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Salvador Pérez Moreno

Universidad de Málaga
Dpto. Economía Aplicada (Política Económica)
Campus El Ejido
29071 - Málaga
Tel. 952131280 – Fax 952137259
Email: sperezmoreno@uma.es

Is Financial Development Good for the Poor?

Development economics theory provides different predictions about the impact of financial development on poverty as well as on income inequality, considering that both concepts are different although closely related. We can assert, therefore, that consensus does not exist in the theoretical literature on whether financial development benefits the whole population equally, or whether it disproportionately benefits the rich or the poor.

In this context, this paper examines whether financial development is good for poverty reduction in developing countries through a causal analysis. To this end, we apply a modified form of traditional Granger causality tests to suit the short time series that are available. The empirical evidence reveals that in the period of the 1970s-1980s financial development, measured by liquid assets of the financial system as a share of GDP or by money and quasi money as a percentage of GDP, leads to the reduction of moderate poverty. These results do not appear for the period of the 1980s-1990s or when financial development is measured by the ratio of the value of credits granted by financial intermediaries to the private sector to GDP.

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1 Introduction

The links between financial development and the pace of economic growth have been extensively researched since Schumpeter (1911), yielding considerable evidence that financial development correlates with growth. In recent decades, numerous authors have examined this relationship, contributing important theoretical and empirical arguments (Goldsmith 1969, McKinnon 1973, Shaw 1973, Gupta 1984; Jung 1986; Demetriades and Hussein 1996; Levine 1997; Arestis and Demetriades 1997; Levine *et al*. 2000; Arestis *et al*. 2001; Calderón and Liu 2003; Christopoulos and Tsionas 2004, among others). In general terms, the empirical results suggest that financial development enhances economic growth and, simultaneously, growth propels financial development, as the expansion of the real sector may have a notable influence on the development of the financial sector.

At the same time, another topic extensively studied in development economics is the relationship between economic growth and poverty reduction. Indeed, in current literature there is widespread consensus regarding the major importance of growth in order to reduce poverty, though initial inequality may affect the impact of growth on poverty reduction. This relationship has been widely proven in different contexts and circumstances by considering the poor as a pre-specified proportion of the population –usually the lowest quintile (Dollar and Kray 2002; Foster and Szekely 2000)–, and by using a definition of poverty in which the poor are people with income/expenditure levels below a pre-determined threshold –for instance, Purchasing Power Parity (PPP) adjusted US$1 per person per day, or a country-specific poverty line computed on the basis of the cost of a country-specific subsistence package (Ravallion and Chen 1997; Adams 2004)–.

In contrast to the significant attention paid to these relationships, the link between financial development and poverty has received much less attention in the literature. In this context, this paper attempts to carry out a causal analysis in the direction from financial development to poverty in developing countries.

In any case, the problem of testing for causality between financial development and poverty is considerable because of the scarcity of uniform annual data for most countries. The implementation of traditional time-series Granger causality tests requires long time series. For this reason, this study relies on other econometric techniques that allow using a data panel of different countries and exploiting the cross section variation. To that end, we have reconsidered and modified the original spirit of Granger's (1969) paper to apply it to the case of panel data by taking the methodological scheme used by Weinhold and Reis (2001) and Perez-Moreno (2009) as reference, though we use bootstrapped standard errors in the application of the sum-difference test in order to obtain more robust standard errors.

The rest of the paper is organized as follows. In the next section, we briefly review the theoretical and empirical literature. Section 3 presents the panel data set and the methodology. Section 4 goes on to discuss the empirical results. Finally, the last section summarizes the conclusions reached.

2 Brief literature review

Development economics theory provides different predictions about the impact of financial development on poverty as well as on income inequality, considering that both concepts are different although closely related. We can assert, therefore, that consensus does not exist in the theoretical literature on whether financial development benefits the whole population equally, or whether it disproportionately benefits the rich or the poor.

A common view is that financial development might benefit the rich. In this way, Rajan and Zingales (2003) explain that the financial system, especially when institutions are weak, might mainly channel money to the rich and well connected, who are able to offer collateral and who might be more likely to repay the loan, while excluding the poor. As financial sectors become more developed, they might lend more to people who are able to provide collateral but continue to neglect the poor, who remain unable to invest in human and physical capital, or start new businesses. Therefore, high-income households benefit more from financial development than low-income households.

Other theoretical models suggest that financial development enhances growth and reduces inequality. Capital market imperfections, such as information and transaction costs, may especially affect the poor who lack collateral and credit histories. In this context, Galor and Zeira (1993), Banerjee and Newman (1993), Aghion and Bolton (1997) and Galor and Moav (2004) argue that 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. From this perspective, financial development reduces poverty both by improving the efficiency of capital allocation, which accelerates aggregate growth, and by relaxing credit constraints that restrain the poor more extensively.

A third approach is the proposal developed by Greenwood and Jovanovic (1990), who suggest that it is possible that different mechanisms dominate at different levels of financial development, and predict a nonlinear relationship between income inequality and financial sector development. In their model, income inequality first increases as the financial sector develops but later declines as more people gain access to the system. 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[1].

From the empirical point of view, several studies have recently examined the relationship between financial development and income distribution with various conclusions as well, focusing particularly on the impact of financial development on poverty and inequality (Dollar and Kraay 2002; Honohan 2004; Clarke *et al*. 2006; Beck *et al*. 2007; Guillaumont and Kpodar 2008).

Dollar and Kraay (2002) show that financial development, together with other pro-growth macroeconomic policies, raises average income but with little systematic effect on its distribution. However, Honohan (2004) proves that finance-intensive growth (measured by banking depth) is empirically associated with lower poverty ratios, even after allowing for mean income and inequality. Likewise, Clarke *et al*. (2006) find that, in the long run, inequality is less when financial development is greater and, at the same time, suggest that inequality might increase as financial sector development increases at very low levels of financial sector development, although this result is not robust. In turn, Beck *et al*. (2007) find 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. They also reveal that financial development is strongly linked to declines in the fraction of the population living on less than $1 per day. Finally, Guillaumont and Kpodar (2008) seek to identify and

[1] In relation to the impact of poverty on financial development, explicit references are scarce in the literature. Beck *et al*. (2007: 34), for instance, indicate some examples that may explain the causal links from poverty and inequality to financial development. They suggest that reductions in poverty may stimulate demand for financial services, and 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.

quantify the positive and negative channels through which financial development affects poverty, and conclude that financial development is on average good for the poor, with the direct effect being stronger than the effect through economic growth. However, these authors also point out that financial instability hurts the poor and partially offsets the benefits of financial development.

3 Data and methodology

This section describes the database and discusses the methodological framework used in this paper to analyze the causal relationship between financial development and poverty in developing countries[2].

3.1 The data

We use a panel of 35 developing countries for the years 1970, 1980, 1990 and 1998, with poverty data estimated by Sala-i-Martin (2002) for the conventional poverty lines of $1 and $2 a day in 1985 purchasing power parity (PPP) rates, and financial development data from *World Development Indicators* and Beck *et al*. (2000), updated in 2007. The sample consists of all developing countries for which Sala-i-Martin (2002) provides poverty data and for which there exist financial development data for all years considered. By regions, it comprises 14 countries from Sub-Saharan Africa, 14 from Latin America and the Caribbean, 4 from South Asia, and 3 from East Asia and the Pacific (see Appendix 1 for countries by region).

In measuring poverty, we therefore use two different poverty indicators that reflect the incidence (or prevalence) of poverty: poverty headcount ratio at $1 a day (extreme poverty) and poverty headcount ratio at $2 a day (moderate poverty). These

[2] Note that finance studies typically focus on both developed and developing countries. In this paper, in contrast to Dollar and Kraay (2002), Clarke *et al*. (2006) and Beck *et al*. (2007), we only consider developing economies.

indicators measure the share of the population living on less than $1 and $2 a day, respectively, based on the 1985 PPP exchange rate.

On the other hand, financial development is measured, in principle, by two indicators commonly used in the literature, which capture different aspects of financial development:

i. *M3/GDP*: The liquid assets of the financial system (currency plus demand and interest-bearing liabilities of banks and non banks)[3] as a share of gross domestic product (GDP). This indicator is related to the ability of financial systems to provide transaction services and saving opportunities.

ii. *Private credit/GDP*: The value of credits granted by financial intermediaries to the private sector as a share of GDP. It comprises credit to private firms and households from banks and nonbank financial intermediaries (but excludes central banks as lenders and government and state-owned enterprises as borrowers). This indicator is a good proxy variable for the extent to which private sector agents have access to financial intermediation or access to loans.

According to Guillaumont and Kpodar (2008: 10), although the indicator *Private credit/GDP* has the advantage of measuring more accurately the role of financial intermediaries in channeling funds to productive agents and possibly to the poor, the use of a liquidity ratio is fundamental, as it allows us to assess whether financial intermediaries are actually helpful for the poor in supplying money balances or credits.

[3] Liquid assets are also known as broad money, or M3. They are the sum of currency and deposits in the central bank (M0), plus transferable deposits and electronic currency (M1), plus time and savings deposits, foreign currency transferable deposits, certificates of deposit, and securities repurchase agreements (M2), plus travelers checks, foreign currency time deposits, commercial paper, and shares of mutual funds or market funds held by residents.

In order to assess the robustness of the results obtained from using a broad measure of the money stock as an indicator of financial development, we additionally consider the ratio of money and quasi money (M2) to GDP (*M2/GDP*), given that it is also a measure commonly used in financial development literature for causality studies (see, e.g., Gupta 1984, Jung 1986, and Calderón and Liu 2003). A higher M2/GDP ratio implies a larger financial sector and therefore greater financial intermediary development.

The data on private credit over GDP proceed from the database on financial development and structure developed by Beck *et al*. (2000), updated in 2007, whilst the data on liquid assets of the financial system as a share of GDP, and money and quasi money as a percentage of GDP proceed from *World Development Indicators*, as well as those on GDP per capita (constant 1995 US$), which are utilized in our models to control for the time-invariant characteristics.

3.2 The methodology

In respect to the objective of our study outlined above, our central concern is essentially a time series question: we would like to know whether financial development over time is causally related to poverty.

In this sense, it seems obvious that a cross-section analysis, even of growth rates, will not be able to fully capture such dynamic effects. Actually, we would need to adopt some econometric technique for panel model evaluation to test for a type of Granger causality. Hence, we should basically test whether knowledge about past financial development could help us predict future changes of poverty.

Let us recall that Granger's classic (1969) paper established a presently well-known method of testing the direction of causality in econometric models. The underlying premise of the test is based on the notion that if some variable x causes some other variable y, then the addition of lagged values of x in a regression of y on its own lagged values and other explanatory variables should significantly improve the forecasting power of the model.

We have reconsidered and modified the original spirit of Granger's (1969) paper to apply it to the case of panel data. We have taken into account the following two models:

$$Vpov_{it} = \alpha + \beta_1 Vpov_{it-1} + \beta_2 Lpov_{it-1} + \beta_3 Vfd_{it-1} + \beta_4 Lfd_{it-1} + \beta_5 Vgdp_{it-1} + \beta_6 Lgdp_{it-1} + \varepsilon_{it} \quad (1)$$

$$Vpov_{it} = \alpha + \beta_1 Vpov_{it-1} + \beta_2 Lpov_{it-1} + \beta_3 Vgdp_{it-1} + \beta_4 Lgdp_{it-1} + \varepsilon_{it} \quad (2)$$

where $Vpov$ and $Lpov$ are the variation rate and log-level of the respective poverty indicators (poverty headcount ratio at \$1 and \$2 a day), Vfd and Lfd are the variation rate and log-level of the financial development measures (the ratio of the liquid assets to GDP –*M3/GDP* –, the ratio of the value of credits granted by financial intermediaries to the private sector to GDP –*Private credit/GDP*–, and the ratio of money and quasi money to GDP –*M2/GDP*–), while $Vgdp$ and $Lgdp$ are the variation rate and log-level of GDP per capita. Following standard procedure, we take log on the variables and interpret their first differences as variation rates. Note that the level terms are measured at the beginning of the period.

We control for the specific time-invariant characteristics (so-called "fixed effects") that could be driving the levels of poverty rates by modeling our variables as variation rates and by controlling for initial log-levels of both the dependent and the independent variables. We include the log-level of the GDP per capita and its first difference as control variables in so far as GDP per capita and its variation rate may be interpreted as summary variables reflecting the situation of many other socioeconomic variables.

Models (1) and (2) are rival models of poverty variations. Model (1) includes information on past variation rates and levels of both variables under consideration, and model (2) only includes lagged endogenous variables. Thus, if model (1) can forecast poverty variations more accurately than model (2) we deduce that information about past financial development variations was important. However, if model (2) forecasts better than model (1), or there is no difference, then we conclude that including information about financial development variations does not help to predict poverty variations and therefore there is no causal relationship in the direction from financial development to poverty.

Following Granger and Huang (1997) and Weinhold and Reis (2001), we have adopted a sum-difference test that takes the following form. Consider the forecast errors $\eta_{1it} = \eta_{2it}$ from models (1) and (2), where i and t denote not-in-sample cross section countries and time periods. The null hypothesis is

$$H_0 : \eta_{1it}^2 = \eta_{2it}^2 \quad (3)$$

It then follows that if H_0 can be rejected, the model with the lowest forecast error variance should be accepted as being significantly superior to the competing model. For this purpose, Granger and Huang suggest constructing the following variables:

$$SUM_{i12} = \eta_{1i} + \eta_{2i} \quad (4)$$

$$DIF_{i12} = \eta_{1i} - \eta_{2i} \quad (5)$$

Then a test of the null hypothesis is equivalent to a test of whether $\delta = 0$ from the regression

$$SUM_{i12} = \alpha + \delta \cdot DIFF_{i12} + \xi_i \quad (6)$$

In our case, we regress the model (6) using bootstrapped standard errors, which are more robust than traditional standard errors.

Since the methodological approach proposed only requires two observations of the variation rates and therefore three time observations of the level variables, our data set allows examining the causal linkages from financial development to poverty in two different periods: firstly the 1970s and 1980s and, secondly, the 1980s and 1990s.

An advantage of this approach for data like ours, which are quite limited in the time series, is that we do not rely on precise estimates of the sample parameters but rather on running a model competition in which all models are equally handicapped by the scarcity of time series observations. In turn, the ten-year periodicity of the data implies that each observation embodies a great deal of unique information and the subsequent time series variation is less likely to be driven by cyclical and short term shocks. If the average periodicity were only a few years, then the data could be more correlated and the detection of important aspects of the dynamics would be more difficult.

Nevertheless, the short time series does preclude a traditional Granger-causality approach in which we predict out-of-sample across time. With our short panel data set we take advantage of the fact that we have variation across space as well as through time. In particular, we estimate the models on N-1 cross section observations and use the resulting coefficient estimates to generate a forecast of the dependent variable for the remaining (not-in-sample) unit. In this way, we systematically generate N different forecast errors for each model. Then, we test whether these forecast errors are statistically different from each other, as described above.

4 Empirical results

In Tables 1 and 2 we present the estimated results of the proposed models for the periods of the 1970s-1980s and the 1980s-1990s. Although the scarcity of data entails important limitations in estimating the models and the adjustments are not satisfactory enough, these estimations are useful in order to chiefly assess the sign and significance of the linkages between the variation rates of poverty in time t $(Vpov_{it})$ and the variation rates of financial development in time t-1 (Vfd_{it-1}).

In Table 1 the estimated models reflect that Vfd_{it-1} is a negative exploratory variable of $Vpov_{it}$, which might be interpreted as evidence that those countries with a growth of financial development in the 1970s reduced poverty in the 1980s and conversely. This linkage is highly significant when financial development is measured by liquid assets of the financial system as a share of GDP (*M3/GDP*) and by money and quasi money as a percentage of GDP (M2/GDP), and poverty by the headcount ratio at $2 a day. However, Table 2 shows that in the period of the 1980s-90s this connection between financial development and poverty is positive, although not significant, with all the indicators.

TABLE 1: Models of poverty variation including and excluding financial development variation (1970s-1980s)[a]

Dependent variable $Vpov_{it}$	*M3/GPD*				*Private credit/GDP*				*M2/GPD*			
	Poverty headcount ratio at $1 a day		*Poverty headcount ratio at $2 a day*		*Poverty headcount ratio at $1 a day*		*Poverty headcount ratio at $2 a day*		*Poverty headcount ratio at $1 a day*		*Poverty headcount ratio at $1 a day*	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Constant	19.2712	5.9563	4.9704	3.5701	1.6874	5.9563	2.6457	3.5701	17.5950	5.9563	4.2340	3.5701
	(2.31)**	(1.29)	(3.48)***	(2.20)**	(0.30)	(1.29)	(1.34)	(2.20)**	(2.31)**	(1.29)	(2.86)***	(2.20)**
$Vpov_{it-1}$	-0.3759	-0.2293	0.5801	0.3992	-1.1703	-0.2293	0.4709	0.3992	-0.2703	-0.2293	0.5757	0.3992
	(-0.61)	(-0.27)	(1.71)*	(0.93)	(-0.22)	(-0.27)	(1.12)	(0.93)	(-0.44)	(-0.27)	(1.59)	(0.93)
$Lpov_{it-1}$	-0.9176	-0.8102	-0.5580	-0.5689	-0.8295	-0.8102	-0.5619	-0.5689	-0.7887	-0.8102	-0.4832	-0.5689
	(-6.09)***	(-2.00)*	(-4.60)***	(-3.19)***	(-3.25)***	(-2.00)*	(-3.22)***	(-3.19)***	(-4.85)***	(-2.00)*	(-3.56)***	(-3.19)***
Vfd_{it-1}	-6.2249		-0.7686		-1.1572		-0.1193		-6.4788		-0.6830	
	(-1.62)		(-4.32)***		(-0.56)		(-0.76)		(-1.64)		(-3.28)***	
Lfd_{it-1}	-4.6742		-0.8290		-1.1578		-0.1750		-4.8280		-0.7714	
	(-1.88)*		(-5.28)***		(-1.02)		(-1.37)		(-1.99)*		(-4.77)***	
$Vgdp_{it-1}$	-4.3458	-5.1068	0.8645	0.4136	-4.1188	-5.1068	0.5891	0.4136	-4.9830	-5.1068	0.7554	0.4136
	(-1.01)	(-0.99)	(1.57)	(0.60)	(-0.90)	(-0.99)	(0.84)	(0.60)	(-1.12)	(-0.99)	(1.34)	(0.60)
$Lgdp_{it-1}$	-0.2137	-0.6283	-0.0439	-0.2386	-0.2833	-0.6283	-0.1500	-0.2386	-0.0126	-0.6283	-0.0160	-0.2386
	(-0.29)	(-0.99)	(-0.31)	(-1.38)	(-0.39)	(-0.99)	(-0.70)	(-1.38)	(-0.02)	(-0.99)	(-0.11)	(-1.38)
R^2	0.5385	0.3612	0.6893	0.4237	0.3867	0.3612	0.4492	0.4237	0.5601	0.3612	0.6545	0.4237
Ajusted R^2	0.4396	0.2761	0.6227	0.3468	0.2553	0.2761	0.3312	0.3468	0.4659	0.2761	0.5805	0.3468
N	35	35	35	35	35	35	35	35	35	35	35	35

[a] Estimates were obtained using ordinary least squares, with the dependent variable being the difference in log of the respective poverty measure ($Vpov_{it}$). Heteroskedasticity-consistent t-statistics are shown in parentheses.

* Significant at the 0.10 level.

** Significant at the 0.05 level.

*** Significant at the 0.01 level.

TABLE 2: Models of poverty variation including and excluding financial development variation (1980s-1990s)[b]

Dependent variable $Vpov_{it}$	*M3/GPD*				*Private credit/GDP*				*M2/GPD*			
	Poverty headcount ratio at $1 a day		*Poverty headcount ratio at $2 a day*		*Poverty headcount ratio at $1 a day*		*Poverty headcount ratio at $2 a day*		*Poverty headcount ratio at $1 a day*		*Poverty headcount ratio at $1 a day*	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Constant	2.6446	1.9344	-0.7936	-1.158	4.9692	1.9344	-1.8278	-1.158	0.1369	1.9344	-0.8814	-1.158
	(0.41)	(0.28)	(-0.55)	(-1.19)	(0.52)	(0.28)	(-1.66)	(-1.19)	(0.02)	(0.28)	(-0.69)	(-1.19)
$Vpov_{it-1}$	-0.1042	-01259	0.6463	0.6238	-0.0533	-01259	0.6477	0.6238	-0.0014	-01259	0.6116	0.6238
	(-0.37)	(-0.67)	(4.14)***	(5.64)***	(-0.27)	(-0.67)	(4.27)***	(5.64)***	(-0.01)	(-0.67)	(5.04)***	(5.64)***
$Lpov_{it-1}$	-0.0833	-0.0337	0.1937	0.1760	-0.0135	-0.0337	0.1918	0.1760	-0.0038	-0.0337	0.2005	0.1760
	(-0.12)	(-0.05)	(1.34)	(1.77)*	(-0.02)	(-0.05)	(1.72)*	(1.77)*	(-0.01)	(-0.05)	(1.74)*	(1.77)*
Vfd_{it-1}	3.9563		0.3177		1.3762		0.0174		4.3668		0.1301	
	(1.09)		(1.07)		(1.05)		(0.10)		(1.14)		(0.49)	
Lfd_{it-1}	-0.1000		-0.2894		0.8479		-0.1271		0.5926		-0.2613	
	(-0.05)		(-1.03)		(0.77)		(-1.01)		(0.36)		(-1.02)	
$Vgdp_{it-1}$	-5.7451	-5.2281	0.0503	-0.1914	-5.8074	-5.2281	-0.0754	-0.1914	-5.5643	-5.2281	-0.0152	-0.1914
	(-1.20)	(-1.29)	(0.12)	(-0.59)	(-1.36)	(-1.29)	(-0.20)	(-0.59)	(-1.21)	(-1.29)	(-0.04)	(-0.59)
$Lgdp_{it-1}$	-0.4881	-0.4143	0.1350	0.0570	-0.6536	-0.4143	0.1178	0.0570	-0.4654	-0.4143	0.1262	0.0570
	(-0.43)	(-0.46)	(0.95)	(0.55)	(-0.58)	(-0.46)	(1.03)	(0.55)	(-0.47)	(-0.46)	(0.97)	(0.55)
R^2	0.1622	0.0746	0.6260	0.5656	0.1028	0.0746	0.5881	0.5656	0.1811	0.0746	0.5975	0.5656
Ajusted R^2	-0.0174	-0.0488	0.5458	0.5077	-0.0895	-0.0488	0.4998	0.5077	0.0056	-0.0488	0.5112	0.5077
N	35	35	35	35	35	35	35	35	35	35	35	35

[b] Estimates were obtained using ordinary least squares, with the dependent variable being the difference in log of the respective poverty measure ($Vpov_{it}$).
Heteroskedasticity-consistent t-statistics are shown in parentheses.

* Significant at the 0.10 level.

** Significant at the 0.05 level.

*** Significant at the 0.01 level.

Tables 3 to 6 reflect the results of the modified form of the traditional Granger causality test discussed in the previous section. In particular, Tables 3 and 4 present summary statistics of the mean squared forecasting error from the two competing models of poverty variations (models 1 and 2) for the period of the 1970s-1980s and the 1980s-1990s. In addition, Tables 5 and 6 include the corresponding results of the sum-difference test by using bootstrapped standard errors.

In Table 3 we observe that in the 1970s-1980s period, when financial development is measured by *M3/GDP* or *M2/GDP*, the models of poverty variations that include information on former variations of financial development (model 1) perform better at out-of-sample forecasting than the model that excludes financial development variations (model 2). The sum-difference test results presented in Table 5 indicate that the difference is statistically significant, particularly when we consider moderate poverty (threshold of $2 a day) rather than extreme poverty (threshold of $1 a day)[4]. Thus, there is compelling evidence to indicate that in this first period examined financial development leads to decreases of the percentage of the population living on less than $2 a day, as the financial development indicator basically reflects the ability of financial systems to provide transaction services and saving opportunities. Nevertheless, Table 4 shows that in the second period (1980s-1990s) the models of poverty variations do not perform better when information on financial development is included in the specification. Hence we find that the causality relationship from financial development to poverty does not appear in the later period, in contrast with the earlier one. To properly interpret these differences in the results between both periods, it would be necessary to research in depth the historical context and circumstances of developing

[4] Although the models of poverty variations with the headcount ratio at $1 a day also show a better forecasting performance when information on financial development is included, the difference of performance is hardly statistically significant (Table 5).

countries during the three decades considered, examining key issues such as the evolution of the world economy, the political situation in developing nations, the financial sector reforms and the monetary and financial policies implemented at the international and national level, the debt crisis and its social costs, the IMF and the World Bank adjustment programs, or the pro-growth and pro-poor policies applied in these countries over time.

If financial development is measured by the value of credits granted by financial intermediaries to the private sector as a share of GDP (*Private credit/GDP*), all the models of poverty variations, irrespective of the poverty line and period studied, show worse forecasting performance when information on financial development is included. Therefore, we cannot conclude that there exists a causal link from financial development to poverty when we focus on the access of private sector agents to financial intermediation and loans to measure financial development[5].

The discrepancies in the impact of financial development on poverty as a consequence of the financial development measure used are consistent with the results obtained by other researchers, using, however, different methodological approaches. Thus, for instance, Guillaumont and Kpodar (2008) find that *M3/GDP* level and instability are significantly correlated with the mean income of the poor, and draw attention to the positive direct effect of financial development on the standard of living of the poor and the negative impact of financial instability on the income of this sector of the population. Nevertheless, they also confirm that the link between the mean income of the poor and the credit indicators (level and instability) related to *Private credit/GDP* is not significant. This suggests that in developing countries an increase in

[5] On the other hand, we also observe that there is no evidence of Granger causality from poverty to financial development, since information on poverty variations does not in any case improve forecasts of future financial development variations.

the private credit ratio does not necessarily translate into improved well-being for the poor. In consequence, these authors conclude that access to credit for the poor remains a challenge in the developing world and that the main channel for the impact of financial development on this segment of the population is the McKinnon conduit effect captured by the liquidity ratio.

TABLE 3: Mean-squared forecast error (1970s-1980s)[c]

	M3/GPD		*Private credit/GDP*		*M2/GPD*	
	Poverty headcount ratio at $1 a day N=35	*Poverty headcount ratio at $2 a day* N=35	*Poverty headcount ratio at $1 a day* N=35	*Poverty headcount ratio at $2 a day* N=35	*Poverty headcount ratio at $1 a day* N=35	*Poverty headcount ratio at $2 a day* N=35
Model 1	12.5990	0.1505	15.9716	0.2623	12.3581	0.1688
	(3.6012)	(0.3934)	(4.0527)	(0.5189)	(3.5655)	(0.4163)
Model 2	15.5094	0.2587	15.5093	0.2587	15.5094	0.2587
	(3.9940)	(0.5154)	(3.9940)	(0.5154)	(3.9940)	(0.5154)

[c] Out-of-sample causality test. Standard deviations of the forecast error are shown in parentheses.

TABLE 4: Mean-squared forecast error (1980s-1990s)[d]

	M3/GPD		*Private credit/GDP*		*M2/GPD*	
	Poverty headcount ratio at $1 a day N=35	*Poverty headcount ratio at $2 a day* N=35	*Poverty headcount ratio at $1 a day* N=35	*Poverty headcount ratio at $2 a day* N=35	*Poverty headcount ratio at $1 a day* N=35	*Poverty headcount ratio at $2 a day* N=35
Model 1	14.8072	0.1422	14.1285	0.1479	13.7793	0.1462
	(3.8880)	(0.3825)	(3.7961)	(0.3900)	(3.7549)	(0.3879)
Model 2	13.3870	0.1384	10.6626	0.1384	13.3870	0.1384
	(3.6968)	(0.3773)	(3.3077)	(0.3773)	(3.6968)	(0.3773)

[d] Out-of-sample causality test. Standard deviations of the forecast error are shown in parentheses.

TABLE 5: Sum-difference test results for poverty variation (models 1 and 2) (1970s-1980s)[e]

	M3/GPD		*Private credit/GDP*		*M2/GPD*	
	Poverty headcount ratio at $1 a day N=35	*Poverty headcount ratio at $2 a day* N=35	*Poverty headcount ratio at $1 a day* N=35	*Poverty headcount ratio at $2 a day* N=35	*Poverty headcount ratio at $1 a day* N=35	*Poverty headcount ratio at $2 a day* N=35
Constant	-0.0938	-0.0273	-0.2370	-0.0542	-0.1911	-0.0420
	(-0.08)	(-0.19)	(-0.17)	(-0.30)	(-0.16)	(-0.28)
$DIFF_{ij}$	-0.5406	-0.9438	0.2864	0.2688	-0.6557	-0.9907
	(-1.14)*	(-2.93)**	(0.26)	(0.26)	(-1.19)*	(-2.50)**

[e] T-statistics shown in parentheses based on bootstrapped standard errors obtained from 100 bootstrap replications.
* Significant at the 0.25 level; ** Significant at the 0.01 level

TABLE 6: Sum-difference test results for poverty variation (models 1 and 2) (1980s-1990s)[f]

	M3/GPD		*Private credit/GDP*		*M2/GPD*	
	Poverty headcount ratio at $1 a day N=35	*Poverty headcount ratio at $2 a day* N=35	*Poverty headcount ratio at $1 a day* N=35	*Poverty headcount ratio at $2 a day* N=35	*Poverty headcount ratio at $1 a day* N=35	*Poverty headcount ratio at $2 a day* N=35
Constant	0.6695	0.0145	0.2710	0.0168	0.6363	0.0149
	(0.48)	(0.11)	(0.23)	(0.12)	(0.46)	(0.11)
$DIFF_{ij}$	0.8359	0.1429	1.5572	0.7332	0.3342	0.6744
	(1.38)	(0.23)	(2.40)	(0.79)	(0.43)	(0.67)

[f] T-statistics shown in parentheses based on bootstrapped standard errors obtained from 100 bootstrap replications.
* Significant at the 0.25 level; ** Significant at the 0.01 level

5 Conclusions

The study of the linkages between financial development and poverty has received relatively limited attention in development economics literature. Nonetheless, the views and theoretical and empirical conclusions reached by development researchers are considerably varied and, on occasions, contradictory.

In this paper we carry out a causal analysis of the relationship between financial development and poverty in developing countries, in which we apply a modified form of traditional Granger causality tests to suit the short times series that are available. In order to assess the possible causal relationship in the direction from financial development to poverty, we use panel data model evaluation techniques to test the out-of-sample forecasting performance of competing models rather than relying on in-sample fit or coefficient estimates. Among the conclusions obtained from our analysis, we can highlight the following:

(1) The results mainly depend on the nature of the financial development indicator used. In particular, when financial development is measured by the liquid assets of the financial system as a share of GDP or the ratio of money and quasi money to GDP, forecasts of future poverty variations are significantly improved when information on past financial development variations is included.

(2) When financial development is measured by the value of credits granted by financial intermediaries to the private sector as a share of GDP, the empirical evidence shows that there is no causal link from financial development to poverty.

(3) The detected causal link only occurs in the first period analyzed, the 1970s-1980s, but not in the second one, the 1980s-1990s. It highlights that a general conclusion on such a link in developing countries cannot be adopted as a rule, since the

causality relationship examined is influenced by the particular historical context and the economic, political and social circumstances existing in each period.

(4) The mentioned relationship is especially significant between financial development and moderate poverty rather than extreme poverty. It indicates that financial development does not primarily benefit the poorest, but instead poor people with a certain level of income/expenditure.

In short, in the 1970s-1980s period the empirical evidence supports the hypothesis that financial development leads to the reduction of moderate poverty. In other words, the results indicate that financial development, measured by the ratios *M3/GDP* or *M2/GDP*, may cause moderate poverty reduction, in a Granger-causal fashion.

These findings involve significant implications for development policies. As financial development seems to contribute to the reduction of moderate poverty, we can conclude that financial development may not only be a pro-growth action, but also pro-poor. Our empirical analysis suggests that a key element that explains the beneficial effect of financial development on the moderately poor is the improvement in savings opportunities, which can help them face their liquidity constraints and increase their physical and human capital investments. Moreover, the poor can gradually start improving their access to credit as well, because of savings accumulation and greater credit availability in the financial system.

Appendix 1: Countries by region

Country	Region
Barbados	Latin America & Caribbean
Burkina Faso	Sub-Saharan Africa
Burundi	Sub-Saharan Africa
Colombia	Latin America & Caribbean
Costa Rica	Latin America & Caribbean
Cote d'Ivoire	Sub-Saharan Africa
Dominican Republic	Latin America & Caribbean
Ecuador	Latin America & Caribbean
El Salvador	Latin America & Caribbean
Gabon	Sub-Saharan Africa
Gambia, The	Sub-Saharan Africa
Ghana	Sub-Saharan Africa
Guatemala	Latin America & Caribbean
Honduras	Latin America & Caribbean
India	South Asia
Jamaica	Latin America & Caribbean
Kenya	Sub-Saharan Africa
Madagascar	Sub-Saharan Africa
Malaysia	East Asia & Pacific
Mexico	Latin America & Caribbean
Nepal	South Asia
Niger	Sub-Saharan Africa
Nigeria	Sub-Saharan Africa
Pakistan	South Asia
Panama	Latin America & Caribbean
Paraguay	Latin America & Caribbean
Philippines	East Asia & Pacific
Rwanda	Sub-Saharan Africa
Senegal	Sub-Saharan Africa
Sierra Leone	Sub-Saharan Africa
South Africa	Sub-Saharan Africa
Sri Lanka	South Asia
Thailand	East Asia & Pacific
Trinidad and Tobago	Latin America & Caribbean
Venezuela	Latin America & Caribbean

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