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An Empirical Reassessment of the Relationship Between Finance and Growth

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Abstract

This paper reexamines the empirical relationship between financial development and economic growth. It presents evidence based on cross-section and panel data using an updated dataset, a variety of econometric methods, and two standard measures of financial development: the level of liquid liabilities of the banking system and the amount of credit issued to the private sector by banks and other financial institutions. The paper identifies two sets of findings. First, in contrast with the recent evidence of Levine, Loayza, and Beck (2001), cross-section and panel-data-instrumental-variables regressions reveal that the relationship between financial development and economic growth is, at best, weak. Second, there is evidence of nonlinearities in the data, suggesting that finance matters for growth only at intermediate levels of financial development. Moreover, using a procedure appropriately designed to estimate long-run relationships in a panel with heterogeneous slope coefficients, there is no clear indication that finance spurs economic growth. Instead, for some specifications, the relationship is, puzzlingly, negative.

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Contents

Tables

Figures

I. Introduction

There is a fair amount of consensus in the growth literature that financial development promotes economic growth. The main theoretical explanation is that financial intermediaries encourage the mobilization of saving, ameliorate asymmetric information, and provide greater opportunity for risk spreading and risk pooling. At the aggregate level, this translates into higher saving and more efficient allocation of resources with positive effects for the rate of capital accumulation and technological innovation.[2]

Several empirical studies have confirmed these theoretical predictions. In an influential paper, King and Levine (1993) use ordinary-least-squares (OLS) estimates on a large cross-section of countries and find that indicators of banking development are good predictors of future economic growth. Similarly, Levine and Zervos (1996, 1998) find that other measures of financial development, such as stock market development, are associated with higher income per capita. Using extreme-bound analysis, these authors even conclude that banks and stock markets are robust determinants of long-run economic growth.

Despite the well-known econometric problems associated with OLS cross-country regressions, similar findings are reported in a series of more elaborated analyses by Levine, Loayza, and Beck (2001); Beck, Loayza, and Levine (2001); and Beck and Levine (2002). These authors use a general-method-of-moments (GMM) estimator for dynamic panel data to answer the question whether financial development causes economic growth. The GMM panel estimator improves upon cross-section estimators because it directly controls for the potential bias induced by the omission of country-specific effects and the endogeneity of all regressors. The overall conclusion of this research agenda is that the positive correlation between bank development and growth is not due to simultaneity bias and that financial development exerts a first-order effect on long-run economic growth.

This paper re-examines and extends the analysis of Levine, Loayza and Beck (2001) (hereinafter referred to as LLB). In line with their work, it presents evidence based on cross-section and panel data, using a larger and updated dataset of countries, a variety of econometric methods, and two standard measures of financial development: the level of liquid liabilities of the banking system and the amount of credit issued to the private sector by banks and other financial institutions.

In the first part of the paper, the analysis is conducted on a cross-section of countries. OLS estimates suggest that the relationship between finance and growth is positive, sizeable, and robust to outlier and functional form specification, corroborating and reinforcing the

[2] See for example Greenwood and Jovanovic (1990), Bencivenga and Smith (1991), King and Levine (1993) and Greenwood and Smith (1997). A survey of this literature is in Levine (1997).

findings of King and Levine (1993). However, when the likely endogeneity of financial development is addressed by instrumental-variables regression, the OLS results are upset and the statistical significance of financial development becomes tenuous. This result stands in sharp contrast with LLB's paper and the reason presumably lies in our use of a dataset comprising different countries and time periods.

The second part of the paper exploits the time-series dimension of the data and, following LLB, presents GMM panel data estimates. Unlike those obtained from LLB's analysis, though, the estimates are not based on the two-step GMM estimator, which is asymptotically efficient in the presence of heteroskedastic errors. As is well known (see Arellano and Bond, 1991, and Blundell and Bond, 1998), this estimator can be highly inaccurate, with standard errors downward biased in finite samples. Estimates based on the more appropriate one-step GMM estimator reveal that the relationship between finance and growth is, at best, weak. For most of the specifications considered, the contribution of financial development to growth is statistically insignificant and the magnitudes of the estimated effects are not economically large. Moreover, the finance-growth relationship is sensitive to different combinations of control variables and sample periods.

The third part of the paper extends the panel-data analysis in one particular direction. It relaxes the assumption that countries obey a common linear specification and investigates the effects of permitting parameter heterogeneity across countries. The findings are twofold. First, using a nonparametric approach, the data support the presence of a nonlinear relationship between the level of the credit in the economy and GDP growth, suggesting that the financial sector exerts positive effects on growth only at intermediate levels of financial development. This result is in line with the predictions of some theoretical models where threshold effects and multiple equilibria arise as economies progress through different stages of financial development (see Acemoglu and Zilibotti 1997, 1999). Second, using a procedure specifically designed to estimate panel data with varying slope coefficients, our study finds that the effects of financial development differ considerably across countries and display no obvious pattern related to geographic location, the level of economic development, or institutional characteristics. As a consequence, standard growth regressions estimated by previous authors, which tend to mask these properties of the data, may be misspecified. The central finding of this analysis is that the level of financial development has ambiguous effects on economic growth. The effects are positive for some specifications and, surprisingly, negative for others. Since the main requirement for implementing this empirical strategy is to use panel data with observations kept in annual format, it may be argued that business cycles and measurement errors are the driving forces of these findings. Yet the conflicting results are puzzlingly confined to the indicators of financial development while standard growth determinants maintain their expected contribution to GDP growth.

The outline of the paper is as follows. Section II describes the data and presents some descriptive statistics. Section III discusses the empirical framework used for the cross-section analysis of Section IV and the panel data estimates of Section V. Section VI introduces the empirical strategy that allows slope parameters to vary across countries and discusses the empirical findings. Section VII concludes.

II. Preliminaries

A. The Data

The dataset refers to an unbalanced panel of roughly 85 countries observed from 1960 to 1998. A detailed list of countries is presented in Table 1. In contrast to the LLB paper, the dataset includes a larger number of countries, mainly African, observed for a longer time period. However, the indicators of financial development and the set of control variables, which I now discuss, are similar to those used by LLB.

Financial Variables

Following the vast literature on this topic, the focus will be on two indicators of financial development. The first, LLY, measures the amount of liquid liabilities of the financial system, including liabilities of banks, central banks and other financial intermediaries. This indicator is meant to capture the overall size of the financial sector and its ability to provide broad transaction services. The second measure, PCY, is defined as the value of loans made by deposit money banks and other financial institutions to the private sector. PCY is a better proxy of financial development since it only accounts for credit granted to the private sector, as opposed to credit issued to government and other non-private institutions. It also excludes credit issued by the central bank and is thus a more accurate measure of the savings that financial intermediaries channel to the private sector. Both indicators are appropriately deflated and expressed in percentage of real GDP.[3] The source for this data is the International Financial Statistics of the IMF.

Control Variables

The choice of control variables is crucial, since a central concern of the cross-country empirical literature is that the results may be sensitive to the set of variables held constant in the regressions. In order to make the analysis comparable to LLB, the set of controls includes, as in their paper, proxies for initial conditions, measures of macroeconomic stability and indicators of trade openness. Initial conditions are proxied by the level of real per capita GDP (Y0) and the average years of attainment in secondary and higher education (SEC). Indicators of external openness are the ratio of export plus import over GDP (OPEN) and the black market premium on foreign exchange transactions (BMP). Measures of macroeconomic instability are the ratio of government consumption to GDP (GOV) and the

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[3] Since LLY and PCFY are measured at the end of the period and GDP is measured over the year, the two financial ratios are deflated as in LLB:

$$\frac{0.5 \times \left[F_t / P_t^e + F_{t-1} / P_{t-1}^e\right]}{GDP_t / P_t^a}$$

where F is our measure of financial development, P^e and P^a are end-of-period and average CPI, and GDP is nominal GDP.

level of inflation rate (INF). Previous studies have shown that these variables correlate significantly with GDP growth (Barro and Sala-i-Martin, 1995, and Barro, 1999).

Differently from LLB, however, I also control for the ratio of gross domestic investment to GDP (INV), since the effects of finance on growth could be channeled through higher physical capital or through increasing the efficiency of investment. After controlling for INV, the estimated coefficients on LLY and PCY should capture the effects of financial development on the efficiency of investment. Including INV can therefore reduce the effects of finance on growth if these effects are operative through factor accumulation. On the other hand, omitting INV from the set of controls can inappropriately attribute too large an effect to PCY or LLY.

The data for real GDP, investment, government expenditure and export plus imports is obtained from the Penn World Table 6.1. Data for human capital is from Barro and Lee (2000) and the index for black market premium is taken from Easterly and Sewadeh (2002). A more detailed description of the data is given in Table 2.

B. Summary Statistics and Some Stylized Facts

Before embarking on the estimation of the effects of financial development on economic growth it is worth presenting some properties of the data. Summary statistics for all variables used in this paper are given in Table 3. These statistics refer to a panel with observations kept in yearly format. The table suggests that most of the variability in the data occurs between country, yet some variables—including the two indicators of financial development—also have large within-country variations. In a typical OECD country (i.e., France), the level of PCY varies, for example, from 44 percent to 102 percent over the 1960–1998 period; for a typical African economy (i.e., Chad), PCY oscillates between 6 percent and 48 percent.

To further highlight the time series and cross-sectional properties of the two indicators of financial development, Figures 1a and 1b plot the distribution of PCY and LLY for different groups of countries. The scattered dots refer to the dispersion of PCY and LLY over the whole sample, the upward sloping curves are group-specific time averages, and the horizontal line is the overall mean across time and units. The interesting feature of Figure 1 is that the two ratios vary a great deal across countries and also over time. In all cases the distributions drift upward, reflecting an increase in the financial sector's size, though the trend is less pronounced for the poorest countries, those in Africa and Latin America. On average, the poorest countries are also the least financially developed, having a group mean below the cross-sectional average. The size of the financial sector is the largest for the OECD countries; for the Asian economies, both indicators exhibit a spectacular trend dominated to a large extent by countries such as Thailand, Singapore, Malaysia and Korea, while the time pattern for the Middle Eastern countries is predominantly flat.

Some insights into the correlations between the two measures of financial deepening and the level of economic development can be gained by looking at Figure 2. In the attempt to isolate similar levels of economic and financial development, countries are again divided by geographical area; the series reported are also standardized, to facilitate the comparison.

Figure 2 relates the level of financial development with the level of real per capita GDP. The graph indicates the existence of a clear long-run equilibrium relation among the series. Over the long-run, both financial variables, and PCY in particular, appear to share the same trend of real per capita GDP, indicating that as the economy develops the size of the financial sector gets larger. This evidence is striking when compared with a similar exercise (figure not reported) that relates PCY and LLY to the level of real investment INV—taken as an alternative measure of economic development. The time series properties of PCY, LLY and INV are significantly different from those of Figure 2, indicating that no clear-cut long-run relationship seems to hold for these series over the entire sample period.

The pairwise correlations matrix for the variables of interest is reported in Table 4, using both cross-section and panel data. All signs are as expected: the growth rate of GDP per capita correlates positively with the level of human and physical capital, the degree of openness and both indicators of financial development. In addition, the level of investment is on average positively correlated with the level of financial development, whereas a high level of inflation appears to correlate negatively with the size of the financial sector. Based on the graphical evidence presented above, the high correlation between LLY and PCY is also expected.

III. A Framework for Empirical Analysis

The empirical framework adopted in the remainder of the paper to evaluate the independent effect of financial development on economic growth is the one based on conditional convergence, as used extensively in the empirical growth literature. Specifically, the effects of financial development on economic growth are evaluated by estimating the following convergence regression:

$$y_{it} - y_{i,t-1} = \lambda y_{i,t-1} + \beta' x_{it} + \gamma FIN_{it} + v_{it} \tag{1}$$

$$v_{it} = \mu_i + \nu_t + \varepsilon_{it} \tag{2}$$

which is based on a linear approximation around the steady state of the standard neoclassical growth model. In equation (1), y_{it} is the logarithm of income per capita in country i in period t, x_{it} is a vector of "fundamental" determinants of growth, FIN_{it} is an indicator of financial development and v_{it} is a general disturbance, including a country specific unobservable effect, μ_i, a time specific factor ν_t, and an idiosyncratic disturbance ε_{it}. The fixed effects μ_i act as proxy for other determinants of a country's steady state not already included in x_{it} and the time specific factor ν_t controls for shocks common to all countries. In the neoclassical growth model, diminishing returns to factor accumulation imply that the economy's growth rate $y_{it} - y_{i,t-1}$ decreases with the level of income, represented by $y_{i,t-1}$. For a given $y_{i,t-1}$ a permanent increase in x_{it} or FIN_{it} initially raises the growth rate and over time the level of income per capita. Therefore, in the long-run an increase, say, in the amount of bank credit has an impact on the level of per capita output, not its growth rate.

Equation (1) is usually estimated by OLS on a single cross-section of countries, under the assumption that the fixed effects μ_i are the same across countries (and thus relegated to the error term) and the error v_{it} is uncorrelated with the set of control variables. In the empirical literature on finance and growth, this approach is used, among others, by King and Levine (1993) and Levine and Zervos (1996, 1998). Cross-section estimates, with data averaged over the entire sample period, are meant to uncover low-frequency properties of the data and, for the purpose of this paper, to provide information about the long-run effects of financial development on GDP growth. The major problem of this estimation strategy, however, is that parameter estimates are inconsistent if the regressors are endogenous or correlated with the unobserved individual effects, a point made familiar by Caselli et al. (1996).

In the absence of good instruments and suitable proxies for country specific effects, a solution is to use panel data methods. Panel data allow to control for individual effects and to use lags of the regressors as instruments for the endogenous variables. The additional advantage is that the time series variation of the data expands the sample information. This information is valuable for the measures of financial development that, as documented in Section II, vary a great deal over time. Application of panel data methods to study the link between financial development and long-run growth are in Levine, Loayza and Beck (2001); Beck, Levine and Loayza (2002); and Beck and Levine (2002). These authors, in particular, use a GMM estimator to simultaneously address the issue of unobserved intercept heterogeneity and regressor endogeneity. Their empirical method is thus more suitable for drawing conclusions about the casual effects of financial development on economic growth.

One potential limitation of the GMM approach is that not much heterogeneity is allowed across countries. Heterogeneity is restricted to the intercept but is not permitted in the slope coefficients. Yet, if the slope coefficients vary across units lagged, values of serially correlated regressors cannot be used as valid instruments. Pesaran and Smith (1995) show that if in a dynamic panel model, such as equation (1), slope coefficients are assumed constant but in fact vary across units, traditional panel estimators (i.e., fixed effects or GMM estimators) yield inconsistent estimates, even in a panel with a sufficiently large number of cross-sections and time series. In our context, estimates of the long-run effects of FIN_{it} on y_{it} will be upward biased if the regressor FIN_{it} is positively serially correlated and the slope parameter γ is heterogeneous across units.

Throughout this paper I estimate variants of equation (1). In Sections IV and V, I use OLS cross-section and GMM panel estimators, mainly to compare the results with previous work. In section VI, I estimate a generalized version of (1) that allows for slope coefficients to vary across units.

IV. Cross-Sectional Evidence

I start the analysis by exploiting the cross-sectional variation in the data and estimating equation (1) by OLS on a single cross-section. The dependent variable is the log difference of GDP between 1960 and 1998 and the independent variables are period averages, except for lagged per capita GDP and educational attainment, measured at the beginning of the period.

A. Cross-Section Results

Table 5 shows the results. Column 1 refers to the benchmark specification used in LLB. In line with their findings, the level of financial development is positively and significantly related to economic growth. The overall effect on growth is also economically large. According to the coefficient on PCY, Argentina, whose average PCY is 16 percent, had a growth disadvantage relative to the mean country (for which PCY is 34 percent) of around 0.75 percent per year, during the period 1960-1998.[4] This is a sizable number given that, over the same period, the average growth rate for the cross-section was only 1.6 percent. When multiplied by 2.5 (=1/0.404) to measure the effect on long-run income, the coefficient on PCY also implies that GDP per capita is 1 percentage point higher for every 1 percentage point increase in the amount of bank credit to the private sector.

In column 2, the investment ratio is included as additional regressor. The major effect is that the point estimates for PCY and LLY are reduced by roughly one half, indicating that half of the effect of PCY or LLY on growth goes through an increase in the efficiency of investment, and half through an increase in the volume of investment. Both PCY and LLY remain, however, significantly correlated to GDP growth.

To control for unobserved regional effects, columns 3 and 4 augment the previous specifications with two continent dummies, AFRICA for sub-Saharan countries and LAC for Latin American and Caribbean countries. This modification does not alter the positive and significant correlation of PCY and LLY with GDP growth, although the size of the estimated coefficients is further reduced. Since the two dummies are significantly different from zero, and their inclusion increases the goodness of the fit substantially, some regularity appears to be missing from the empirical model. This is an indication that there exists some degree of heterogeneity among the countries in the sample and that the cross-section estimates may be biased due to the omission of unobserved fixed effects. This problem is addressed in Sections V and VI using panel data methods.

As a final remark, it is worth noticing that, although in some specifications some regressors are not significant, the majority of control variables has the expected sign. The only exception is the positive (yet always insignificant) coefficient for inflation. This contrasts with the conventional wisdom, but supports the findings—discussed among others

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[4] $0.389\times[\ln(34)-\ln(16)]\times100/39$

in Fisher (1993) and Bruno and Easterly (1998)—that the negative correlation between inflation and growth is hard to detect with cross-sectional data.

B. Robustness Tests

Although the OLS estimates are in line with the results reported in previous studies, it remains useful to assess their robustness. To this aim, I perform a series of experiments. Namely, I control for outliers, question the assumption of a common linear specification for all countries, and confront the issue of endogeneity for the two measures of financial development.

Outliers

Outliers may occur for several reasons: measurement errors, omitted variables or parameter heterogeneity—each of which is likely to arise in a cross-section of heterogeneous countries. Following Temple (1998), the influence of outliers is evaluated by running a re-weighted least squares (RWLS) regression. This is a standard OLS regression after dropping observations identified as outliers through the residuals of the least trimmed squares (LTS) estimator. As discussed in Rousseeuw and Leroy (1987), this method disregards bad leverage points (i.e., values of the explanatory variables which lie far away from the bulk of the data) and is far less sensitive than OLS to deviant observations.

The results are shown in Table 6 using specifications similar to those in Table 5. The list of outliers (not reported) reveals that the majority of countries receiving zero weight in the RWLS regression belong to the African group; depending on the specification, however, some OECD and Asian countries were also dropped. A comparison with the estimates of Table 5 indicates that the exclusion of these outliers has no material effect on the estimated coefficients for PCY and LLY. Indeed, the point estimates are larger and more precise, though the magnitude remains smaller if the level of investment rate is included among the control variables.

Threshold Effects

The results presented so far are based on the assumption that all countries obey a common linear specification. Since this assumption may not be valid in a panel of heterogeneous countries, I investigate the possibility of threshold effects. Specifically, regressions of the following form are estimated:

$$y_{it} - y_{i,t-1} = \lambda y_{i,t-1} + \beta' x_{it} + \gamma FIN_{it} d_i(\tau) + v_{it}$$

where $d_i(\tau) = \{FIN_i \leq \tau\}$ is an indicator function and τ is the unknown threshold level of FIN_i. In this model, the regression parameter γ is allowed to differ depending on the value of FIN_i, and the sample is split into two groups based on the estimated values of τ. A Lagrange multiplier test (LM) suggested by Hansen (2000) is used to test the existence of a threshold effect, under the assumptions that the error term is normally distributed and the regressors are strictly exogenous.

Table 7 reports p-values for the null of no threshold, the least square estimates of τ with the associated 95 percent asymptotic confidence intervals, and the estimated coefficients of PCY and LLY across sub-samples. The evidence regarding the absence of threshold effects is mixed. It largely depends on the set of controls and, for each specification, on the indicator of financial development considered. The estimated thresholds, however, are very similar across specifications and approximately correspond to the cross-sectional median level of PCY (24 percent) and LLY (31 percent). In most cases, however, the number of countries that fall in the 95 percent confidence interval is so large, that any attempt to classify countries into the first or the second regime must be made with caution. Overall, the evidence suggests that there is some indication of a sample split based on PCY or LLY. The coefficients on PCY and LLY remain positive across sub-samples, despite not being significative when INV and/or the two regional dummies are used as control variables. In these cases, however, inference must be taken with care given the reduced number of observations in each sub-sample. On balance, the results do not differ substantially from the overall picture that emerges from the baseline regressions in Table 5.

Experiments were also conducted to check the possibility of additional regimes. In particular, the initial level of GDP per capita was used as threshold variable, to check if the coefficients on the financial variables could vary depending on the level of economic development. In this case, however, the LM test could not find evidence of such a threshold effect.

Reverse Causality

As mentioned earlier, OLS estimates may be plagued by problems of reverse causality. If economic development leads to a larger financial sector, the error term in the growth regression is positively correlated with PCY and LLY and the estimated coefficients biased upward. A way to address this problem is to use initial values of PCY and LLY. This approach is taken by King and Levine (1993) to check if the predetermined components of financial development are good predictors of long-run growth. My results (not reported) indicate that the initial values of PCY and LLY are significant predictors of subsequent growth, regardless of the set of controls used and the sample of countries considered.

A more appropriate way to address the same problem is to estimate the linear regression (1) via an instrumental variables (IV) estimator. This approach is pursued by LLB. I follow their analysis and use national legal origins as instrumental variables for the two indicators of financial development. In choosing these instruments, LLB rely on the evidence of La Porta et al. (1998), which show that the origin of a country's legal system significantly affects the structure and development of its financial system. The instruments (indicators of legal origins) are dummy variables for countries whose legal system has roots in the French, German or English legal tradition.

Table 8 summarizes the IV estimates and reports p-values for the Hansen test of instruments validity. To compare the results with the corresponding OLS estimates, I use the same specifications of Table 5. Consider first the estimates of column 1, which reports the baseline regressions. Compared with the OLS estimates, the coefficients on PCY and LLY decrease by one half, with the t-statistics indicating that these variables are no longer significantly related to GDP growth. The drop in the magnitude of the coefficients is even more dramatic in column 2, where investment is added as additional control. For this specification the magnitude of the coefficients for PCY and LLY falls to 0.041 and 0.051, respectively. The drop in these coefficients means that the contribution to growth for Argentina, if it had increased its average level of PCY towards the mean country, is now of only 0.07 percent per year.

Further indications that the OLS estimates may be biased, due to reverse causality but also because of unobserved omitted variables, arise in the regressions of column 3 and 4. After controlling for the two continent dummies, the size of the coefficients for PCY and LLY becomes larger, though their statistical significance remains fragile. Interestingly, for all specifications the J-statistic does not detect any problem with instrument validity. Moreover, the contribution to growth of LY0, INV, SEC and GOV is of the same size and has the same statistical significance as the OLS estimates.

C. Summary of the Cross-Section Results

The central message of the cross-sectional evidence is that the correlation between financial development and economic growth is positive, statistically significant and robust to outliers and functional form misspecifications. These results corroborate and reinforce the findings of King and Levine (1993). However, if the problem of reverse causality is addressed using IV regressions, the contribution of financial development to economic growth seems to become negligible. This result stands in contrast with that recently reported by LLB, despite the fact that the same set of instrumental variables is used. Differently from LLB's conclusion, there is no indication that the exogenous component of financial development encourages economic growth. For some specifications, there is also evidence that country-specific characteristics have been omitted from the growth regression. The size and the *t*-statistics for the coefficients of the two continental dummies are taken as evidence of misspecification in this direction. In an attempt to control for this additional potential bias and to correct for the endogeneity of all regressors, and not just of financial development, I now turn to the evidence from panel data methods.

V. Panel Data Evidence

Most of the analysis conducted by LLB is based on a GMM estimator for panel data. As mentioned above, this technique improves upon cross-sectional estimates because it directly controls for the potential bias induced by the omission of country-specific effects and the endogeneity of all regressors. Furthermore, it has the advantage of accounting for variation of financial development over time within a country, which is neglected by the cross-section analysis.

A. The System GMM Estimator

The GMM estimator used in LLB's paper is the system GMM estimator (SYS-GMM) of Arellano and Bower (1995) and Blundell and Bond (1998). The basic idea behind this estimator is as follows. First, the unobserved fixed effects μ_i are removed by taking first difference of equation (1):

$$\Delta(y_{it} - y_{i,t-1}) = \lambda(y_{i,t-1} - y_{i,t-2}) + \beta'(x_{it} - x_{it-1}) + \gamma(FIN_{it} - FIN_{it-1}) + \Delta\nu_t + \Delta\varepsilon_{it} \qquad (3)$$

Second, the right hand side variables are instrumented using lagged values of the regressors, and the equations in first differences (3) and in levels (1) are jointly estimated in a system of equations. Under the assumption that the error ε_{it} is serially uncorrelated, and the regressors $X_{it} = (x_{it}, FIN_{it})$ are endogenous, valid instruments for the equation in first difference are levels of the series lagged two periods. In addition, assuming that $\Delta(y_{it} - y_{i,t-1})$ and ΔX_{it} are uncorrelated with μ_i, valid instruments for the equation in levels are lagged first differences of the series.[5]

Third, the validity of the instruments is tested using a standard Sargan test of over-identifying restrictions and a test for the absence of serial correlation of the residuals, since the moment conditions are valid if the error term is not serially correlated.

A final point worth stressing is that the system GMM estimates can be based on either a one-step or a two-step estimator.[6] Although the two-step estimator is asymptotically more efficient in presence of heteroskedasticity of the error term ε_{it}, Monte Carlo simulation in

[5] Notice that this SYS-GMM estimator differs from the traditional first difference GMM estimator (DIF-GMM) of Arellano and Bond (1991)—and introduced into the growth literature by Caselli, Esquivel and Lefort (1996)—because lagged first differences of the series are also used for the level equations. As discussed in Blundell and Bond (1998) the SYS-GMM estimator is to be preferred to the first difference estimator in two special cases: 1) when the time series are highly persistent, and 2) when the number of time periods available is small. Both features are typical in the empirical growth research and have the effect of making the lagged level of the regressors weak instruments for the equation in first-differences. See Bond, Hoefler and Temple (2001) for a comparison of the DIF-GMM and SYS-GMM estimators in the context of empirical growth models, and Bond (2002) for a user-guide application of these GMM panel estimators.

[6] In the one-step estimator, the error term ε_{it} is assumed independent and homoskedastic across countries and time; in the two-step estimator, the residuals of the first step are used to estimate consistently the variance-covariance matrix of the residuals, relaxing the assumption of homoskedasticity.

Arellano and Bond (1991) and Blundell and Bond (1998) shows that standard errors associated with the two-step estimates are downward biased in small samples. Inference based on the two-step estimator can thus be highly inaccurate and a one-step GMM estimator with standard errors corrected for heteroskedasticity is to be preferred. It is worth stressing this point because the results of LLB appear to be based on the two-step GMM estimator. However, as will be shown below, the statistical significance of the financial variables may become rather weak in the growth regression, if the more appropriate one-step estimator is employed.

B. The GMM Results

To replicate the results of LLB, the SYS-GMM estimator is applied to a panel with annual observations divided into intervals of five years. The dependent variable is the growth rate of GDP per capita for each five-year period and the independent variables are averages over the same five-year intervals, except for the initial level of GDP and the level of school attainment, which are measured at the beginning of each sub-period. All variables are also expressed in deviations from cross-sectional means, which eliminates the need for time dummies ν_t.

The results are shown in Table 9. Columns 1 and 3 refer to the two-step estimates; columns 2 and 4 report the one-step estimates. The bottom part of the table includes p-values for the Sargan test and the *m2* test for the absence of a second order serial correlation of the residuals in the differenced regression, $\Delta\varepsilon_{it}$, implying that the error term in the level regression, ε_{it}, is not serially correlated. High *p*-values give support to the validity of the instruments and hence the consistency of the GMM estimates.

The results for the two-step estimator of column 1 are, by and large, similar to those of LLB. The estimates associated with the financial variables are positive and highly significant, suggesting that the exogenous component of financial development accelerates economic growth.[7] The remaining control variables also have the expected sign and are very tightly estimated. Moreover, the Sargan test and the *m2* test do not detect any problem with instrument validity.

In column 2, however, the more reliable one-step estimator reveals that the statistical significance of some regressors is rather weak, including PCY. Although the point estimates are similar to those of column 1, the *t*-statistics suggest that PCY, the preferred indicator of financial development, is no longer significantly related to economic growth. LLY, instead, remains significant at the 5 percent level. The estimated impact on GDP growth coming from PCY is also smaller than the corresponding cross-section effect: if bank credit in Argentina had been at the level of the mean country during the period 1996–98 (48 percent), instead of

[7] The point estimates associated to LLY and PCY, however, are much smaller than those reported in Table 5 of LLB. Their estimates are 0.147 for LLY and 0.076 for PCY.

its actual level (21 percent), Argentina would have grown at 0.35 percent faster per year; the long-run effect on GDP per capita would have been 0.7 percent.

The results for PCY change more sharply in column 4, where the level of investment is also included as control variable in the regression. Its coefficient is now insignificant and essentially zero, while the point estimates for the remaining covariates hardly change. Similar results emerge when the regression includes LLY. Notice that, in column 3, where the two-step estimates are displayed, all regressors continue to be highly significant.

Overall, in accord with the IV cross-section estimates of the previous section, the one-step GMM estimator indicates that PCY is not significantly related to GDP growth. Also, in line with the cross-section results, INV and GOV (and SEC for the specification including PCY) remain important determinants of long-run economic growth. Worth noticing is the sign of the estimated coefficients on INF: higher levels of inflation, now, have harmful effects on economic growth, in agreement with the panel evidence in the growth literature.

C. Robustness Checks

This section compares the SYS-GMM estimates with alternative panel data estimates and checks whether the results change across sub-samples or for different combinations of control variables.

Alternative Panel Estimators

Table 10 displays the estimated coefficients for PCY and LLY using the OLS level estimator (OLS), Within Group estimator (WG) and GMM first-difference estimator (DIF-GMM). Although it is well known that in a large N small T panel these estimators give a biased estimate of the autoregressive coefficient, precise biases results have not yet been extended to the remaining parameters (i.e., β and γ in equation (1)) when the regressors are endogenous. For this reason, it is instructive to compare the results across different estimators. For each estimator, the first column refers to the baseline regression of Table 9, while the second column also controls for the level of investment.[8] The SYS-GMM estimates of Table 9 are reproduced in the last two columns, for the sake of comparison.

There are minor variations in the coefficients for PCY and LLY. The estimated parameters for both variables are marginally significant only with the OLS and WG estimators and if INV is excluded from the set of controls. In the remaining cases the coefficients are always poorly estimated. Overall, the statistical performance of PCY and LLY does not appear to change substantially across different panel estimators. It remains in line with the indications from the one-step SYS-GMM estimator: financial development is a not a good predictor of economic growth.

[8] In the pooled OLS regressions (columns 1 and 2), we add the two continent dummies, AFRICA and LAC, as additional controls.

Subsample Stability

Table 11 assesses the stability of the GMM estimates across sub-samples. It considers the 1960–85 and 1970–98 sub-periods, to account for the fact that in recent years financial innovation has mainly occurred outside the banking system. Given that the two indicators of financial development refer solely to the banking sector, a smaller effect of PCY and LLY on growth is expected in the 1970–98 sample. When the T size of the panel is reduced, however, the properties of some panel estimators are also affected. The biases for the WG and DIF-GMM are expected to worsen whereas the SYS-GMM should provide more reliable estimates. For this reason, I also compare the results across estimators. Tables 11a–11b show that the preferred panel estimator, the SYS-GMM, does not indicate any substantial differences in the finance-growth link, over different intervals. The point estimates for PCY and LLY are very similar across samples, and in all cases are not significantly different from zero, apart from the OLS estimates in the sample 1960–85. In some cases, the coefficients are all insignificant or, surprisingly, negative.

Tables 12a and 12b report the results of two additional experiments. Table 12a uses the same sample of countries as LLB. As can be seen, the SYS-GMM estimates do not differ much from the baseline regressions. In Table 12b the data is divided in sub-periods of 10-year intervals. The puzzling effect is that PCY is now significantly related to GDP growth, whereas LLY is not. Also, the estimated coefficients for LLY become negative if INV is held constant.

Control Variables

As a final check, Table 13 presents estimates using a smaller set of covariates. In each case, I control for initial conditions and include INV, INF and GOV in different combinations. BMP and OPEN are dropped because they were invariably insignificant. The one step SYS-GMM results suggest that, with the exception of the parsimonious specification of column 1, PCY is never significantly related to growth. By contrast, LLY becomes insignificant when I jointly control for the level of INF and INV.

D. Summary of the Panel Data Results

Altogether, the conclusion of these experiments is that financial development, as measured by PCY, is not significantly related to long-run economic growth. The results are slightly different for LLY—which is found to be significant in some regressions—although they are not robust to different specifications and across sub-samples. Clearly, this conclusion contrasts with the evidence reported in LLB. The robustness checks reported above suggest that the main reason is not due to differences in the set of countries or sample period used. Rather, it appears to be the use of the more appropriate one-step GMM estimator.

VI. Nonlinearities and Heterogeneity

This section extends the analysis presented so far by relaxing the assumption that the slope coefficients in equation (1) are constant across units. There are several reasons that motivate the desire to move away from the standard framework.

First, although linearity is a convenient assumption, it is not tenable in a panel where countries differ along several dimensions. In principle, financial deepening may have growth-promoting effects at all stages of economic development. In practice, a variety of non-linear relationships may arise. One may conjecture that at early stages of economic development countries have no capital to invest and factors other than financial development are crucial for economic growth. Similarly, as the economy develops, but the quality of institutions supporting credit markets remain poor, it may be the case that only a few productive investments are undertaken while the effects of a larger banking sector for output performance remain of secondary importance. Finally, it can be conjectured that as the system of financial intermediation becomes more sophisticated, other forms of financing become available outside the banking system; in this case indicators of banking development are not very informative for evaluating the effects of financial development on economic growth. Models of economic development emphasizing thresholds effects (Azariadis and Drazen, 1990) are fully consistent with these non-linearities, as argued by Acemoglu and Zilibotti (1997, 1999) in the finance-growth context.

Second, in a multi-country panel setup, forcing parameters to be exactly equal in all units may create systematic distortions. In the empirical growth literature this objection has been raised by Durlauf and Johnson (1996), Lee et al. (1997) and Canova and Marcet (1998), who document widespread heterogeneity in the context of convergence of per capita income across countries; and by Liu and Stengos (1999), Kalaitzidakis et al. (2001) and Durlauf et al. (2001), who present evidence that standard growth determinants affect the growth rate of GDP in a non-linear way.

Third, the assumption of slope homogeneity in equation (1) has statistical shortcomings. If parameters are heterogeneous but held constant across units, traditional dynamic panel estimators are inconsistent. The source of inconsistency is that slope heterogeneity causes the disturbances to be serially correlated as well as contemporaneously correlated with the included regressors. Consequently, the presence of a lagged dependent variable renders the estimates of λ, β and γ inconsistent, even in a panel with uncorrelated regressors and with a sufficiently large number of countries and time series. The problems are aggravated if the regressors display serial correlation—as is likely for most of the variables of this paper. In these cases, estimation by GMM is no longer valid, since lagged values of serially correlated regressors cannot be used as instruments. (see Pesaran and Smith, 1995 and Pesaran, Smith and Im, 1999).

In what follows, the issue of parameter heterogeneity is addressed in two steps. First, I document the existence of widespread heterogeneity in the parameter γ of equation (1) by using a semiparametric model, where no functional form assumption is imposed on the relationship between finance and growth. Second, the average long-run effect of finance on

GDP per capita is re-examined using the Pooled Mean Group (PMG) estimator of Pesaran, Shin and Smith (1999), which is specifically designed to consistently estimate a dynamic panel in the presence of slope heterogeneity.

A. Nonlinearities: Empirical Specification and the Evidence

A straightforward way to question the linearity assumption for the relationship between financial development and economic growth, is to rewrite equation (1) as follows:

$$y_{it} - y_{i,t-1} = \lambda y_{i,t-1} + \beta' x_{it} + \theta(FIN_{it}) + v_{it} \tag{4}$$

where $\theta(FIN_{it})$ is a smooth function of unknown form, and the vector of point-wise derivatives $\gamma_{it}(FIN_{it}) = \partial\theta(FIN_{it})/\partial FIN_t$ contains varying response coefficients (both across countries and time).

Following Li and Wooldridge (2002), the functions $\theta(FIN_{it})$ and $\gamma_{it}(FIN_{it})$ are estimated by a local linear kernel method, after "partialling out" the linear part of the model using a non parametric kernel method, as in Robinson (1988) or Stock (1989).[9] I use the same panel of the previous section with data averaged over 5-year periods. The vector of controls x_{it} includes the baseline regressors and the two regional dummies, AFRICA and LAC. All variables are also expressed in deviation from the cross-sectional mean to eliminate common time period effects.

Figure 3 plots the estimates of $\theta(FIN_{it})$ (dotted curve) and the corresponding pooled OLS regression line (solid curve) to highlight the difference between the semiparametric and the linear model. On the horizontal axis, both graphs have the logarithm of PCY or LLY in deviation from the cross-sectional mean.

The first interesting result is that for both indicators of financial development, the relationship between finance and growth is non-linear. The graphical impression is also confirmed by the functional form test of Li and Wang (1998). Under the null of a linear model (equation (1)) against a semiparameteric alternative (equation (4)), the test has an asymptotic standard normal distribution. For PCY and LLY the values of the corresponding statistics were 1.955 and 2.129, respectively, rejecting the null of linearity at conventional significance levels.

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[9] We use a Gaussian kernel, with bandwidth chosen according to the formula $h = k_0 s_{FIN} n^{-1/5}$ where $n = NT$ is the number of observation, s_{FIN} the sample standard deviation of *FIN* and k_0 is a constant. k_0 has been fixed to 0.8, 1 and 1.2, respectively. To save space, only the results for $k_0 = 1$ are presented since for the remaining values of k_0 the results were similar.

The second useful piece of information comes from the shape of the two functions. Both have an inverted S form, suggesting that $\theta(FIN_{it})$ is monotonically increasing only for intermediate levels of financial development. This pattern is more pronounced for LLY than PCY and the indication is that as the size of the banking sector gets larger countries experience higher growth rates. However, at either very low or very high levels of financial development, the slopes of these functions are inverted. Admittedly, only a few observations fall into the lowest and highest percentiles of the PCY and LLY distribution. Still, it is instructive to note that countries whose financial sector is least developed are also in the very early stage of their economic development, while countries with high financial ratios are the most advanced economies.[10] While it is plausible to suppose that in poor countries there is a shortage of low-risk and highly productive projects and that therefore a limited amount of savings and credits cannot have first order effects on economic growth, it is more difficult to rationalize the puzzling negative slope of $\theta(FIN_{it})$ at high levels of financial development. A possible explanation is that for these countries other indicators, such as measures of stock and bond market development, provide more direct information about the positive effects of financial deepening on economic growth. Although this additional investigation is left for future research, it is important to stress that some of the uncovered non-linearities may also be influenced by unrepresentative observations.[11]

Figure 4, which plots the slope coefficients $\gamma_{it}(FIN_{it})$, presents more compelling evidence of pervasive heterogeneity in the parameters of interests. The sample means of the slope coefficient for PCY and LLY—which are taken as estimators of the average effect of financial development on growth—are 0.009 (*s.d.* = 0.043) and 0.036 (*s.d.* = 0.084), respectively. These values are much lower than the corresponding OLS and GMM estimates of the previous section, suggesting that parameter heterogeneity may affect in a non-trivial way the overall evaluation of the effects of finance on growth.[12]

By construction, however, these parameters are allowed to vary across units and over time, and it is therefore difficult to single out the time series variations from the cross-country variations. To uncover more information in this direction, Figure 5 plots the slope coefficient associated with PCY when countries are grouped according to their geographical location. It is clear from the graph that, regardless of the group of countries considered, $\gamma_{it}(FIN_{it})$ exhibits ample oscillations. This result crucially depends on the fact that different levels of financial development are recorded within countries of the same regional group.

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[10] For those countries whose function $\theta(.)$ is negatively sloped, the lowest ratio of PCY is recorded for the African and Latin American ones, whereas the highest ratios are for almost all OECD countries, some advanced Latin American countries (Chile and Venezuela) and South Africa.

[11] For example, Paraguay, Syria and Kenya seems to fall in the range of high developed countries having a negative sloped $\theta(.)$ function.

[12] Notice that for these estimates the level of investment is not included among the set of controls. If the investment ratio is also held constant in each regressions, the average values of $\gamma_{it}(PCY_{it})$ and $\gamma_{it}(LLY_{it})$ are -0.001 (*s.d.* = 0.038) and 0.022 (*s.d.* = 0.088), respectively.

Since the OECD and the African groups include the richest and the poorest economies, respectively, the graphs suggest that heterogeneous behavior is likely to occur even for countries with similar institutional characteristics and similar levels of economic development.[13]

Overall, this evidence gives further support to the claim that the relationship between financial development and economic growth is characterized by a substantial degree of heterogeneity. Similar experiments were also conducted on each of the remaining non-financial regressors. Although a full set of results is not reported, plots of the corresponding slope coefficients reveal that heterogeneity is not confined to the financial variables but pertains to most of the control variables in the regression. With the exception of INF and BMP, the Li and Wang test always reject the null of linearity.

VII. THE POOLED MEAN GROUP ESTIMATOR

Having shown that heterogeneity in the γ coefficient is quite pronounced across countries, I now estimate a dynamic panel that allows parameters to vary across units. To this aim, following Pesaran and Smith (1995), I rewrite equation (1) in terms of an autoregressive distributed lag model of order *(p,q...,l)*, or simply *ARDL(p,q,...,l)*:

$$y_{it} = \sum_{j=0}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \beta'_{ij} x_{i,t-j} + \sum_{j=0}^{l} \gamma_{ij} FIN_{i,t-j} + \alpha_i t + \mu_i + \nu_t + \varepsilon_{it} \qquad (5)$$

where y_{it}, $x_{i,t}$, $FIN_{i,t-j}$, μ_i and ν_t have the same interpretation as in (1), t is a linear time trend and the general lag structure is meant to control for different short-run output dynamics across countries.

To simplify the exposition, it is useful to assume that the model contains only one regressor, $x_{i,t}$, and displays a simple dynamics with $p = q = 1$:

$$y_{it} = \lambda y_{i,t-1} + \beta_{0i} x_{it} + \beta_{1i} x_{it-1} + \alpha_i t + \mu_i + \nu_t + \varepsilon_{it} \qquad (6)$$

In this case, stacking the time series observations for each country, equation (6) can be reparameterized in an error correction form (ECM) as follows:

$$\Delta \mathbf{y}_{it} = \phi_i (\mathbf{y}_{i,-1} - \theta_i \mathbf{x}_i) - \beta_{1i} \Delta \mathbf{x}_i + \alpha_i t + \boldsymbol{\eta}_i \qquad (7)$$

[13] Analogous indications arise when the sample is split into high-income versus low-income countries, depending on whether the country's average real GDP is above or below the respective cross-sectional median.

where Δ is the first difference operator and $\phi_i = -(1-\lambda_i)$ is the country specific equilibrium correction parameter, $\theta_i = (\beta_{0i} + \beta_{1i})/\phi_i$ the country specific long-run coefficient, β_{1i} the country specific short-run coefficient and μ_i a stationary disturbance. Notice that in the special case of $q = 0$, β_{1i} is zero and equation (7) is identical to (1).[14]

There are two ways to estimate the long-run parameters, θ_i, in (7) when T and N are large. Pesaran and Smith (1995) propose the Mean Group estimator (MG), which is an unweighted average of country specific long-run coefficients $E(\theta_i)$. Although this estimator yields consistent estimates of $E(\theta_i)$ it is very sensitive to outliers. An alternative approach, due to Pesaran, Shin and Smith (1999), is the Pooled Mean Group estimator (PMG), which can be thought of as a weighted average of individual group estimators, with weights proportional to the inverse of their variance. The PMG estimator allows for heterogeneous short-run coefficients yet constrains long-run parameters to be the same across units, i.e. $\theta_i = \theta$. It therefore averages the short-run country parameters and pools the long-run parameters, combining the efficiency of the pooled estimation while avoiding the inconsistency problem of pooling heterogeneous dynamic relationships. For the analysis of this paper, the advantage of using the PMG estimator is that it allows for the level of financial development to have similar effects across countries in the long-run, while permitting heterogeneous short-run adjustments across groups to changes in the level of financial development. The poolability restriction of the long-run parameters is tested using a Hausman type test applied to the difference between the MG and the PMG estimators.

A. Caveats

Before estimating the model two caveats are worth discussing. First, the main requirement to implement the PMG estimator is to have a large N, large T panel. In contrast with most empirical studies in the growth literature, it is therefore necessary to use a panel of data with annual observations. This raises the question of how informative a growth analysis can be when long-run properties of the data are likely to be dominated by high frequency movements. The PMG estimator permits to address this concern in part. The formulation outlined in equation (5) has the noteworthy advantage of allowing short-run output dynamics to differ across countries. This is a convenient feature of the empirical strategy, given that main interest is in estimating the long-run parameters. In fact, even if the underlying economic theory relating fundamental variables to GDP growth is not well specified at high frequency, the PMG estimator can still be used to draw inference on the long-run parameters,

[14] This ECM parameterization is allowed insofar as $-1 < \phi_i = -(1-\lambda_i) < 0$. Thus a sufficient condition to express (6) as (7) is that there exists conditional convergence. As will be shown below, this assumption is always supported in our estimates.

provided an appropriate short-run specification is imposed on each country to control for high frequency influences.[15]

Second, in the general formulation of equation (6), the error term is assumed to be independently and identically distributed across countries and time and uncorrelated with the regressors x_{it}. Neither of these assumptions, however, is too restrictive for estimating the long-run parameters. As suggested by Pesaran, Smith and Shin (1999), it is sufficient to take each variable in deviation from its cross-sectional mean and appropriately increase the lag order of y_{it} and x_{it} to attenuate the dependence of the errors across units and time. Moreover, as shown in Pesaran (1997) and discussed further in Pesaran and Shin (1999), if x_{it} has a finite order autoregressive representation, then augmenting the ARDL specification with an adequate number of lags makes the estimation of the long-run coefficients immune to endogeneity problems, irrespective of whether the regressors are stationary or not.

B. Evidence with the PMG Estimator

Baseline Results

Estimates of the long-run coefficients are displayed in Table 14. The set of controls excludes SEC and BMP since data for these variables is either not available on a yearly basis or missing for many years in several countries. For each ARDL specification, I include a country-specific linear trend to allow for possible heterogeneity in the rate of technology progress across countries. Moreover, to remove possible dependence of the error term $v_{it} = \mu_i + v_t + \varepsilon_{it}$ across i—due, for example, to a common stochastic trend—each variable is demeaned using the corresponding cross-sectional mean for every period. The PMG estimates of Table 14 refer to an ARDL model that uses the Schwarz Bayesian criterion (SB) to select, for each country, the maximum lag order of 2.[16] Next to the PMG estimates, there are p-values for the Haussman test (h-test) of no difference between the MG and PMG estimates. This is a test of long-run homogeneity restrictions for each of the parameters of interest; at the bottom of the table the p-values for the H-test refer to the null of the joint homogeneity restriction for all the long-run parameters.

Starting with the non-financial variables, the coefficients for INV, GOV and INF have all the predicted signs and are significantly related to long-run growth, regardless of the specification considered. The contribution of OPEN, instead, is less clear as the coefficient

[15] It may even be argued that this way of addressing business cycles influences is superior to the standard practice of averaging data over a fixed window of 5-year given the well-documented lack of synchronizations of business cycles across countries.

[16] Test of model specifications for alternative ARDL models (not reported) suggested that the performance of the SB≤2 model was superior to other specifications in terms of fitting, standard error of the regression and serial correlation and heteroskedasticity in the residual for each country regression.

changes sign when INV is entered into the regression. These results are consistent with the evidence of the previous sections.

The effect of financial development on growth is ambiguous. If INV is excluded from the set of controls, the long-run coefficients for PCY and LLY are positive and significant. However, the estimated effect of finance on growth becomes, surprisingly, negative, if INV is included as control variable in the regression. The quantitative effects are in all cases small when compared with those of the previous sections. For example, the long-run elasticity of GDP per capita to PCY indicates that a 1 percent increase in PCY has a positive effect on long-run output of only 0.045 percent (using the coefficient of column 1) or a negative effect of approximately -0.025 percent (using the coefficient of column 3).[17]

Since the fit of both regressions is similar (according to the country average adjusted-R^2) and tests of model specification do not favor one regression over the other,[18] the contrasting results for the coefficients on PCY and LLY are presumably due to the widespread degree of heterogeneity in the underlying parameters. Inspection of the group-specific estimates for PCY and LLY reveals, for instance, that for the regressions in columns 3 and 4, the coefficient on PCY ranges from -2.001 (Togo) to 1.564 (Portugal), and that on LLY varies more widely from -4.906 (Cote d'Ivoire) to 8.224 (Japan).[19]

Table 15 lists the countries with positive and negative estimated long-run coefficients for PCY and LLY, based on the two regressions of columns 3 and 4 of Table 14. The list indicates a substantial degree of heterogeneity, with no obvious pattern related to geographic location or the level of economic development. Moreover, some countries with a positive coefficient for PCY tend to have a negative coefficient for LLY, suggesting that the contribution of the two measures of financial development to growth varies considerably across and within countries. Only countries with a low level of financial development (mainly African ones) have coefficients on PCY and LLY with the same sign.

[17] These effects are much lower than those of the previous sections and in line with the theoretical predictions that assuming homogenous slope coefficients in a dynamic panel with heterogeneous units yields upward biased estimates of the long run coefficients (see Pesaran and Smith, 1995).

[18] For example, in the specification of column 1, only 6 countries out of 71 show signs of residual serial correlation and 7 displayed problems of residual heteroskedasticity. For the specification of column 3, the corresponding numbers of countries were 11 and 2, respectively. These diagnostic tests are based on the Lagrange multiplier statistics described in Pesaran and Pesaran (1997).

[19] The cross-sectional average of the long-run country-specific estimates,—i.e., the Mean Group estimates—were -0.003 (0.069) for PCY and 0.314 (0.248) for LLY, with standard errors in parenthesis. Evidently, the presence of some outlying countries such as Rwanda, whose long run LLY coefficient is 11.361 (238.07), influenced the MG estimates. Dropping this country from the sample hardly changes the PMG estimates, but reduces the MG estimates to -0.067 (0.154). This is an indication that the MG estimates are quite sensitive to outliers, while the PMG estimates are more robust.

Lag Structure and Time Trend

Since the negative and significant coefficients for PCY and LLY in Table 14 are difficult to explain on a theoretical basis, it is useful to explore the robustness of previous results to additional experiments.

To verify that the estimates are not influenced by the selection of an inappropriate lag order, Table 16 shows the results of using different model specifications, holding constant the same control variables of Table 14.[20] Columns 1 and 3 specify tight short-run dynamics for each country, imposing a lag of order 1 for both the dependent variable and each covariate; in columns 2 and 4, the lag order is chosen according to the SB information criterion, subject to a maximum of one lag; columns 3 and 5 report the results when all the variables enter in the regressions with two lags. The surprising result is that the coefficients on both PCY and LLY are negative, while the remaining control variables maintain the same sign of the baseline regressions as in Table 14.[21] These results, together with the evidence of Table 14, indicate that the interplay between parameter heterogeneity and dynamic specifications is likely to affect, in a non-trivial way, the estimates of the long-run coefficients of PCY and LLY.

Another issue worth discussing is that a country-specific linear trend was included in the baseline regressions of Table 14. As documented in Section II, however, the level of financial development exhibits a pronounced trend. It is thus possible that the inclusion of a linear trend biases downward the coefficients on the financial variables. To check for this possibility, the same ARDL specifications of Table 14 were estimated without a linear trend component. The results are not reported since the coefficients for the financial variables were essentially unaltered, although tests of model specifications favored the model with a country-specific time trend.

Control Variables, Outliers and Subsample Stability

Table 17 assesses the robustness of the previous results to different sets of controls. The purpose is to examine to what extent the negative coefficients for PCY and LLY in Table 14 are due to the inclusion of INV among the control variables. In the first three columns of Table 17, I continue to include INF as control variable and add GOV and OPEN in turn. The general finding is that the coefficients on the financial variables are often negative and, when positive, is not significantly different from zero. Columns 4 to 7 check if inflation affects the results. I exclude INF from the regressions, continue to include INV and add OPEN and GOV one after the other. The results suggest that, except for the specification of column 6, the estimated coefficients on PCY or LLY remain negative. Finally, column 8

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[20] For convenience, this table only reports the p-values for the joint test of homogeneity of all the regressors.

[21] A specification including up to 3 lags for each regressor was also estimated. The results are not reproduced but were roughly the same.

only controls for GOV and OPEN as growth determinants. In this case, the estimated coefficient for LLY is large and significant, whereas the coefficient for PCY is essentially zero. These results are taken as evidence of a very fragile link between financial development and economic growth, as they are very sensitive to the set of controls used in each instance. It is worth noting that all the control variables (except for OPEN) have the expected sign and are very tightly estimated in each specification; moreover the H-test does not reject the null of homogeneity of the long-run coefficients.

Additional sensitivity analysis was performed to check if some outlying observations were responsible for the findings of Table 14. In a first attempt, I dropped from the regressions of columns 3 and 4 those countries for which the adjustment coefficients φ_{i} were not negative, i.e. countries for which no long-run relationship existed among the variables of interest.[22] The results were, however, not at all affected by this additional experiment. In another attempt, I dropped countries whose long-run coefficients for the financial variables were implausibly large and poorly estimated.[23] While there is no theoretical justification for doing so, it is of practical interest to ensure that the PMG estimates are not distorted by a few deviant observations. None of the results in Table 14 were affected by this additional modification.

In line with the analysis of the previous section, I have also examined the sensitivity of the results across sub-samples. This additional exercise is also intended to evaluate the incidence of business cycle effects on the parameter estimates. However, the results, not reported, did not change the overall picture, and suggested that while the signs of the controls are consistently the same, the estimated effect of financial development on growth was, surprisingly, negative.[24]

C. Summary of the PMG Estimates

The most important result emerging from the PMG estimates is that the effect of financial development on economic growth is ambiguous and not robust to alternative dynamic specifications, the set of variables included in the conditioning set, and the time period considered. Surprisingly, these results are confined to the measures of financial development and do not extend to such standard determinants of economic growth as investment, government consumption and the inflation rate. There is also ample evidence that the parameters of interest are heterogeneous and that for a number of countries the coefficients for the financial variables are economically implausible. A potential explanation for this last result is that group-specific estimates may be biased due to measurement errors

[22] There were three such countries in the specification of column 3 and five countries in the corresponding regression of column 4.

[23] For example, in the regression of column 4 the long-run coefficient on LLY was 11.361 (*s.d.* = 238.07) for Rwanda, 8.224 (*s.d.* = 67.940) for Japan and -4.906 (*s.d.* = 31.750) for Cote d'Ivoire, respectively. For the regression in column 3, no countries reported implausible estimated coefficients.

[24] In these regressions, the maximum lag order was restricted to 1 in view of the reduced number of time series available for each sub-sample.

or omitted variables and that these biases do not average to zero when pooling the long-run coefficient. Alternatively, the results may just be driven by the considerable heterogeneity in the short-run and long-run parameters. In this case, traditional growth regressions that ignore dynamics and slope heterogeneity across countries are misspecified and may tend to overestimate the importance of financial development as determinant of GDP growth.

VII. Concluding Remarks

This paper has reexamined the relationship between financial development and economic growth. It took the work of Levine, Loayza, and Beck (2001) as a starting point and reevaluated their empirical analysis using an updated dataset and a variety of econometric methods. The results of this paper suggest that financial development does not have a first-order effect on economic growth. Specifically, the evidence presented reveals that (1) the exogenous component of financial development does not spur economic growth; (2) the link between financial development and economic growth is not linear; and (3) if a dynamic specification and slope heterogeneity across countries are taken into account, the estimated effect of financial development on GDP growth is often negative.

Although result (1) appears to be quite robust, results (2) and (3) must be taken with some qualifications. It can be argued, for example, that measurement errors, business-cycle effects, and omitted variables may affect the validity of these findings. Despite these objections, the informational benefit from an analysis that acknowledges heterogeneous behavior across countries is important. The conventional interpretation that finance promotes economic growth is, in fact, based on average effects. Yet average statistics may be difficult to interpret if, as documented, the relationship between finance and growth is quite diverse among countries, even those with similar levels of economic and financial development.

The more general implication from this paper is that the proxies of financial development considered might be inadequate to capture the beneficial effects of a good system of financial intermediation. As is common in the literature, I have focused on measures of the size of the banking system. Theory instead refers to the effects of financial intermediaries in ameliorating information frictions and transaction costs, for which empirical proxies are not, in general, available. In this regard, the documented heterogeneity across countries may reside in a lack of careful investigation of the several channels through which financial development affects economic growth. Further research is therefore needed to bring together theoretical models and more sophisticated proxies of financial depth.

Table 1. Country Coverage

OECD	Latin America and Caribbean	Middle East and Asia	Africa
United States	Argentina	Cyprus	Algeria
United Kingdom	Bolivia	Iran, Islamic Rep. of	Burundi [2,3]
Austria	Brazil [3]	Israel	Cameroon
Belgium	Chile	Jordan [3]	Central African Rep. [3]
Denmark [3]	Colombia	Syria	Chad [2,3]
France	Costa Rica	Egypt, Arab Rep. [1]	Congo Rep. of [3]
Germany	Dominican Republic	Bangladesh [3]	Benin
Italy [3]	Ecuador	Sri Lanka	Ethiopia [1,2]
Netherlands	El Salvador	India	Gabon [1,2]
Norway	Guatemala	Indonesia	Gambia [1]
Sweden	Haiti	Korea	Ghana
Switzerland	Honduras	Malaysia	Côte d'Ivoire [1,2]
Canada	Mexico	Nepal	Kenya
Japan	Nicaragua [3]	Pakistan	Lesotho [3]
Finland	Panama [3]	Philippines	Madagascar [1,2]
Greece	Paraguay	Singapore	Malawi [3]
Iceland [3]	Peru	Thailand	Mali [3]
Ireland	Uruguay	Papua New Guinea [3]	Mauritania [2,3]
Portugal	Venezuela		Mauritius
Spain	Barbados		Morocco [1,2]
Turkey	Jamaica		Niger
Australia	Trinidad and Tobago		Nigeria [1,2]
New Zealand			South Africa
			Zimbabwe [3]
			Rwanda [1]
			Senegal
			Sierra Leone [3]
			Tanzania [3]
			Togo
			Uganda [3]
			Zambia [3]

Notes: [1] countries missing in the cross-section analysis; [2] in the 5 years panel data; [3] for the PMG estimator

Table 2. Definition of Variables and Sources

Variable	Definition	Source
Y0	Real per capita GDP chain index - RGDPCH	PWT 6.1
INV	Real domestic investment as share of real per capita GDP -- KI	Ibid.
GOV	Real government consumption as share of real per capita GDP -- KG	Ibid.
OPEN	Sum of real exports and imports as share of real per capita GDP -- KOPEN	ibid.
PCY	Credit by deposit money bank and other financial institutions to the private sector -- line 22d+42d	IFS
LLY	Liquid liabilities -- line 55l or 35l	ibid.
GDP	Nominal GDP in local currency -- line 99b	ibid.
CPI	Consumer price index -- line 64	ibid.
INF	Log difference of consumer price index	ibid.
SEC	Average years of school of the population aged 15 and over	Barro and Lee (2002)
BMP	Black market premium	Easterly and Sewadeh (2002)
British	Dummy variable for Bristish legal origin	ibid.
French	Dummy variable for French legal origin	ibid.
German	Dummy variable for German legal origin	ibid.
AFRICA	Dummy variable for sub-Saharan Africa countries	--
LAC	Dummy variable for Latin American and Caribbean countries	--

Table 3. Summary Statistics - Panel Data (yearly data)

Variable		Mean	Std. Dev.	Min	Max	Observations	
Growth	overall	0,018	0,059	-0,543	0,492	N*T	3586
	between		0,016			N	95
	within		0,057			T	37,75
SEC	overall	4,811	2,795	0,120	11,890	N*T	670
	between		2,664			N	89
	within		1,001			T	7,53
INV	overall	15,712	9,563	-3,459	101,132	N*T	3688
	between		8,127			N	95
	within		5,147			T	38,82
GOV	overall	19,429	11,196	2,178	107,276	N*T	3688
	between		9,503			N	95
	within		5,982			T	38,82
OPEN	overall	60,899	44,156	2,644	341,827	N*T	3689
	between		38,318			N	95
	within		22,569			T	38,83
INF	overall	14,032	30,847	-15,200	477,490	N*T	3195
	between		19,777			N	95
	within		25,579			T	33,63
BMP	overall	58,687	930,449	-28,21	49990	N*T	3274
	between		205,213			N	95
	within		907,269			T	34,46
PCY	overall	37,078	33,856	0,730	221,940	N*T	3001
	between		28,419			N	95
	within		16,705			T	31,59
LLY	overall	38,616	23,208	2,110	144,440	N*T	2987
	between		20,417			N	95
	within		10,496			T	31,44

Table 4. Pairwise Correlation Matrices

(a) Cross-Section Data

	GROWTH	SEC	INV	GOV	OPEN	INF	BMP	PCY	LLY
GROWTH	1,000								
SEC	0,388	1,000							
INV	0,676	0,638	1,000						
GOV	-0,290	-0,297	-0,285	1,000					
OPEN	0,185	-0,084	0,142	0,194	1,000				
INF	-0,150	-0,121	-0,043	0,133	-0,188	1,000			
BMP	-0,197	-0,195	-0,131	0,106	0,012	0,463	1,000		
PCY	0,484	0,641	0,666	-0,299	-0,039	-0,248	-0,125	1,000	
LLY	0,502	0,515	0,616	-0,181	0,062	-0,319	-0,108	0,842	1,000

(b) Panel Data: 5 years average

	GROWTH	SEC	INV	GOV	OPEN	INF	BMP	PCY	LLY
GROWTH	1,000								
SEC	0,136	1,000							
INV	0,396	0,539	1,000						
GOV	-0,125	-0,270	-0,178	1,000					
OPEN	0,092	-0,012	0,218	0,151	1,000				
INF	-0,224	-0,061	-0,096	0,177	-0,168	1,000			
BMP	-0,127	-0,071	-0,066	0,134	-0,016	0,513	1,000		
PCY	0,129	0,640	0,573	-0,287	0,072	-0,197	-0,070	1,000	
LLY	0,192	0,527	0,562	-0,162	0,147	-0,227	-0,033	0,820	1,000

(c) Panel Data: yearly observations

	GROWTH	SEC	INV	GOV	OPEN	INF	BMP	PCY	LLY
GROWTH	1,000								
SEC	0,090	1,000							
INV	0,191	0,497	1,000						
GOV	-0,098	-0,241	-0,148	1,000					
OPEN	0,028	-0,050	0,226	0,164	1,000				
INF	-0,157	-0,030	-0,092	0,149	-0,142	1,000			
BMP	-0,029	-0,073	-0,030	0,090	-0,010	0,178	1,000		
PCY	0,074	0,633	0,554	-0,278	0,050	-0,174	-0,035	1,000	
LLY	0,101	0,499	0,542	-0,143	0,128	-0,200	-0,002	0,815	1,000

Table 5. Cross-Section Data – OLS Estimates
Dependent Variable Log-difference GDP per capita. Sample 1960-1998

	(1)		(2)		(3)		(4)	
log(YO)	-0,404	-0,394	-0.367	-0.364	-0,484	-0,476	-0,475	-0,467
	4,14	3,27	3.66	2.96	6,54	5,58	6,10	5,51
log(INV)			0.379	0.329			0,067	0,070
			2.08	1.98			0,41	0,41
log(1+SEC)	0,490	0,516	0.347	0.385	0,423	0,453	0,401	0,427
	3,27	3,18	2.08	2.37	3,63	3,62	2,99	3,17
log(OPEN)	-0,277	-0,332	-0.203	-0.249	0,305	-0,336	-0,290	-0,318
	2,26	2,75	1.78	2.27	3,40	3,53	3,13	3,29
log(GOV)	0,020	-0,021	-0.042	-0.061	0,137	0,105	0,121	0,091
	0,20	0,22	0.40	0.60	1,51	1,18	1,27	0,95
log(1+INF)	0,055	0,437	-0.281	0.010	0,567	0,618	0,470	0,510
	0,11	0,79	0.53	0.02	1,49	1,39	1,03	0,99
log(1+BMP)	-0,021	-0,096	0.001	-0.050	-0,208	-0,228	-0,194	-0,212
	0,11	0,49	0.01	0.29	1,40	1,46	1,32	1,34
AFRICA					-0,837	-0,798	-0,801	-0,764
					5,62	4,79	4,59	3,98
LAC					-0,364	-0,280	-0,339	-0,261
					3,46	2,23	2,77	1,87
log(PCY)	0,389		0.244		0,215		0,198	
	3,88		1.82		2,54		2,09	
log(LLY)		0,612		0.407		0,331		0,301
		4,74		2.71		2,27		1,95
N.obs	83	83	83	83	83	83	83	83
R^2	0,47	0,49	0.52	0.53	0,66	0,65	0,66	0,65

Note: Estimation by OLS. Robust t-statistics in small fonts below the corresponding coefficients

Table 6. Cross-Section Data – RWLS Estimates
Dependent Variable Log-difference GDP per capita. Sample 1960-1998

	(1)		(2)		(3)		(4)	
log(YO)	-0.368	-0.659	-0.340	-0.335	-0.513	-0.534	-0.479	-0.490
	5.10	8.32	5.15	4.76	11.36	11.42	9.84	11.20
log(INV)			0.842	0.730			0.271	0.229
			8.16	5.95			2.87	2.50
log(1+SEC)	0.479	0.585	0.183	0.290	0.354	0.438	0.501	0.465
	4.18	4.83	1.63	2.55	5.20	6.51	2,99	6.41
log(OPEN)	-0.376	-0.375	-0.145	-0.152	-0.499	-0.209	-0.235	-0.250
	3.91	4.20	1.91	1.79	8.07	3.45	3.82	4.32
log(GOV)	0.166	0.121	-0.154	-0.144	0.142	0.075	0.000	0.139
	2.16	1.87	2.24	1.93	3.00	1.61	0.02	2.88
log(1+INF)	0.912	1.403	0.043	-0.189	1.055	1.022	0.412	2.382
	2.35	3.91	0.08	0.48	4.52	4.54	1.43	4.80
log(1+BMP)	0.168	-0.568	1.124	0.882	-0.110	-1.223	0.102	-0.885
	1.32	5.01	5.13	3.88	1.38	6.74	1.25	8.00
AFRICA					-1.141	-0.957	-0.688	-0.970
					11.74	11.51	7.08	10.58
LAC					-0.316	-0.078	-0.280	-0.155
					4.59	1.09	3.59	2.05
log(PCY)	0.545		0.187		0.311		0,113	
	6.90		2.23		5.91		1,92	
log(LLY)		0.709		0.257		0.427		0.582
		7.05		2.22		5.28		6.56
N.obs	74	66	64	68	62	63	68	62
R^2	0.66	0.74	0.80	0.75	0.90	0.90	0.87	0.91

Note: Asymptotic t-statistics in small fonts below the corresponding coefficients
Estimation by Reweighted Least Squares using residuals from Least Trimmed Squares Regression

Table 7. Cross-Section Data- Threshold Regression Model
Dependent Variable Log-difference GDP per capita. Sample 1960-1998

	(1)				(2)				(3)				(4)			
Controls	X1				X1+INV				X1+Dummy				X1+INV+Dummy			
Threshold Variable	PCFY		LLY		PCFY		LLY		PCFY		LLY		PCFY		LLY	
LM test for no Threshold	0.078		0.024		0.030		0.087		0.331		0.393		0.073		0.454	
Threshold Estimate	27.353		31.198		24.518		31.198		24.518		30.791		24.518		30.791	
95% C.I	[27.353 -- 27.353]		[24.014 -- 46.224]		[11.453 -- 27.353]		[26.429 -- 33.854]		[11.490 -- 66.991]		[24.545 -- 46.224]		[12.088 -- 25.378]		[26.429 -- 43.174]	
N. Countries in 95% C.I.	1		32		44		15		69		31		35		24	
Regime	<=27.353	>27.353	<=31.198	>31.198	<=24.518	>24.518	<=31.198	>31.198	<=24.518	>24.518	<=30.791	>30.791	<=24.518	>24.518	<=30.791	>30.791
log(PCY)	0,346	0,411			0,276	0,103			0,162	0,316			0.151	0.110		
	3,45	2,34			1,44	0,87			1,57	1,97			#VALUE!	#VALUE!		
log(LLY)			0.569	0.434			0.444	0.159			0.183	0.320			0.120	0.206
			2,43	1,92			1,75	0,84			0,78	1,49			0,58	1,05
N.obs	44	39	38	45	38	45	38	45	38	45	37	46	38	45	37	46
R^2	0.37	0.68	0.48	0.53	0.49	0.71	0.49	0.66	0.72	0.63	0.69	0.68	0.72	0.72	0.69	0.70

Note: Estimation by OLS. Robust t-statistics in small fonts below the corresponding coefficients

LM test reports p-values for the null of a threshold effect. 95% C.I: is the confidence interval associated to the estimated threshold

X1 includes: ln(Y0), ln(SEC), ln(GOV), ln(OPEN), ln(1+INF), ln(1+BMP)

Dummies are for AFRICA and LAC

Table 8. Cross Section Data -- IV Estimates
Dependent Variable Log-difference GDP per capita. Sample 1960-1998

	(1)		(2)		(3)		(4)	
log(YO)	-0,329	-0,320	-0,303	-0,299	-0,486	-0,472	-0,479	-0,462
	1,81	1,91	1,77	2,05	4,68	4,76	3,80	4,55
log(INV)			0,515	0,516			0,061	0,083
			1,67	1,68			0,23	0,38
log(1+SEC)	0.479	0,621	0,375	0,381	0,422	0,459	0,400	0,428
	2,28	2,67	1,95	2,18	2,64	3,40	2,84	3,16
log(OPEN)	-0,305	-0,329	-0,196	-0,201	-0,304	-0,336	-0,291	-0,315
	2,14	2,43	1,70	1,40	3,18	3,50	3,11	2,76
log(GOV)	0,023	0,006	-0,063	-0,067	0,137	0,111	0,122	0,093
	0,21	0,06	0,54	0,59	1,48	1,13	1,22	0,99
log(1+INF)	-0,306	-0,181	-0,651	-0,635	0,573	0,594	0,489	0,471
	0,35	0,15	0,72	0,55	1,20	1,09	0,66	0,66
log(1+BMP)	-0,008	-0,036	0,020	0,015	-0,208	-0,228	-0,209	-0.885
	0,04	0,16	0,13	0,07	1,39	1,48	1,29	1,28
AFRICA					-0,834	-0,814	-0,800	-0,773
					3,85	3,74	4,40	3,92
LAC					-0,362	-0,296	-0,338	-0,272
					2,66	1,59	2,78	1,76
log(PCY)	0,171		0,041		0,222		0,210	
	0,41		0.10		0,74		0,59	
log(LLY)		0,243		0,050		0,300		0,269
		0,42		0,10		0,81		0,71
J Test (p-val)	0,93	0,92	0,93	0,95	0,91	0,91	0,90	0,92
R^2	0,43	0,44	0,50	0,50	0,66	0,66	0,66	0,66
N.obs	83	83	83	83	83	83	83	83

Note: Estimation by IV. Robust t-statistic in small fonts below the corresponding coefficients
J-Test refers to the Hansen test for the null that instruments are not correlated with the residuals
Instruments are: French, German and British legal origins

Table 9. Panel Data – SYS-GMM Estimates
Dependent Variable Log-difference GDP per capita

Estimation	Two-Step SYS-GMM		One-Step SYS-GMM		Two-Step SYS-GMM		One-Step SYS-GMM	
	(1)		(2)		(3)		(4)	
log(YO)	-0.037	-0.025	-0.030	-0.027	-0.053	-0.051	-0.053	-0.054
	6.23	7.91	1.21	1.06	8.68	13.60	2.10	2.09
log(INV)					0.078	0.033	0.088	0.094
					8.03	3.12	2.57	2.77
log(1+SEC)	0.128	0.056	0.119	0.054	0.101	0.033	0.087	0.048
	11.78	9.20	2.14	1.00	7.88	3.12	1.68	0.91
log(OPEN)	0.042	0.028	0.038	0.022	0.040	0.023	0.035	0.021
	11.79	6.22	1.06	0.72	7.57	5.26	1.06	0.75
log(GOV)	-0.075	-0.078	-0.069	-0.078	-0.076	-0.073	-0.080	-0.079
	13.28	14.47	1.77	2.01	7.96	13.75	2.52	2.41
log(1+INF)	-0.168	-0.104	-0.173	-0.107	-0.170	-0.091	-0.163	-0.121
	19.63	9.41	2.65	1.44	14.70	5.49	2.68	1.67
log(1+BMP)	-0.012	-0.040	-0.015	-0.038	-0.012	-0.031	-0.014	-0.025
	4.04	11.20	0.72	1.75	5.03	7.70	0.73	1.33
log(PCY)	0.024		0.021		0.009		0.006	
	7.32		0.83		4.18		0.29	
log(LLY)		0.072		0.074		0.060		0.048
		10.94		2.00		7.25		0.91
Sargan test	0.81	0.79	0.81	0.79	0.88	0.92	0.88	0.92
m2 test	0.90	0.81	0.90	0.81	0.90	0.75	0.90	0.75
N. Countries	87	87	87	87	87	87	87	87
N.obs	529	529	529	529	529	529	529	529

Note: SYS-GMM Estimates. Robust t-statistics are in samll fonts below the corresponding coefficients.
Sargan test and m2 test are p-values for the null of instruments validity
Instruments: Y0 and SEC are considered predetermined. The remaining variables endogenous
Data is in deviation from cross-section mean

Table 10. Panel Data Estimates
Dependent Variable Log-difference GDP per capita

Estimation	OLS				WG				Dif GMM				SYS GMM			
Controls	X1		X1+Inv		X1		X1+Inv		X1		X1+Inv		X1		X1+Inv	
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
log(PCY)	0.018		0,007		0,025		0,012		0.027		0.029		0.021		0.006	
	1.69		0,72		1,67		0,91		0.79		0.83		0.83		0,29	
log(LLY)		0.033		0,017		0,039		0,015		0.034		0.016		0.074		0.048
		2.00		1,03		1,70		0,69		0.70		0.34		2.00		0.91
Sargan Test									0.57	0.60	0.60	0.65	0.81	0.79	0.88	0.92
m2 test									0.73	0.59	0.83	0.62	0.90	0.81	0.90	0.75
N. Countries	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87
N.obs	529	529	529	529	442	442	442	442	442	442	442	442	529	529	529	529

Note: Estimators are, Pooled OLS (OLS), Within Groups (WG), First Difference GMM (DIF-GMM) and system GMM (SYS-GMM) estimates. Robust t-statistics are in small fonts below the corresponding coefficients.
Sargan test and m2 test are p-values for the null of instruments validity
Instruments: Y0 and SEC are considered predetermined. The remaining variables endogenous
X1 includes: ln(Y0), ln(SEC), ln(GOV), ln(OPEN), ln(1+INF), ln(1+BMP)
Data is in deviation from cross-sectional means

Table 11. Panel Data Estimates
Dependent Variable Log-difference GDP per capita.

(a) Sample: 1960-85

Sample	1960-1985				1960-1985			
Estimation	OLS	FE	DIF-GMM	SYS-GMM	OLS	FE	DIF-GMM	SYS-GMM
Controls	X1				X1+Inv			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(PCY)	0.030	-0,014	-0.051	0,008	0.013	-0,024	-0.048	-0,018
	2.00	0,43	0.88	0,18	1.13	0,83	1.03	0,44
Sargan			0.09	0.66			0.14	0.80
S.C 2 ord			0.48	0.57			0.59	0.54
log(LLY)	0.076	-0.006	-0.037	0.053	0.039	-0.024	-0.036	0.006
	3.52	0.13	0.39	0.71	1.84	0.61	0.45	0.14
Sargan			0.11	0.71			0.12	0.86
S.C 2 ord			0.53	0.57			0.71	0.55
N. Countries	73	73	73	73	73	73	73	73
N.obs	308	235	235	308	308	235	235	308

Note: See Notes to Table 8

(b) Sample: 1960-85

Sample	1970-1998				1970-1998			
Estimation	OLS	FE	DIF-GMM	SYS-GMM	OLS	FE	DIF-GMM	SYS-GMM
Controls	X1				X1+Inv			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(PCY)	0.009	0,015	-0.051	0,007	0.000	0,005	-0.051	0,013
	0.77	0,98	1.56	0,35	0.01	0,4	1.56	0,6
Sargan			0.27	0.91			0.28	0.87
S.C 2 ord			0.69	0.82			0.69	0.84
log(LLY)	0.018	0.027	-0.067	0.035	0.006	0.006	-0.033	0.049
	1.05	1.13	1.31	0.87	0.35	0.27	0.43	1.29
Sargan			0.47	0.84			0.29	0.90
S.C 2 ord			0.75	0.91			0.31	0.92
N. Countries	85	85	85	85	85	85	85	85
N.obs	430	345	345	430	430	345	345	430

Note: See notes to Table 8

Table 12. Panel Data Estimates
Dependent Variable Log-difference GDP per capita.

(a) Sample: 1960-98 Using sample of countries as in LLB

Sample	1960-1998 LLB Countries				1960-1998 LLB Countries			
Estimation	OLS	FE	DIF-GMM	SYS-GMM	OLS	FE	DIF-GMM	SYS-GMM
Controls	X1				X1+Inv			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(PCY)	0.032	0,025	0.037	0,021	0.006	0,008	0.033	0,003
	2.61	1,69	1.17	0,74	0.59	0,66	1.12	0,15
Sargan			0.78	0.74			0.98	0.95
S.C 2 ord			0.92	0.85			0.84	0.70
log(LLY)	0.069	0.022	0.013	0.078	0.034	-0.006	0.009	0.051
	4.75	0.96	0.27	2.06	1.99	0.30	0.19	1.45
Sargan			0.89	0.62			0.98	0.94
S.C 2 ord			0.72	0.70			0.66	0.59
N. Countries	73	73	73	73	73	73	73	73
N.obs	492	415	415	492	492	415	415	492

Note: see notes in Table 8

(b) Sample: 1960-98 on 10 years average data

Sample	1960-1998--10Years				1960-1998--10Years			
Estimation	OLS	FE	DIF-GMM	SYS-GMM	OLS	FE	DIF-GMM	SYS-GMM
Controls	X1				X1+Inv			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(PCY)	0.056	0,062	0.029	0,071	0.041	0,043	0.044	0,053
	2.32	1,91	0.43	1,81	1.63	1,25	0.71	1,3
Sargan			0.45	0.51			0.25	0.38
S.C 2 ord			0.44	0.72			0.60	0.73
log(LLY)	0.085	0.077	0.004	0.050	0.065	0.049	-0.018	-0.004
	2.55	1.86	0.054	0.66	1.80	1.14	0.28	0.05
Sargan			0.40	0.30			0.23	0.22
S.C 2 ord			0.63	0.67			0.57	0.71
N. Countries	80	80	80	80	80	80	80	80
N.obs	285	205	205	285	285	205	205	285

Note: see notes in Table 8

Table 13. Panel Data: One-Step GMM Estimates
Dependent Variable: Log-difference GDP per capita. Sample: 1960-1998

	(1)		(2)		(3)		(4)		(5)	
log(YO)	-0.039	-0.033	-0.039	-0.039	-0.073	-0.085	-0.032	-0.027	-0.042	-0.052
	1.26	1.14	1.06	1.15	2.34	2.95	1.21	1.04	1.49	1.73
log(INV)					0,105	0.120	0.096	0.109	0.094	0.124
					2,94	3.51	3.04	3.10	3.16	3.98
log(1+SEC)	0.107	0.066	0.103	0.073	0.058	0.053	0.030	0.006	0.043	0.014
	1.86	1.33	2.05	1.48	1.18	1.14	0.60	0.13	0.93	0.30
log(GOV)			-0.069	-0.075	-0.095	-0.100			-0.075	-0.084
			1.36	1.58	2.34	0.04			1.93	2.07
log(1+INF)			-0.209	-0.175			-0.197	-0.180	-0.201	-0.140
			3.02	1.96			2.90	2.57	2.77	1.92
log(PCY)	0.052		0.021		0.028		0.024		0.016	
	3.24		0.96		1.35		1.33		0.65	
log(LLY)		0.095		0.052		0.063		0.032		0.044
		3.90		1.96		2.16		0.97		1.28
Sargan Test	0.62	0,65	0.69	0,65	0.78	0,71	0.69	0,73	0.50	0.44
m2 test	0.80	0,81	0.95	0,73	0.92	0,67	0.96	0,77	0.86	0.64
N. Countries	87	87	87	87	87	87	87	87	87	87
N.obs	529	529	442	442	442	442	529	529	442	442

Notes: see notes to Table 7

Table 14. Pooled Mean Group (PMG) estimates
Sample 1960-1998

Model	SB<=2				SB<=2			
	PMG	h-test	PMG	h-test	PMG	h-test	PMG	h-test
	(1)		(2)		(3)		(4)	
log(YO)	-0,097		-0,129		-0,126		-0,184	
	5,67		4,17		5,39		5,44	
log(INV)	--		--		0,459	0,13	0,418	0,77
					18,62		23,70	
log(OPEN)	0,144	0,32	0,074	0,34	-0,058	0,92	-0,114	0,29
	6,27		3,91		2,42		6,14	
log(GOV)	-0,028	0,46	-0,038	0,03	-0,069	0,48	-0,282	0,62
	1,89		2,49		4,37		16,96	
log(1+INF)	-0,939	0,34	-1,148	0,11	-0,616	0,76	-0,539	0,26
	9,87		15,88		9,07		9,21	
log(PCY)	0,045	0,91			-0,025	0,74		
	3,13				2,54			
log(LLY)			0,025	0,30			-0,060	0,13
			1,38				3,22	
H-Test	0,67		0,15		0,68		0,14	
Avg. R^2	0,5		0,53		0,63		0,63	
N. Countries	71		71		71		71	
N.Obs	2400		2400		2400		2400	

Note: Asymptotic t-statistics are in small fonts below the corresponding coefficients
h-test reports p-vaules for the Haussman test of no difference between Mean Group and Pooloed Mean Group estimates. High p-values validate the assumption of homogeneity of the corresponding coefficient
H-test refer to the Haussman test for the null of poolability of the all coefficients

Table 15. Country Classification Based on the PMG Estimates of Table 12

PCY<0	PCY>0	LLY<0	LLY>0
(1)		(2)	
United States	Belgium	United Kingdom	United States
United Kingdom	Germany	Austria	Belgium
Austria	Sweden	Germany	France
France	Finland	Sweden	Netherlands
Netherlands	Australia	Switzerland	Norway
Norway	New Zealand	Japan	Canada
Switzerland	Argentina	Greece	Finland
Canada	Bolivia	Portugal	Ireland
Japan	Chile	Spain	Turkey
Greece	Colombia	New Zealand	Australia
Ireland	Ecuador	Argentina	Chile
Portugal	Guatemala	Bolivia	Colombia
Spain	Honduras	Ecuador	Costa Rica
Turkey	Mexico	Guatemala	Dominican Republic
Costa Rica	Paraguay	Haiti	El Salvador
Dominican Republic	Uruguay	Mexico	Honduras
El Salvador	Barbados	Paraguay	Uruguay
Haiti	Trinidad and Tobago	Peru	Venezuela
Peru	Cyprus	Barbados	Trinidad and Tobago
Venezuela	Iran, Islamic Rep. of	Jamaica	Cyprus
Jamaica	Syria	Israel	Iran, Islamic Rep. of
Israel	Sri Lanka	Egypt, Arab Rep.	Syria
Egypt, Arab Rep.	India	Indonesia	Sri Lanka
Indonesia	Nepal	Korea	India
Korea	Pakistan	Malaysia	Nepal
Malaysia	Algeria	Pakistan	Singapore
Philippines	Cameroon	Philippine	Algeria
Singapore	Ethiopia	Thailand	Cameroon
Thailand	Gabon	Kenya	Ethiopia
Côte d'Ivoire	Gambia	Mauritius	Gabon
Kenya	Ghana	Morocco	Gambia
Mauritius	Madagascar	Niger	Ghana
Niger	Morocco	Rwanda	Côte d'Ivoire
Rwanda	Nigeria	Togo	Madagascar
	South Africa		Nigeria
	Senegal		South Africa
	Togo		Senegal

Table 16. PMG Estimates by Model Specification
Sample: 1960-1998.

Model	ARDL(1,1,...1)		SB<=1		ARDL(2,2,...2)		ARDL(1,1,...1)		SB<=1		ARDL(2,2,...2)	
	(2)		(3)		(3)		(5)		(6)		(6)	
log(YO)	-0,086	-0,038	-0,118	-0,105	-0,092	-0,094	-0.080	-0.065	-0,126	-0,109	-0,089	-0,071
	6,96	5,85	5,32	4,90	5,32	4,99	6.99	5,60	5,39	5,55	5,42	5,24
log(INV)	--	--	--	--	--		0.397	0.492	0,448	0,405	0,421	0,424
							14.95	15,03	2,53	19,62	15,16	15,06
log(OPEN)	0,283	0,592	0,226	0,272	0,026	0,116	0.137	-0,029	-0,122	-0,107	-0,008	-0,050
	11,41	8,22	10,68	9,90	11,53	5,70	5.38	2,60	5,69	5,38	0,280	1,56
log(GOV)	-0,132	-0,802	-0,137	-0,151	-0,090	-0,088	-0.022	-0,098	-0,287	-0,336	-0,028	0,000
	8,55	8,97	8,95	6,56	6,87	5,76	1.24	3,80	13,21	15,01	1,55	0,014
log(1+INF)	-0,761	-2,102	-0,820	-1,141	-0,430	-0,838	-0.599	-0,835	-0,588	-0,571	-0,636	-0,711
	8,16	7,51	10,37	11,31	5,63	10,41	6.74	7,47	9,29	9,18	7,46	7,45
log(PCY)	-0,138		-0,146		-0,040		-0.046		-0,054		-0,028	
	6,08		7,52		2,09		2,83		4,54		2,39	
log(LLY)		-0,382		-0,234		0,028		-0,100		-0,033		-0,063
		5,74		6,45		1,39		3,41		1,49		2,46
H-test	0,71	0,91	0,19	0,39	0,64	0,42	0,01	0,09	n.a.	0,55	n.a.	0,25
N. Countries	71	71	71	71	71	71	71	71	71	71	71	71
N.obs	2471	2471	2471	2471	2471	2471	2471	2471	2471	2471	2471	2471

Note: See notes to Table 12

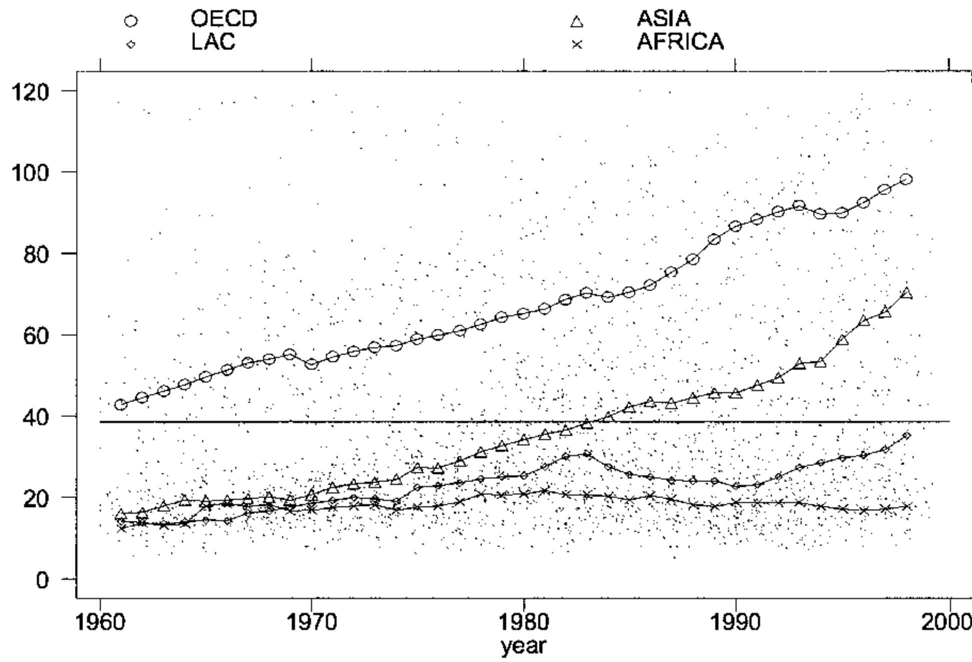
Table 17. PMG Estimates by Set of Control Variables
Sample 1960-1998

Model	SB<=2															
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
log(YO)	-0,095	-0,084	-0,071	-0,111	-0,117	-0,097	-0,072	-0,082	-0,104	-0,092	-0,107	-0,094	-0,144	-0,143	-0,128	-0,101
	6,6	6,8	6,67	4,51	5,82	6,17	4,47	5,83	7,23	6,15	5,33	4,61	6,05	5,07	5,66	4,74
log(INV)							0,698	0,493	0,372	0,386	0,677	0,605	0,381	0,343		
							16,30	15,60	17,68	20,09	19,64	23,21	18,86	24,82		
log(OPEN)					0,166	0,175					-0,24	-0,274	-0,058	-0,045	0,283	0,038
					8,01	8,89					7,38	11,09	2,98	2,93	16,39	1,91
log(GOV)			-0,135	-0,049					-0,284	-0,272			-0,201	-0,308	-0,153	-0,277
			5,16	2,51					12,13	11,51			10,57	17,75	10,13	12,15
log(1+INF)	-1,161	-1,267	-1,329	-1,393	-0,874	-0,822										
	9,13	9,52	9,53	16,07	1,22	10,21										
log(PCY)	0,027		-0,228		0,018		0,033		-0,011		-0,016		-0,016		0,001	
	1,31		7,34		1,22		1,56		0,842		1,11		1,85		0,013	
log(LLY)		-0,018		0,018		-0,113		-0,064		-0,108		0,089		-0,035		0,138
		0,49		0,837		4,33		2,35		4,77		4,35		1,92		5,05
H-test	0,41	0,54	0,71	0,15	0,98	0,64	0,60	0,27	0,44	0,12	0,23	0,00	0,53	0,22	0,23	0,69
N. Countries	71	71	71	71	71	71	71	71	71	71	71	71	71	71	71	71
N.obs	2400	2400	2400	2400	2400	2400	2400	2400	2400	2400	2400	2400	2400	2400	2400	2400

Note: see notes to Table 12

Figure 1: Distribution of *PCY* and *LLY*

(a) Distribution of *PCY*



(b) Distribution of *LLY*

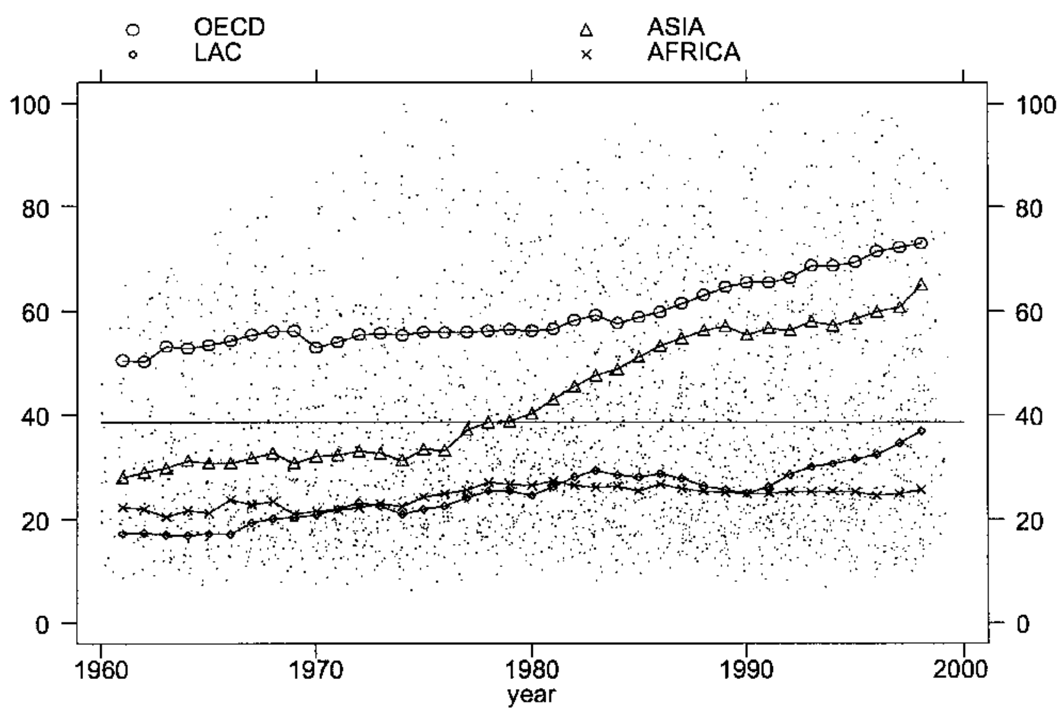


Figure 2. Time series plot for PCY, LLY and GDP

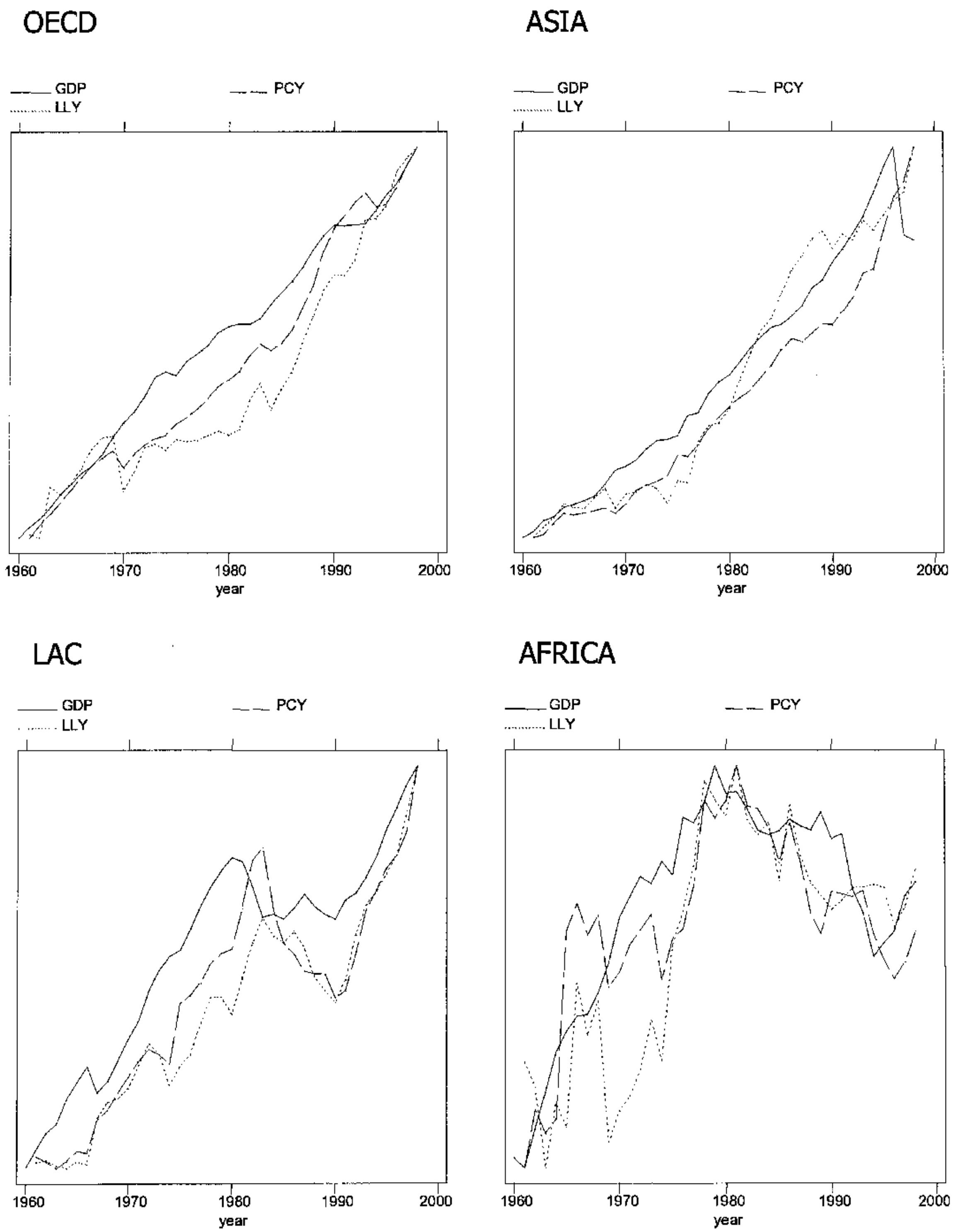


Figure 3: $\theta(.)$ Function for PCY and LLY

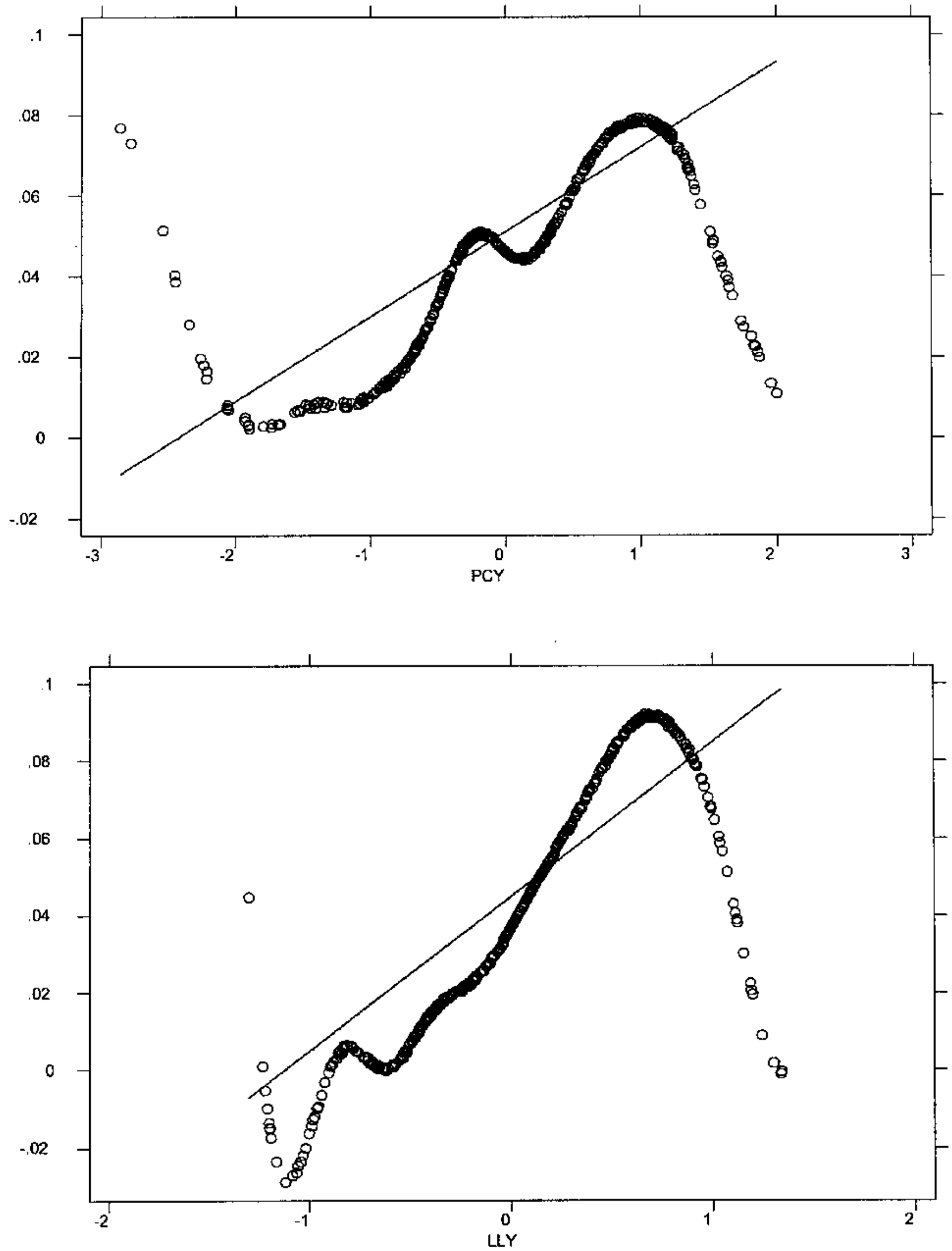
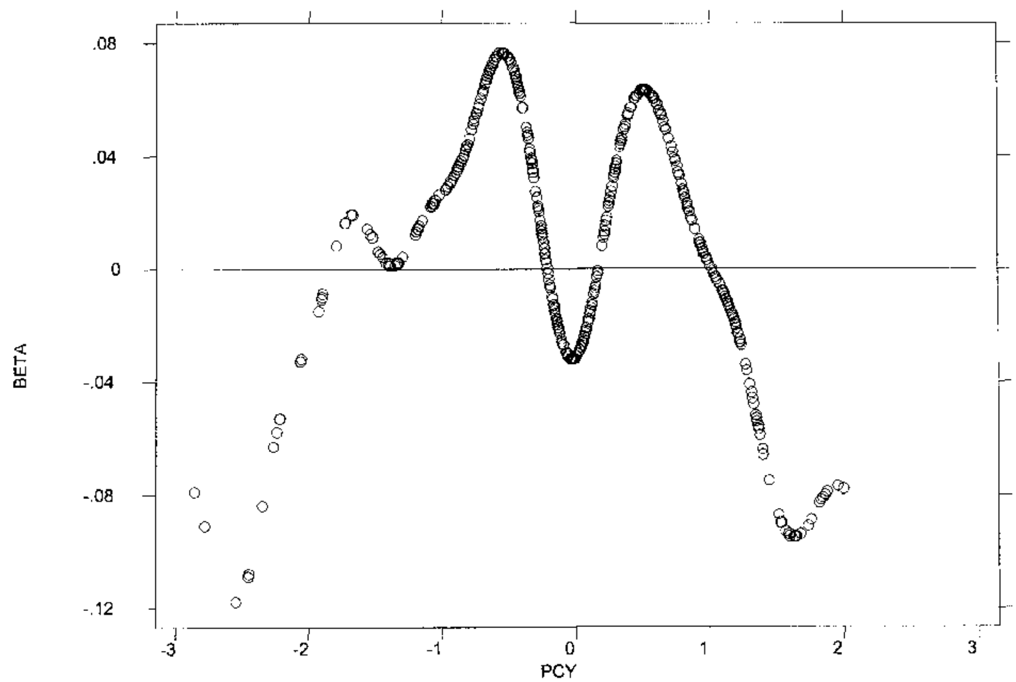


Figure 4: $\beta(.)$ Function for PCY and LLY



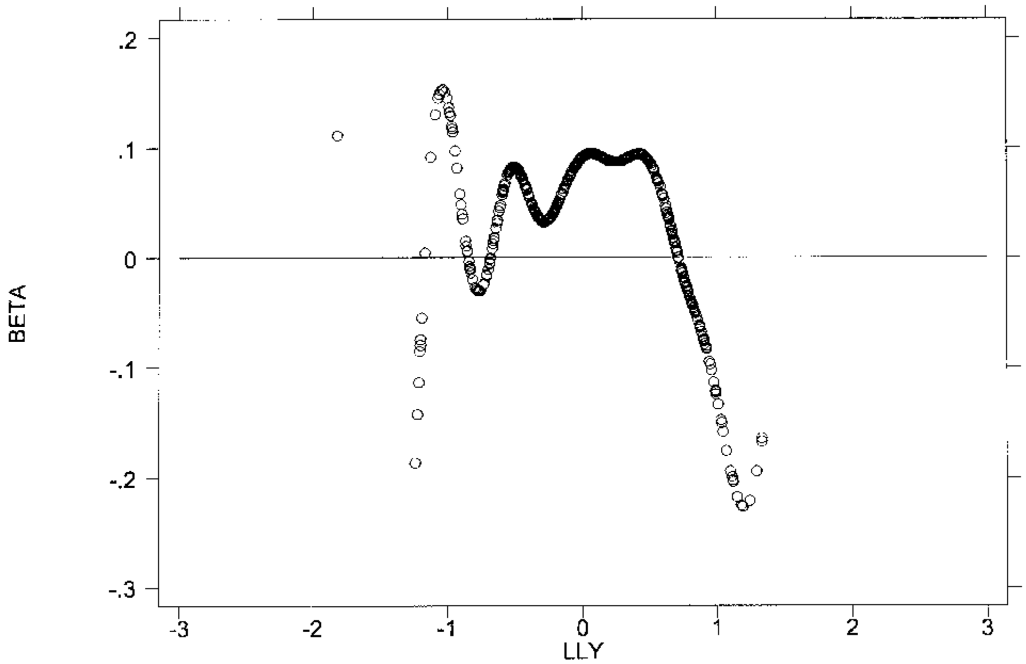
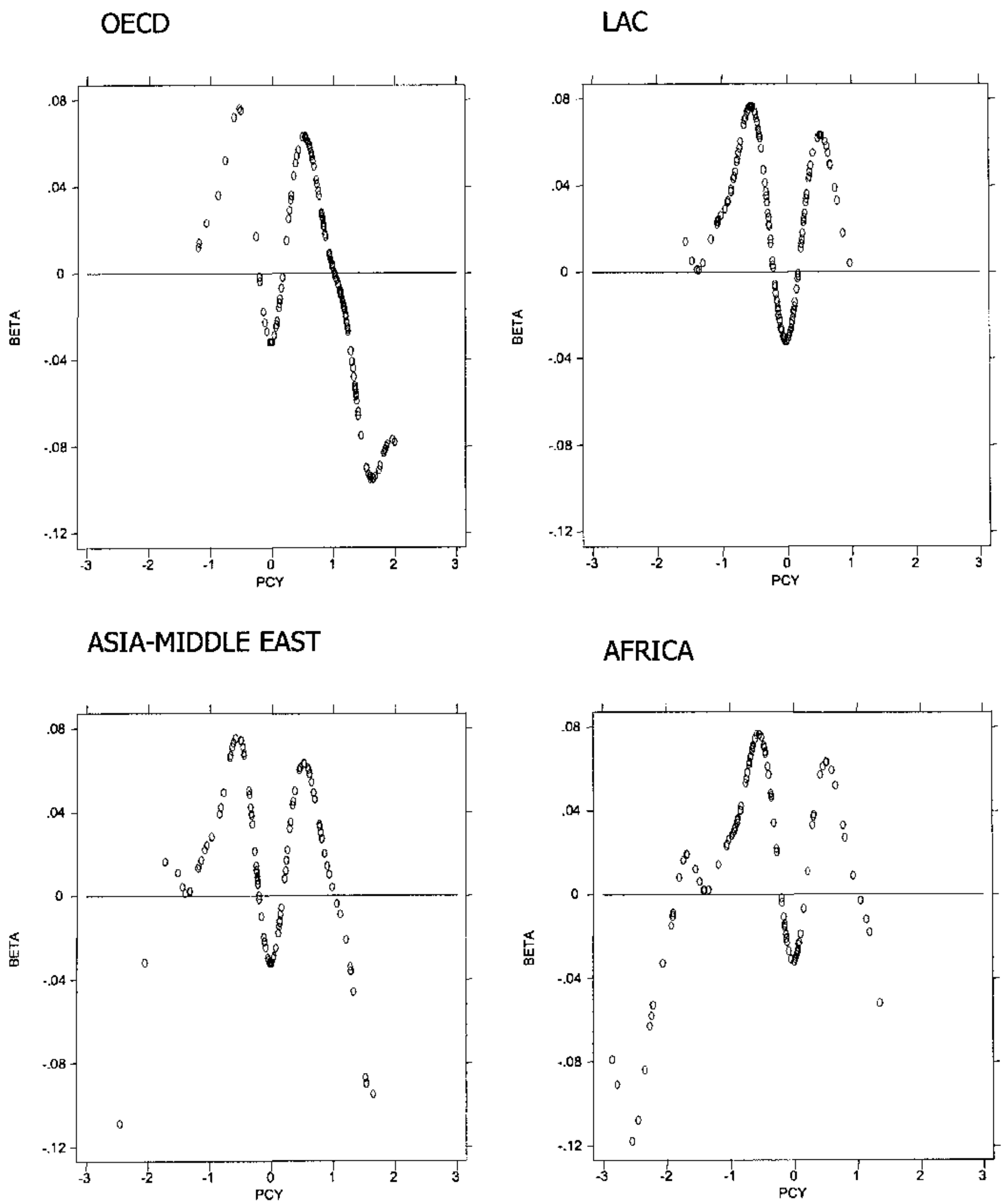


Figure 5. $\beta(.)$ Function for PCY across Countries



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