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REVISITING GROWTH-POVERTY RELATIONSHIP: A MEDIUM-TERM CAUSALITY APPROACH

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Abstract

This article examines the potential medium-term causal relationship between changes in Gross Domestic Product (GDP) per capita and poverty in developing countries during the 1970s–1990s. For this purpose, we use panel data model evaluation techniques to test the out-of-sample forecasting performance of competing models. We conclude that the evidence supports the hypothesis that increases in GDP per capita cause unidirectional poverty reduction, measured by the $1/day poverty rate, in the period 1970s–1980s. The results are similar when analysing low- and middle-income countries and mid-high- and very high-inequality countries separately. However, in the period 1980s–1990s, it is only statistically significant for low-income countries.

JEL Classification: I32, O40

Keywords: Poverty, growth, causality, developing countries

1. INTRODUCTION

There is a large literature on the relationship between economic growth and poverty in developing countries. A wide range of empirical analyses have found that growth is connected to poverty reduction, frequently alleging that economic growth is significant in reducing poverty (see *e.g.* Ravallion and Chen, 1997; Dollar and Kraay, 2002; Bourguignon, 2003; Adams, 2004; Kraay, 2006; Fosu, 2008; Ram, 2011; Johnson *et al.*, 2011; Iniguez-Montiel, 2014). There is much less consensus surrounding the empirical evidence for poverty having a causal impact on aggregate growth, in spite of arguments that link poverty to growth in matters such as sociopolitical instability (see *e.g.* Alesina and Perotti, 1996; Benhabib and Rustichini, 1996), credit constraints (see *e.g.* Galor and Zeira, 1993; Aghion, *et al.*, 1999), taxation and redistribution (see *e.g.* Alesina and Rodrik, 1994; Persson and Tabellini, 1994), and nutritional and associated cognitive deficits (see *e.g.* Dasgupta, 1997; Ravallion, 1997). In this context, some authors argue that the relationship between growth and poverty can run in both directions (see *e.g.* Lustig *et al.*, 2002). They highlight multiple complementarities between growth and poverty reduction, and point out that actions

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to reduce poverty can create virtuous cycles that raise economic growth, in turn reinforcing poverty reduction.

Despite the significant amount of research in this area, it has been difficult to empirically establish causality using traditional methods. Data on poverty indicators for developing countries are scarce and sporadic, generating series that are too short and not appropriate for the usual time series econometric approaches. At the same time, no convincing instruments for either poverty or growth have been identified that would allow for instrumental variables estimation. We address this deficit by investigating whether variations in GDP per capita and poverty are causally related in a Granger fashion. We employ a modified form of Granger causality testing, originally suggested in Granger and Huang (1997), which is adapted specifically for the use of short time series panel data. The approach builds on the evaluation of out-of-sample predictions to identify causality. To the best of our knowledge, in the framework of the vast literature existing on the relationship between economic growth and poverty, this article represents a first attempt at examining the potential medium-term causal relationship between growth and poverty in developing countries covering a period of three decades (1970s–1990s).

In retrospect, numerous developing countries experienced low growth and serious economic difficulties in the last decades of the twentieth century, although there exists a wide diversity of economic performance across countries and regions. According to Nafziger (2012), annual growth from 1973 to 1998 was 0.01% for Africa, 0.34% for the Middle East (West Asia and North Africa), and 0.99% for Latin America. These regions suffered mutually reinforcing negative growth and severe debt crises since 1980. By contrast, despite its financial crisis, Asia continued its high performance, reaching 3.26% yearly.[1] Overall, Easterly (2001) underlines that median per capita income growth in developing countries was 0.0% in 1980–1998,[2] the so-called lost decades.

The 1980s and early 1990s were an exceptionally difficult period for a large number of developing countries, particularly in Africa. Overall, after a considerable economic performance in the 1960s, economic development slowed in the 1970s and stagnated or declined in the 1980s and 1990s. In this context, the World Bank, the International Monetary Fund and Western donors developed and advocated Structural Adjustment Programmes (SAPs) in response to serious balance of payments problems affecting many developing countries, which emphasised macroeconomic stabilisation, privatisation and free market development. SAPs and their associated stabilisation policies were implemented in numerous countries during the 1980s and 1990s. Nowadays, the debate continues on the relevance and effects of SAPs in the developing world, and it may be worth considering to what extent macroeconomic conditions and policy reforms conditioned the potential relationship between growth and poverty.

[1] Asia includes fast-growing China, other East Asia, and South Asia, but not West and Central Asia or Japan and Singapore.

[2] The median weights all countries equally, which seems appropriate if we treat each country as an observation of a given set of country policies and characteristics. The median is 0.0 for both the 1980s and 1990s taken separately.

2. DATA

We use a panel of 52 developing countries for the years 1970, 1980, 1990 and 1998, with absolute[3] poverty data estimated by Sala-i-Martin (2002) for the conventional international poverty lines of \$1/day and \$2/day at 1985 purchasing power parity (PPP) prices,[4] and data of GDP per capita (constant 1995 US\$) from *World Development Indicators* (for descriptive statistics, see Table A1 in the Appendix). The sample consists of all developing countries for which Sala-i-Martin (2002) provides poverty data, and the *World Bank* supplies GDP per capita data for all years considered. In order to test for the relationship between changes in GDP per capita and poverty by using groups of countries with similar key characteristics,[5] we divide economies into income groups according to 1998 GNI per capita, calculated using the *World Bank Atlas* method. In addition, because many of the theoretical mechanisms that link poverty causally to growth involve political-economic relationships that depend on the degree of inequality as well as of poverty (see *e.g.* Ravallion, 2005; Fosu, 2010), we separate the sample into two segments according to the countries' level of inequality. Although most countries examined demonstrate considerable levels of inequality, we differentiate between mid-high inequality and very high inequality. The latest includes those countries that present an average Gini index of 0.50 or more for the period 1970–1998, according to the data from *World Development Indicators*.[6] The countries included by region, income level and inequality level are listed in Table A2 in the Appendix.

3. METHODOLOGY AND RESULTS

Initially, we can consider the contemporaneous correlation between variations in GDP per capita and poverty. This allows us to create a benchmark result against which our dynamic analysis can be compared. Consider the following models:

$$\Delta \mathrm{Lpov}_{it} = \beta_0 + \beta_1 \Delta \mathrm{Lgdp}_{it} + \beta_2 \mathrm{Lgpd}_{it-1} + \beta_3 \mathrm{Lpov}_{it-1} + \varepsilon_{it} \quad (1)$$

[3] Most developing countries measure poverty in absolute terms, using national or international poverty lines. Nevertheless, some authors, such as Garroway and de la Iglesia (2012), propose a set of relative poverty lines for developing countries. They propose that poverty measures based on relative poverty lines be used alongside those based on absolute poverty lines, in order to obtain a clearer and more comparable picture of poverty in developing and advanced countries. To the extent that data availability permits, a challenging extension of this research would be to check the robustness of the results under a relative poverty approach.

[4] These poverty lines were introduced by the 1990 *World Development Report* to assess world poverty with the standards of what poverty meant in the poorest countries. Nevertheless, in the second half of the 2000s the original \$1-a-day poverty line was replaced by a new international poverty line of \$1.25/day at 2005 PPP prices, which is the mean of the national poverty lines found in the poorest 15 countries in terms of consumption per capita.

[5] Note that it favours the reduction of the potential impact of heterogeneity.

[6] There are five countries in the sample for which *World Development Indicators* does not provide Gini index data between 1970 and 1998. Thus, taking into consideration inequality data after 1998 and other additional information, we consider Barbados and Rwanda as middle-high-inequality countries, and Gabon, Sierra Leone and Zimbabwe as very high-inequality countries.

$$\Delta \text{Lgdp}_{it} = \beta_0 + \beta_1 \Delta \text{Lpov}_{it} + \beta_2 \text{Lgpd}_{it-1} + \beta_3 \text{Lpov}_{it-1} + \varepsilon_{it} \tag{2}$$

where ΔLpov and Lpov are the variation rate (or growth rate) and log-level of the respective poverty indicators, and ΔLgdp and Lgdp are the variation rate and log-level of GDP per capita, with level terms measured at the beginning of the period.

If we deal with the contemporaneous correlation between GDP per capita and poverty ($1/day and $2/day) variations, the results are consistent with the mentioned literature: there is a strong, negative connection between changes in GDP per capita and poverty (Tables 1 and 2). However, this contemporaneous analysis does not imply causality; indeed, Lustig *et al.* (2002) argue convincingly that growth and poverty are determined jointly, and if one direction of causality runs from poverty to growth then the model may be mis-specified and may suffer from an endogenous bias. Thus, we turn to the task of attempting to identify the causal channels between growth and poverty.

To test for causality we exploit the fact that the correctly specified version of a causal model will do much better forecasting out of sample than the mis-specified version; we use dynamics to identify causality. In accordance with available data, we use short panels in which each observation represents a 10-year average. While the number of observations is reduced, there are several serious advantages as well: it is unlikely that the periodicity of any causal relationship between GDP per capita and poverty is as short as one year; additionally, the 10-year periodicity of the data implies that each observation embodies a lot of unique information, and the subsequent time series variation is less likely to be driven by cyclical and short term shocks, while annual data may be subject to cyclical influences and noise, which make detecting an underlying relationship especially tricky.

Nevertheless, using a short panel of countries with fewer observations may make it more difficult to detect any causal linkages. In effect, for us to find that there is a Granger-causal relationship from poverty to growth, we must find that poverty levels and poverty variations from ten years ago still help us to make more accurate forecasts about current (average) GDP per capita variations than a model that relies solely on past information about levels and alterations in GDP per capita alone (and vice versa). Thus, a test for Granger causality using 10-year data creates a much "higher" hurdle than in-sample correlation for rejection of the null of no causality. If there is no causal relationship and the contemporaneous correlation is spurious for some reason, or if there is a causal relationship that only acts in the short term, we will fail to reject the null hypothesis of no causality.

We control for initial log-levels of GDP per capita and poverty in each model, thus controlling for all unobserved variables that determined GDP per capita (or poverty) levels at that initial point in time. Inasmuch as these variables are time-invariant, the initial level will capture their effects and therefore reduce the chances of omitted variables and deep simultaneity biases.

We further control for the unobservable time-invariant characteristics that could be driving the levels of both GDP per capita and poverty rates (for instance, institutional quality), by modelling our variables as variation rates (to eliminate the levels' averages). Thus, an identifying assumption here (for unbiased estimates of the coefficients) is that there are no unobserved trends omitted in the variation rates. However, the overall approach we adopt is fairly robust to deviations from these assumptions, as we do not

Table 1. Contemporaneous cross-section analysis[1]

	Dependent variable: $Gpov_{it}$. Poverty rate \$1/day				Poverty rate \$2/day			
	Full sample (1970–1998)	**t=1980 (1970–1980)**	**t=1990 (1980–1990)**	**t=1998 (1990–1998)**	**Full sample (1970–1998)**	**t=1980 (1970–1980)**	**t=1990 (1980–1990)**	**t=1998 (1990–1998)**
Constant	5.3847 (3.08)**	3.4707 (2.40)*	10.8368 (4.40)**	1.7080 (0.86)	1.5551 (1.60)	2.5441 (1.08)	3.0385 (1.17)	−1.9362 (−2.96)**
$Ggdp_{it}$	−4.7883 (−4.99)**	−1.8748 (−3.50)**	−7.2003 (−2.80)**	−4.0912 (−1.96)	−1.6684 (−6.46)**	−1.3137 (−2.98)**	−1.6667 (−3.58)**	−1.2552 (−3.13)**
$Lgdp_{it-1}$	−0.7504 (−3.22)**	−0.6039 (−2.86)**	−1.4815 (−4.05)**	−0.2791 (−0.96)	−0.1989 (−2.12)*	−0.3380 (−1.68)	−0.3182 (−1.33)	0.1424 (1.89)
$Lpov_{it-1}$	−0.3078 (−2.69)**	−0.0252 (−0.23)	−0.6957 (−5.11)**	−0.0823 (−1.05)	−0.0722 (−0.64)	−0.1180 (−0.38)	−0.2595 (−0.79)	0.2659 (4.43)**
R^2	0.3379	0.2311	0.6462	0.1805	0.4206	0.5034	0.5071	0.6335
N	156	52	52	52	156	52	52	52

[1] Estimates were obtained using ordinary least squares, with the dependent variable being difference in log of the respective poverty measure. Heteroskedasticity-consistent t-statistics are shown in parentheses.

* Significant at the 0.05 level.

** Significant at the 0.01 level.

Table 2. Contemporaneous cross-section analysis[1]

	Dependent variable: $Ggdp_{it}$ Poverty rate \$1/day				Poverty rate \$2/day			
	Full sample (1970–1998)	**t=1980 (1970–1980)**	**t=1990 (1980–1990)**	**t=1998 (1990–1998)**	**Full sample (1970–1998)**	**t=1980 (1970–1980)**	**t=1990 (1980–1990)**	**t=1998 (1990–1998)**
Constant	0.1754 (1.14)	−0.1340 (−0.44)	0.5847 (2.27)*	0.0724 (0.38)	0.2401 (1.33)	0.3333 (0.76)	0.6935 (2.01)*	−0.5164 (−2.13)*
$Gpov_{it}$	−0.0467 (−7.21)**	−0.0484 (−1.35)	−0.0495 (−5.83)**	−0.0368 (−2.52)*	−0.2236 (−7.80)**	−0.2414 (−2.00)	−0.2134 (−3.01)**	−0.2676 (−5.17)**
$Lgdp_{it-1}$	−0.0141 (−0.66)	0.0347 (0.76)	−0.0803 (−2.22)*	0.0024 (0.09)	−0.0271 (−1.31)	−0.0379 (−0.84)	−0.0823 (−2.23)*	0.0561 (1.97)
$Lpov_{it-1}$	−0.0038 (−0.51)	0.0271 (1.67)	−0.0190 (−1.75)	−0.0219 (−5.38)**	0.0009 (0.06)	0.0077 (0.14)	−0.0332 (−0.85)	0.0505 (2.53)*
R^2	0.2411	0.1831	0.4449	0.2979	0.3828	0.3637	0.4116	0.4126
N	156	52	52	52	156	52	52	52

[1] Estimates were obtained using ordinary least squares, with the dependent variable being difference in log of GDP per capita. Heteroskedasticity-consistent t-statistics are shown in parentheses.

* Significant at the 0.05 level.

** Significant at the 0.01 level.

rely on our coefficient estimates to identify causality, but instead on the out-of-sample forecasting ability of each model.

Let us consider the following four models:

$$\Delta \mathrm{Lpov}_{it} = \beta_0 + \beta_1 \Delta \mathrm{Lpov}_{it-1} + \beta_2 \mathrm{Lpov}_{it-1} + \beta_3 \Delta \mathrm{Lgdp}_{it-1} + \beta_4 \mathrm{Lgdp}_{it-1} + \sum_r \beta_r \mathrm{Re}g_i^r + \varepsilon_{it} \tag{3}$$

$$\Delta \mathrm{Lpov}_{it} = \beta_0 + \beta_1 \Delta \mathrm{Lpov}_{it-1} + \beta_2 \mathrm{Lpov}_{it-1} + \sum_r \beta_r \mathrm{Re}\, g_i^r + \varepsilon_{it} \tag{4}$$

$$\Delta \mathrm{Lgdp}_{it} = \beta_0 + \beta_1 \Delta \mathrm{Lgdp}_{it-1} + \beta_2 \mathrm{Lgdp}_{it-1} + \beta_3 \Delta \mathrm{Lpov}_{it-1} + \beta_4 \mathrm{Lpov}_{it-1} + \sum_r \beta_r \mathrm{Re}g_i^r + \varepsilon_{it} \tag{5}$$

$$\Delta \mathrm{Lgdp}_{it} = \beta_0 + \beta_1 \Delta \mathrm{Lgdp}_{it-1} + \beta_2 \mathrm{Lgdp}_{it-1} + \sum_r \beta_r \mathrm{Re}\, g_i^r + \varepsilon_{it} \tag{6}$$

where variables are as defined above, with the addition of the regional dummies $\mathrm{Re}g_i^r$ for the following regions: Sub-Saharan Africa, Latin America and the Caribbean, and South Asia, to control for potential regional fixed effects in both GDP per capita and poverty variations.

Models (3) and (4) are rival models of poverty variations, and models (5) and (6) are rival models of GDP per capita variations. For instance, if model (3) can forecast changes in poverty more accurately than model (4), then information about past changes in GDP per capita is important, and we conclude that there is evidence of Granger causality from GDP per capita to poverty. However, if model (4) forecasts more accurately than model (3), we then fail to reject the null hypothesis of no causal relationship.

Following Granger and Huang (1997), Weinhold and Reis (2001) and Pérez-Moreno (2011), among others, we adopt a sum-difference test[7] and consider the forecast errors $\eta_{1it}^2 = \eta_{2it}^2$ from models (3) and (4) (or (5) and (6)), where i and t denote not-in-sample cross section countries and time periods. If $H_0 : E(\eta_{1it}^2) = E(\eta_{2it}^2)$ can be rejected, the model with the lowest forecast error variance should be accepted as being significantly superior to the competing model. Granger and Huang (1997) suggest that a test of the null hypothesis is equivalent to a test[8] of whether $\gamma = 0$ from the regression $\mathrm{SUM}_{i12} = \alpha + \gamma \cdot \mathrm{DIFF}_{i12} + \xi_i$, where $\mathrm{SUM}_{i12} = \hat{\eta}_{1i} + \hat{\eta}_{2i}$ and $\mathrm{DIF}_{i12} = \hat{\eta}_{1i} - \hat{\eta}_{2i}$.

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 generate N different forecast errors for

[7] The sum-difference test is discussed more thoroughly, for instance, in Granger and Newbold (1986) and Diebold and Mariano (1995).

[8] Taking into account Clark and McCracken (2001), in a context of linear, nested models estimated by OLS, the standard *t*-test does not have a limiting normal distribution under the null hypothesis of no Granger causality. In order to take into account this potential drawback, we present the Wald test in addition to the *t*-test; the results of both tests point in the same direction.

each model. Next, we test whether these forecast errors are statistically different from each other as described above.

Tables 3–6 reflect the results of the modified form of the traditional Granger causality test discussed above. In particular, Tables 3 and 4 present summary statistics of the mean squared forecasting error, from the two competing models of poverty variations (models 3 and 4) and from the two competing models of GDP per capita variations (models 5 and 6), for the periods 1970s–1980s and 1980s–1990s, respectively. In addition, Tables 5 and 6 show the corresponding results of the sum-difference test.

The results obtained for 1970s–1980s (Tables 3 and 5) reveal that the model of poverty variations that includes information on former changes in GDP per capita (model 3) performs better at out-of-sample forecasting than the model that excludes changes in GDP per capita (model 4), when poverty is measured using the $1/day poverty rate. In other words, we reject the null of no causality, and find that changes in GDP per capita Granger-causes changes in poverty. This result is consistent across country groups when we split the sample into low/middle-income countries and mid/very high-inequality countries (although for middle-income countries the difference is not statistically significant). However, for the $2/day poverty rate, model 6 performs better at out-of-sample forecasting; thus, in this case, we cannot reject the null hypothesis of no causality from growth to poverty.

Tables 4 and 6 present the results from an analysis of 1980s–1990s. We find that growth Granger-causes poverty reduction, measured by the $1/day poverty rate in low-income countries, while among higher income countries we fail to find Granger causality. In other words, for higher income countries, the poverty variations models that include information on former changes in GDP per capita (model 3) perform worse at out-of-sample forecasting than the model that excludes changes in GDP per capita (model 4), or the difference between the better performance of model 3 as compared to that of model 4 is not statistically significant.

These findings seem consistent with Johnson *et al.* (2011), which points out that the poverty–growth nexus may have weakened and certainly did not strengthen during the 1990s compared with the 1980s. It is worth recalling that SAPs implemented in developing countries were expected to ultimately reduce poverty by fostering economic growth (World Bank, 1981). To the extent that SAPs failed to promote growth, low improvement in poverty should be expected from growth effects in the 1990s. In addition, it is frequently argued that SAPs paid insufficient attention to the social dimension of development and to the institutional weaknesses of developing countries (Heidhues and Obare, 2011). In our case, for the period 1980s–1990s we only find a certain impact of growth on extreme poverty reduction in countries in the first stages of economic development.

Regarding inequality, as pointed out above, some authors have found that higher initial inequality tends to reduce the impact of growth on poverty. Our analysis is not focused on parameter estimation *per se* and thus is not suited to testing for differences in the poverty elasticity of growth. However, we do not find that high inequality breaks the link; indeed, our results suggest that growth Granger-causes poverty reduction in both mid-high- and very high-inequality countries as well.

Finally, none of our results suggest any Granger-causal relationship from poverty reduction to economic growth. In particular, while in some cases the model of GDP per capita variations that includes information on former changes in poverty (model 5)

Table 3. Mean-squared forecast error (1970s–1980s)[1]

	Poverty headcount ratio at $1 a day (PPP)					Poverty headcount ratio at $2 a day (PPP)				
	Full sample	**Low- income countries**	**Middle-income countries**	**Mid-high-inequality countries**	**Very high-inequality countries**	**Full sample**	**Low-income countries**	**Middle-income countries**	**Mid-high-inequality countries**	**Very high-inequality countries**
	N=52	**N=26**	**N=26**	**N=31**	**N=21**	**N=52**	**N=26**	**N=26**	**N=31**	**N=21**
Model 3	7.1703 (2.7037)	12.9264 (3.6665)	15.6214 (4.0296)	11.3004 (3.4171)	2.5412 (1.6091)	0.5717 (0.7623)	0.1684 (0.4184)	1.9322 (1.3989)	0.5118 (0.7197)	0.1410 (0.3843)
Model 4	11.3435 (3.4006)	16.9146 (4.1941)	21.2362 (4.6994)	20.5151 (4.6016)	7.6362 (2.8090)	0.3973 (0.6360)	0.0865 (0.2998)	1.2178 (1.1165)	0.3155 (0.5684)	0.3950 (0.6439)
Model 5	0.0396 (0.2008)	0.0306 (0.1783)	0.0855 (0.2978)	0.0535 (0.2348)	0.0478 (0.2240)	0.0539 (0.2345)	0.0379 (0.1986)	0.0785 (0.2852)	0.1108 (0.3380)	0.0400 (0.2049)
Model 6	0.0400 (0.2019)	0.0267 (0.1666)	0.0869 (0.3004)	0.0498 (0.2268)	0.0383 (0.2005)	0.0400 (0.2019)	0.0267 (0.1666)	0.0869 (0.3004)	0.0498 (0.2268)	0.0383 (0.2005)

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

Table 4. Mean-squared forecast error (1980s–1990s)[1]

	Poverty headcount ratio at $1 a day (PPP)					Poverty headcount ratio at $2 a day (PPP)				
	Full sample	**Low- income countries**	**Middle-income countries**	**Mid-high-inequality countries**	**Very high-inequality countries**	**Full sample**	**Low-income countries**	**Middle-income countries**	**Mid-high-inequality countries**	**Very high-inequality countries**
	N=52	**N=26**	**N=26**	**N=31**	**N=21**	**N=52**	**N=26**	**N=26**	**N=31**	**N=21**
Model 3	4.4013 (2.1181)	0.8932 (0.9638)	13.5818 (3.7575)	5.2337 (2.3239)	8.8406 (3.0380)	0.1585 (0.4019)	0.0230 (0.1545)	0.2692 (0.5278)	0.1620 (0.4087)	0.3744 (0.6265)
Model 4	4.4831 (2.1377)	1.7097 (1.3334)	12.8841 (3.6605)	5.0442 (2.2825)	5.5788 (2.4158)	0.1705 (0.4167)	0.0244 (0.1594)	0.3017 (0.5586)	0.1433 (0.3843)	0.1948 (0.4521)
Model 5	0.0356 (0.1906)	0.1440 (0.3870)	0.0171 (0.1333)	0.0484 (0.2236)	0.0466 (0.2209)	0.0317 (0.1798)	0.1005 (0.3233)	0.0232 (0.1553)	0.0372 (0.1962)	0.0501 (0.2294)
Model 6	0.0313 (0.1785)	0.0538 (0.2365)	0.0223 (0.1522)	0.0350 (0.1901)	0.0427 (0.2116)	0.0313 (0.1785)	0.0538 (0.2365)	0.0223 (0.1522)	0.0350 (0.1901)	0.0427 (0.2116)

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

Table 5. Sum-difference test results (1970s–1980s)

		Poverty headcount ratio at $1 a day(PPP)					Poverty headcount ratio at $2 a day (PPP)				
		Full sample	**Low-income countries**	**Middle-income countries**	**Mid-high-inequality countries**	**Very high-inequality countries**	**Full sample**	**Low- income countries**	**Middle-income countries**	**Mid-high-inequality countries**	**Very high-inequality countries**
		N=52	**N=26**	**N=26**	**N=31**	**N=21**	**N=52**	**N=26**	**N=26**	**N=31**	**N=21**
Models 3 and 4	DIFFij	−1.0717	−2.9536	−1.3423	−1.0288	−1.8763	1.9887	0.5091	1.7393	3.3832	−1.0579
	t-test	(−2.30)*	(−2.24)*	(−1.80)	(−2.10)*	(−2.59)**	(1.60)	(0.84)	(1.91)	(2.27)*	(−1.84)
	Wald test	[5.29]*	[5.00]*	[3.24]	[4.41]*	[6.71]**	[2.55]	[0.71]	[3.64]	[5.16]*	[3.38]
Models 5 and 6	DIFFij	−0.1230	2.6114	−0.1669	0.1855	1.2984	1.5219	0.3502	−0.6097	−1.4586	0.2422
	t-test	(−0.17)	(1.63)	(−0.16)	(0.21)	(0.81)	(0.81)	(0.66)	(−0.76)	(1.15)	(0.24)
	Wald test	[0.03]	[2.67]	[0.03]	[0.04]	[0.66]	[0.66]	[0.43]	[0.58]	[1.33]	[0.06]

* Significant at the 0.05 level.
** Significant at the 0.01 level.

Table 6. Sum-difference test results (1980s–1990s)

		Poverty headcount ratio at $1 a day(PPP)					Poverty headcount ratio at $2 a day (PPP)				
		Full sample	**Low-income countries**	**Middle-income countries**	**Mid-high-inequality countries**	**Very high-inequality countries**	**Full sample**	**Low- income countries**	**Middle-income countries**	**Mid-high-inequality countries**	**Very high-inequality countries**
		N=52	**N=26**	**N=26**	**N=31**	**N=21**	**N=52**	**N=26**	**N=26**	**N=31**	***N*=21**
Models 3 and 4	DIFFij	−0.3158	−4.0211	0.4710	0.7514	2.1184	−0.8907	−0.3290	−0.5871	5.0470	2.2723
	t-test	(−0.42)	(−3.42)**	(0.67)	(0.54)	(2.34)*	(−0.62)	(−0.47)	(−0.60)	(2.77)**	(2.85)**
	Wald test	[0.18]	[11.72]**	[0.45]	[0.29]	[5.48]*	[0.38]	[0.22]	[0.37]	[5.06]**	[8.14]**
Models 5 and 6	DIFFij	7.2355	1.3387	−0.9574	5.5077	0.2261	0.6943	1.1543	0.6046	1.7884	0.4016
	t-test	(3.39)**	(1.32)	(−1.77)	(3.73)**	(0.33)	(0.46)	(0.96)	(0.44)	(0.731)	(0.37)
	Wald test	[11.49]**	[1.73]	[3.13]	[13.93]**	[0.11]	[0.21]	[0.93]	[0.20]	[0.53]	[0.14]

* Significant at the 0.05 level.
** Significant at the 0.01 level.

performs slightly better at out-of-sample forecasting than the model that excludes changes in poverty (model 6), the difference is never statistically significant.

4. CONCLUDING REMARKS

We carry out a bi-directional causal analysis of the relationship between changes in GDP per capita and poverty in developing countries, and exploit a combination of dynamics and out-of-sample forecasting to identify causality. The results for 1970s–1980s show that forecasts of future poverty variations in the different country groups (measured by the $1/day poverty rate) are significantly improved when information on past GDP per capita variations is included. Moreover, information on changes in poverty does not improve forecasts of future changes in GDP per capita. Thus, consistent with existing literature, our analysis suggests that during this period growth causes unidirectional poverty reduction measured by the $1/day poverty rate in a Granger-causal fashion. However, our results are not consistent for poverty rates measured by the $2/day criteria, reflecting that the estimated growth-poverty relationships in the literature may be sensitive to alternative measures of poverty. For the period 1980s–1990s, we observe that the causal relationship in the direction from economic growth to poverty reduction, measured by the $1/day poverty rate, is only statistically significant in low-income countries. Again, we find that when poverty is measured by the $2/day poverty rate, we cannot reject the null hypothesis of no causality, nor can we reject no causality from changes in poverty to growth.

Overall, the findings of our causal analysis are mostly consistent with the conclusions reached in previous (non-causal) empirical studies, in particular, in regard to the impact of aggregate economic growth on extreme poverty reduction, especially in the first stages of economic development. In this regard, it may be recalled that at low levels of development and in conditions of mass poverty agricultural development plays a critical role, with important multiplier effects in terms of income generation and welfare. Agricultural development tends to be considerably equitable, so that a large number of people may share in its benefits and expand their livelihood opportunities. Nevertheless, according to our empirical evidence, economic growth seems to be unable to reduce $2/day poverty in our sample of countries. In other words, despite the relative improvement in the living standards and the reduction of extreme poverty, the causal effects of growth are insufficient to allow the poor to escape from poverty measured at the $2/day level. In this sense, both the pace and pattern of growth should be assessed across countries examined. The key to reducing poverty lies in ensuring that a considerable rate of growth is sustained over the long term and associated with a pro-poor growth pattern. Nonetheless, given the diversity of types of economy, resource availability, levels of development and variations in policy and institutions, it is not possible to arrive at a common strategy that can be applied universally (World Development, 2005).

Finally, the differences in the impacts of growth on poverty between both periods examined should be interpreted in the context of macroeconomic conditions and policy reforms implemented. Economic growth can create opportunities for poor people, but poverty will only fall considerably if the conditions are in place for them to take advantage of those opportunities. In fact, it may be sustained that growth itself does not determine a country's poverty course, but the environment in which growth occurs and the political decisions taken in order to break away from the poverty traps are crucial.

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APPENDIX

Table A1. Descriptive statics

		Obs.	Mean	Std. Dev.	Mix	Max
Poverty headcount ratio at $1 a day	1970	52	17.49	16.30	0.00	60.90
	1980	52	13.38	15.73	0.00	62.60
	1990	52	14.13	16.70	0.00	54.00
	1998	52	16.10	20.05	0.00	61.10
Poverty headcount ratio at $1 a day	1970	52	38.17	23.02	0.00	79.00
	1980	52	32.18	23.80	0.00	79.00
	1990	52	33.05	23.74	0.00	75.00
	1998	52	31.88	27.12	0.00	81.00
GDP per capita	1970	52	1237.78	1298.34	109.37	5333.61
	1980	52	1557.14	1680.06	147.86	6757.62
	1990	52	1536.54	1596.24	187.84	7329.67
	1998	52	1784.09	1880.09	147.25	7913.76

Table A2. Countries by region, income level and inequality level

Country	Region	Income Level	Inequality Level
Bangladesh	South Asia	Low	Mid-high
Barbados	Latin America and the Caribbean	Middle	Mid-high
Bolivia	Latin America and the Caribbean	Middle	Very high
Botswana	ran Africa	Middle	Very high
Brazil	Latin America and the Caribbean	Middle	Very high
Burkina Faso	Sub-Saharan Africa	Low	Mid-high
Burundi	Sub-Saharan Africa	Low	Mid-high
Central African Rep.	Sub-Saharan Africa	Low	Very high
Chile	Latin America and the Caribbean	Middle	Very high
China	East Asia	Low	Mid-high
Colombia	Latin America and the Caribbean	Middle	Very high
Costa Rica	Latin America and the Caribbean	Middle	Mid-high
Cote d'Ivoire	Sub-Saharan Africa	Low	Mid-high
Dominican Republic	Latin America and the Caribbean	Middle	Mid-high
Ecuador	Latin America and the Caribbean	Middle	Very high
El Salvador	Latin America and the Caribbean	Middle	Very high
Gabon	Sub-Saharan Africa	Middle	Very high
Gambia, The	Sub-Saharan Africa	Low	Very high
Ghana	Sub-Saharan Africa	Low	Mid-high
Guatemala	Latin America and the Caribbean	Middle	Very high
Guinea-Bissau	Sub-Saharan Africa	Low	Mid-high
Guyana	Latin America and the Caribbean	Middle	Very high
Honduras	Latin America and the Caribbean	Low	Very high
India	South Asia	Low	Mid-high
Indonesia	East Asia	Low	Mid-high
Jamaica	Latin America and the Caribbean	Middle	Mid-high
Kenya	Sub-Saharan Africa	Low	Mid-high
Lesotho	Sub-Saharan Africa	Low	Very high
Madagascar	Sub-Saharan Africa	Low	Mid-high
Malaysia	South Asia	Middle	Mid-high
Mali	Sub-Saharan Africa	Low	Very high
Mexico	Latin America and the Caribbean	Middle	Mid-high
Nepal	South Asia	Low	Mid-high
Nicaragua	Latin America and the Caribbean	Low	Mid-high
Niger	Sub-Saharan Africa	Low	Mid-high
Nigeria	Sub-Saharan Africa	Low	Mid-high
Pakistan	South Asia	Low	Mid-high
Panama	Latin America and the Caribbean	Middle	Very high
Paraguay	Latin America and the Caribbean	Middle	Very high
Peru	Latin America and the Caribbean	Middle	Mid-high
Philippines	East Asia	Middle	Mid-high
Rwanda	Sub-Saharan Africa	Low	Mid-high
Senegal	Sub-Saharan Africa	Low	Mid-high
Sierra Leone	Sub-Saharan Africa	Low	Very high
South Africa	Sub-Saharan Africa	Middle	Very high
Sri Lanka	South Asia	Middle	Mid-high
Thailand	East Asia	Middle	Mid-high
Trinidad and Tobago	Latin America and the Caribbean	Middle	Mid-high
Uruguay	Latin America and the Caribbean	Middle	Mid-high
Venezuela	Latin America and the Caribbean	Middle	Mid-high
Zambia	Sub-Saharan Africa	Low	Very high
Zimbabwe	Sub-Saharan Africa	Low	Very high