariate cointegration regression involving the Gini coefficient, financial development, and real GDP per capita to assess the long-run impact of financial development on income inequality. We begin by considering a model of the form:

$$G_{it} = \alpha_i + \delta_i t + \beta_1 F_{it} + \beta_2 Y_{it} + \varepsilon_{it} \tag{1}$$

Where α_i are country-specific fixed effects and δ_t are country specific time trends included to control for any country-specific omitted factors that are relatively stable over time. G_{it} is the Gini coefficient over time periods t = 1, 2, …., T and countries i = 1, 2, …., N, F_{it} is a measure of financial development and Y_{it} is the log of real GDP per capita in country. The Gini coefficient is based on households' income before taxes and is from Solt's (2009) Standardized World Income Inequality Database (SWIID). To measure financial development, we employ: (i) the index of total financial development (TFD_{it}) developed recently by IMF staff, which is designed to capture the depth, access and efficiency dimensions of financial institutions (banks and nonbanks) and financial markets (see Svirydzenka, 2016); (ii) the two key sub-indices that of the financial development index that reflect separately the contributions from the development of financial institutions ($FDINS_{it}$) and financial markets ($FDMKT_{it}$); and (iii) the more commonly used ratio to GDP of bank credit to the private sector ($PCRED_{it}$) (e.g., Levine 2005). GDP per capita (2010 US$) is from the World Bank's World Development Indicators database. Our panel is unbalanced and comprises annual data for 119 advanced and developing countries for the period 1980-2015.[3]

[3] The countries included in the panel are listed in the appendix where inclusion guided by data availability.

3. Results

We begin by examining the basic time-series properties of the data and then test for the existence of a long-run or cointegrating relationship between G_{it}, F_{it}, and Y_{it}. To examine the unit root properties of the series we employ the panel unit root test of Im et al. (2003, henceforth IPS). However, as this procedure assumes cross-sectional independence that might lead to spurious inferences if the errors, ε_{it}, are not independent across i, we also consider the cross-sectionally augmented IPS (CIPS) test proposed by Pesaran (2007), which allows for cross-sectional dependence by augmenting the ADF regression with the cross-section averages of lagged levels and first-differences of the individual series (see, e.g., Herzer and Vollmer, 2012; Baltagi and Pesaran, 2007). The results are reported in Table 1 and show that for both the IPS and CIPS tests the null hypothesis cannot be rejected for the level series, while it is rejected for the first differenced series—i.e., the individual series in Eq. (1) appear to be non-stationary I(1) processes.

We test for cointegration with the panel and group test statistics suggested by Pedroni (1999) and report the Fisher statistic proposed by Maddala and Wu (1999) which follows a χ^2 distribution with 2 x N degrees of freedom. However, as these tests do not account for potential cross-sectional dependence, we follow Francois and Keinsley (2019) and Pedroni (1999) and adopt a residual-based, two-step approach. In addition, we extend the approach with a Common Correlated Effects (CCE) estimation procedure developed by Pesaran (2006) by augmenting the cointegrating regression with the cross-sectional averages of the dependent variable and the observed regressors as proxies for the unobserved factors, which takes account of possible cross-sectional dependence from unobserved common factors. The second step involves the computation of the CIPS statistic for the residuals from the individual CCE long-run relations (Baltagi and Pesaran, 2007). The cointegration results are reported in Table 2 and show that under all of these cointegration procedures the null hypothesis of no integration is rejected and the Fisher χ^2-statistics support the existence of at least one cointegrating vector. Accordingly, the results indicate the presence of a long-run relationship between income inequality, financial development (on all measures) and real GDP per capita.

We estimate the long-run growth effect of financial development on income inequality using the between-dimension group-mean panel dynamic ordinary least squares (DOLS) estimator of Pedroni (2001), which allows for greater flexibility in the presence of heterogeneous cointegrating vectors. The panel DOLS regression is given by:

$$Gini_{it} = \alpha_i + \delta_i t + \beta_{1i} F_{it} + \beta_{2i} \log(Y_{it}) + \sum_{j=-ki}^{ki} \Phi_{1ij} \Delta F_{it-j} + \sum_{j=-ki}^{ki} \Phi_{2ij} \Delta \log(Y_{it-j}) + \epsilon_{it} \quad (2)$$

where Φ_{1ij} and Φ_{2ij} are coefficients of the lead and lag differences that account for potential serial correlation and endogeneity of the regressors. A feature of the DOLS procedure is that it produces unbiased estimates for variables that are cointegrated even in the presence of endogenous regressors. In the case of financial development, there might be reverse causality, for example, if low income households were successful in demanding more credit to reduce their consumption disparities with high-income households. For example, Fischer et al. (2019) report panel regression results suggesting that within country increases in income inequality lead to a higher ratio of private credit to GDP in economies with low incomes and weak legal rights, though the effect vanishes and even becomes negative in economies with higher incomes and stronger legal rights.[4] The group-mean panel DOLS estimator is computed as:

$$\hat{\beta}_{m}=N^{-1}\sum_{i=1}^{N}\hat{\beta}_{mi} \quad (3)$$

where m =1, 2 and $\hat{\beta}_{mi}$ is the conventional time-series DOLS estimator applied to the *i*th country of the panel. We account for cross-sectional dependence that might be induced by common shocks and/or spillovers among countries by applying the DOLS procedure to the demeaned data.

The DOLS estimates for the coefficients on financial development and real GDP per capita are reported in Table 3 where for completeness we report results for the demeaned and unadjusted data. The coefficients on each measure financial development are negative and statistically significant for both the demeaned and unadjusted data. A one percentage point increase in financial development will induce a reduction in the Gini coefficient by

[4] We acknowledge—as pointed out by the anonymous referee—that the methodology employed may not completely rule out potential biases associated with reverse causality and other sources of endogeneity bias.

between 0.21 to 1.30 percentage points depending on the measure of financial development in the case of demeaned data, and between 0.92 and 1.75 percentage points in the case of the unadjusted data. In contrast, the coefficient on real GDP per capita is consistently positive and statistically significant and indicate that income inequality increases as countries become richer. This is consistent with greater financial development being a buffer against the tendency for income inequality to increase as countries develop.

Finally, several studies have found that the impact of financial development on income inequality depends in part on the level of development. For example, Altunbaş and Thornton (2019) recently reported that financial development increases income inequality in high- and lower- income countries but promotes greater inequality in upper-middle-income countries. We test whether the long-run effect of financial development on income inequality differs according to income group by re-estimating Eq. (2) for high-income, upper-middle, and lower income countries.[5] The results from the demeaned series are reported in Table 4. In the case of the total financial development index, TFD_{it}, financial development reduces income inequality for all income groups; for the other measures of finance, the coefficient is either also negative and statistically significant or (mainly for lower income countries) not significant. For each group, income inequality increases with economic growth.

4. Conclusion

[5] The World Bank's classification scheme for 2015 defined high-income economies are those with a GNI per capita of $12,476 or more and upper middle-income economies are those with a GNI per capita between $4,036 and $12,475.

We find that financial development reduces income inequality in the long-run in a panel of 119 countries advanced and developing economies. This result is robust to several measures of financial development and is generally consistent across country income classifications. It is consistent with financial development acting as a buffer against the tendency for income inequality to increase as countries become richer.

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Table 1
Panel unit roots tests.

Variable	Deterministic trend	IPS statistics	CIPS statistics
Levels			
G_{it}	c, t	7.686	-2.162
TFD_{it}	c, t	-1.107	-2.423
$FDINS_{it}$	c, t	2.086	-2.532
$FDMKT_{it}$	c, t	-2.313	-2.423
$PCRED_{it}$	c, t	3.432	-2.138
Y_{it}		3.369	-1.571
First difference			
ΔG_{it}	c	-1.306***	-4.436***
ΔTFD_{it}	c	-5.030***	-5.844***
$\Delta FDINS_{it}$	c	-4.871***	-5.839***
$\Delta FDMKT_{it}$	c	-4.722***	-5.567***
$\Delta PCRED_{it}$		-3.097***	-4.941***
ΔY_{it}	c	-2.971***	-4.579***

Notes: Variables are in logs. For the level data, we allow for both individual country effects (c) and country-specific time trends (t). In the case of the first differenced data we allow for individual country effects (c). Lag length selection based on SIC to adjust for autocorrelation. The IPS statistic is distributed as N(0,1). The relevant 5% (1%) critical value for the CIPS statistics with is −2.54 (−2.62) with an intercept and a linear trend, and −2.06 (−2.14) with an intercept.
***, ** and* indicate significance at the 1, 5 and 10 percent levels, respectively.

Table 2
Panel cointegration tests.

	Cointegration rank r = 0	r = 1	r = 2
(a)$Gini_{it}, TFD_{it}, Y_{it}$			
Fisher statistics	175.4***	45.65	22.45
CIPS statistic		-3.1618***	
Panel PP statistic		-1.7751***	
Panel ADF statistic		-0.5482***	
Group PP statistic		-2.2840**	
Group ADF statistic		-2.1236**	
(b)$Gini_{it}, FDINS_{it}, Y_{it}$			
Fisher statistics	154.56***	43.54	19.53
CIPS statistic		-3.5576***	
Panel PP statistic		-1.7252***	
Panel ADF statistic		-0.5854**	
Group PP statistic		-1.0157***	
Group ADF statistic		-2.6148***	
(c)$Gini_{it}, FDMKT_{it}, Y_{it}$			
Fisher statistics	175.67***	44.64	20.54
CIPS statistic		-2.5977***	
Panel PP statistic		-1.0964***	
Panel ADF statistic		-0.5525***	
Group PP statistic		-2.9885***	
Group ADF statistic		-2.6646***	
(d) $Gini_{it}, PCRED_{it}, Y_{it}$			
Fisher statistics	200.14**	34.53	21.64
CIPS statistic		-3.1984***	
Panel PP statistic		-1.3316**	
Panel ADF statistic		-1.3404**	
Group PP statistic		-1.2679**	
Group ADF statistic		-2-2223**	

Notes: The Fisher statistic is distributed as χ^2 with 2 × N degrees of freedom. The relevant 5% (1%) critical value for the CIPS statistic is −2.11 (−2.23). The number of lags was determined by the Schwarz criterion with a maximum of four lags. **Denote a rejection of the null hypothesis of no cointegration at the 5% level. ***Denote a rejection of the null hypothesis of no cointegration at the 1% level.

Table 3
DOLS estimates of the coefficient on financial development and GDP per capita

(a) Total financial development	TFD_{it}	Y_{it}
Demeaned data	-0.211***	2.150***
	(0.046)	(0.045)
Unadjusted data	-1.541***	5.080***
	(0.063)	(0.2074)
(b) Financial institutions development	$FDINS_{it}$	Y_{it}
Demeaned data	-1.183**	0.225***
	(0.4985)	(0.0042)
Unadjusted data	-0.921**	0.5022***
	(0.4254)	(0.0161)
(c) Financial markets development	$FDMKT_{it}$	Y_{it}
Demeaned data	-1.3028***	0.473***
	(0.0899)	(0.0089)
Unadjusted data	-0.929***	0.612***
	(0.0055)	(0.0065)
(d) Bank credit to the private sector	$PCRED_{it}$	Y_{it}
Demeaned data	-1.201***	4.268***
	(0.2320)	(0.0758)
Unadjusted data	-1.751***	3.479***
	(0.0912)	(0.1811)

Notes: Variables are in logs. The dependent variable is G_{it}. Standard errors in parentheses. The number of leads and lags in the individual DOLS regressions was determined by the Schwarz criterion with a maximum of three lags. The unadjusted data assumes cross-section independence.
***Indicates significance at the 1 percent level.

Table 4
DOLS estimates for countries by income group (demeaned series)

	TFD_{it}	Y_{it}
High-income countries	-1.448***	0.956***
	(0.293)	(0.036)
Upper-middle income countries	-0.827**	2.684***
	(0.340)	(0.622)
Lower-middle and low-income countries	-0.397*	0.675***
	(0.222)	(0.696)
	$FDINS_{it}$	Y_{it}
High-income countries	-0.593***	1.157***
	(0.079)	(0.051)
Upper-middle income countries	0.669	1.047***
	(0.467)	(0.051)
Lower-middle and low-income countries	0.616	1.832***
	(1.004)	(0.233)
	$FDMKT_{it}$	Y_{it}
High-income countries	-0.191***	0.839***
	(0.064)	(0.041)
Upper-middle income countries	-0.579**	0.575***
	(0.236)	(0.015)
Lower-middle and low-income countries	-0.814	0.560***
	(0.925)	(0.046)
	$PCRED_{it}$	Y_{it}
High-income countries	-0.329***	1.124***
	(0.054)	(17.160)
Upper-middle income countries	-1.683***	0.618***
	(0.587)	(38.161)
Lower-middle and low-income countries	0.267	.483***
	(0.809)	(0.061)

Notes: Variables are in logs. The dependent variable is G_{it}. Standard errors in parentheses. The number of leads and lags in the individual DOLS regressions was determined by the Schwarz criterion with a maximum of three lags.
***, ** and * indicates significance at the 1, 5 and 10 percent levels, respectively.

Appendix

Countries in the sample

High-income:

Australia, Austria, Barbados, Belgium, Canada, Chile, Croatia, Czech Republic, Denmark, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Singapore, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Trinidad and Tobago, United Kingdom, United States, and Uruguay.

Upper-middle income:

Albania, Algeria, Argentina, Azerbaijan, Belarus, Botswana, Brazil, Bulgaria, China, Colombia, Costa Rica, Dominican Republic, Ecuador, Fiji, Georgia, Guyana, Iran, Jamaica, Jordan, Kazakhstan, Lesotho, Macedonia, Malaysia, Mauritius, Mexico, Namibia, Panama, Paraguay, Peru, Romania, Russia, South Africa, Thailand, Turkey, and Venezuela.

Lower-income:

Armenia, Bangladesh, Bolivia, Burkina Faso, Burundi, Cameroon, Central African Republic, Cote d'Ivoire, Egypt, El Salvador, Estonia, Ethiopia, Ghana, Guatemala, Guinea-Bissau, Haiti, Honduras, India, Indonesia, Kenya, Kyrgyz Republic, Madagascar, Malawi, Mali, Moldova, Mongolia, Morocco, Mozambique, Nepal, Nicaragua, Niger, Nigeria, Pakistan, Papua New Guinea, Philippines, Rwanda, Senegal, Sierra Leone, Sri Lanka, Tanzania, Tunisia, Uganda, Ukraine, Vietnam, and Zambia.

Note: Countries classified according to the World Bank's 2015 income classification system. Lower-income includes low-income and lower-middle income classifications.