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FINANCIAL DEVELOPMENT, FINANCIAL FRAGILITY, AND GROWTH

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Abstract

This paper attempts to reconcile the apparent contradiction between two strands of the literature on the effects of financial intermediation on economic activity. On the one hand, the empirical growth literature finds a positive effect of financial depth as measured by, for instance, private domestic credit and liquid liabilities (e.g., Levine, Loayza, and Beck 2000). On the other hand, the banking and currency crisis literature finds that monetary aggregates, such as domestic credit, are among the best predictors of crises and their related economic downturns (e.g., Kaminski and Reinhart 1999). This paper starts by illustrating these opposing effects by, first, analyzing the dynamics of output growth and financial intermediation around systemic banking crises and, second, showing that the growth enhancing effects of financial depth are weaker in countries that experienced such crises. After these illustrative exercises, the paper attempts an empirical explanation of the apparently opposing effects of financial intermediation. This explanation is based on a distinction between transitory and trend effects of domestic credit aggregates on economic growth. Working with a panel of cross-country and time-series observations, the paper estimates an encompassing model of long- and short-run effects, following Pesaran, Shin, and Smith (1999)'s Pooled Mean Group Estimator. The main result of the paper is that a positive long-run relationship between financial intermediation and output growth co-exists with a, mostly, negative short-run relationship.

JEL Classification: G21, N1, N2.

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FINANCIAL DEVELOPMENT, FINANCIAL FRAGILITY AND GROWTH

I. INTRODUCTION

This paper attempts to reconcile the apparent contradiction between two strands of the literature on the effects of financial intermediation on economic activity. On the one hand, the empirical growth literature finds a positive effect of measures of private domestic credit and liquid liabilities on per capita GDP growth. This is interpreted as the growth enhancing effect of financial development (e.g., King and Levine, 1993; Levine, Loayza, and Beck, 2000). On the other hand, the banking and currency crisis literature finds that monetary aggregates, such as domestic credit, are among the best predictors for crises (e.g., Demirguc-Kunt and Degatriache, 1998 and 2000; Gourinchas, Landerretche, and Valdes, 1999; Kaminsky and Reinhart, 1999). Since banking crises usually lead to recessions, an expansion of domestic credit would then be associated to growth slowdowns.

A similar divide exists at the theoretical level. According to the endogenous growth literature, financial deepening leads to a more efficient allocation of savings to productive investment projects (see Greenwood and Jovanovic, 1990; Bencivenga and Smith, 1991). Conversely, the financial crisis literature points to the destabilizing effect of financial liberalization as it leads to overlending. Overlending would occur through a combination of channels, including a limited monitoring capacity of regulatory agencies, the inability of banks to discriminate good projects during investment booms, and the existence of an explicit or implicit insurance against banking failures (Shneider and Tornell, 2000; Aghion, Bacchetta and Banerjee, 1999). Not surprisingly, each strand of the literature has produced its own set of policy implications. Thus, researchers that emphasize the findings of the endogenous growth literature advocate financial liberalization and deepening (e.g., Roubini and Sala-i-Martin, 1992), while those that concentrate on crises caution against "excessive" financial liberalization (e.g., Balino and Sundarajan, 1991; Gavin and Hausman, 1995).

This paper seeks to contribute to the debate from an empirical perspective. In section II we examine how the relationship between measures of financial depth and economic growth is affected by the presence of financial crises. For this purpose, we first describe the behavior of financial intermediation and output growth around episodes of banking crises. We then reconsider the evidence on the positive growth effect of financial deepening by analyzing whether this effect is weaker in countries afflicted by financial crises.

In section III the paper attempts an empirical explanation of the apparently contradictory effects of financial intermediation on economic activity. This explanation is based on the distinction between cycle and trend changes of financial intermediation and their corresponding effects on output growth. Working with a panel of cross-country and time-series observations, we estimate an encompassing model of long- and short-run effects. Section IV concludes.

II. The Relationship between Financial Depth and Growth in the Presence of Financial Crises

In this section we examine how the relationship between measures of financial depth and economic growth is affected by the presence of financial crises. First, we describe the behavior over time of financial intermediation and output growth around banking crises. We do it by using an event-study methodology applied to a panel of countries that have experienced such crises, as identified by Caprio and Klingbiel (1999). Second, we revisit the evidence on the positive growth effect of financial deepening by testing whether this effect is weaker in countries that have experienced banking crises. For this purpose, we follow the GMM cross-country panel-data approach to growth empirics in Levine, Loayza and Beck (2000).[1]

A. The behavior of financial intermediation and economic activity around episodes of financial crises

Here we describe the behavior of financial intermediation and economic activity in a typical country before and after the start of a banking crisis. We use total liquid liabilities and domestic credit to the private sector, both as ratios to GDP, as the measures of financial intermediation. Economic activity is measured with total and per capita GDP growth rates.

[1] See also Caselli, Esquivel, and Lefort (1996), Easterly, Loayza, and Montiel (1997), and Beck, Levine, and Loayza (2000).

We first identify the episodes of banking crises for a large sample of countries following Caprio and Klingbiel (1999). According to the Caprio and Klingbiel classification, a systemic banking crisis is a situation where all or most of the capital of the banking system is eroded. In this situation, even if some banks stay solvent, the net worth of the banking system as a whole is negative. A banking crisis is almost always associated with a ratio of non-performing assets larger than 10% and a rescue cost higher than 2% of annual GDP. The list of countries and time periods where systemic banking crises occurred is given in Appendix A.

Second, applying an event-study methodology, we make country experiences comparable by re-scaling calendar time into crisis-centered time for each country. Moreover, to eliminate country-specific effects, we demean each observation with the corresponding country average.

We focus the analysis on the 12-year widow centered on the start of the banking crisis. Figure 1 presents the behavior of the typical country-year observation, which is given by the median across countries in a particular year for each measure of financial intermediation and output growth. Table 1 presents Students' t-tests for the significance of level and correlation changes over the 12-year period.

Both liquid liabilities and private credit rise rapidly before the crisis then drop drastically once it starts. They recover partially in the following years but remain far below their pre-crisis levels. On the other hand, total and per capita GDP growth rates fall in the years prior to the banking crisis, reach the bottom at the onset of the crisis, and recover gradually afterwards. The correlation between the measures of financial intermediation and economic activity depend on the period where the correlation is computed. In general, however, the correlation between growth and financial intermediation is negative in the years prior to and after the crisis. In the case of private credit, its correlation with growth is strongly negative prior to the crisis, and it becomes close to neutral in the aftermath.

In summary, this first exercise shows that credit booms do precede banking crisis and that the relationship between financial intermediation and growth is negative in the years surrounding banking crises.

Figure 1a: Financial Intermediation

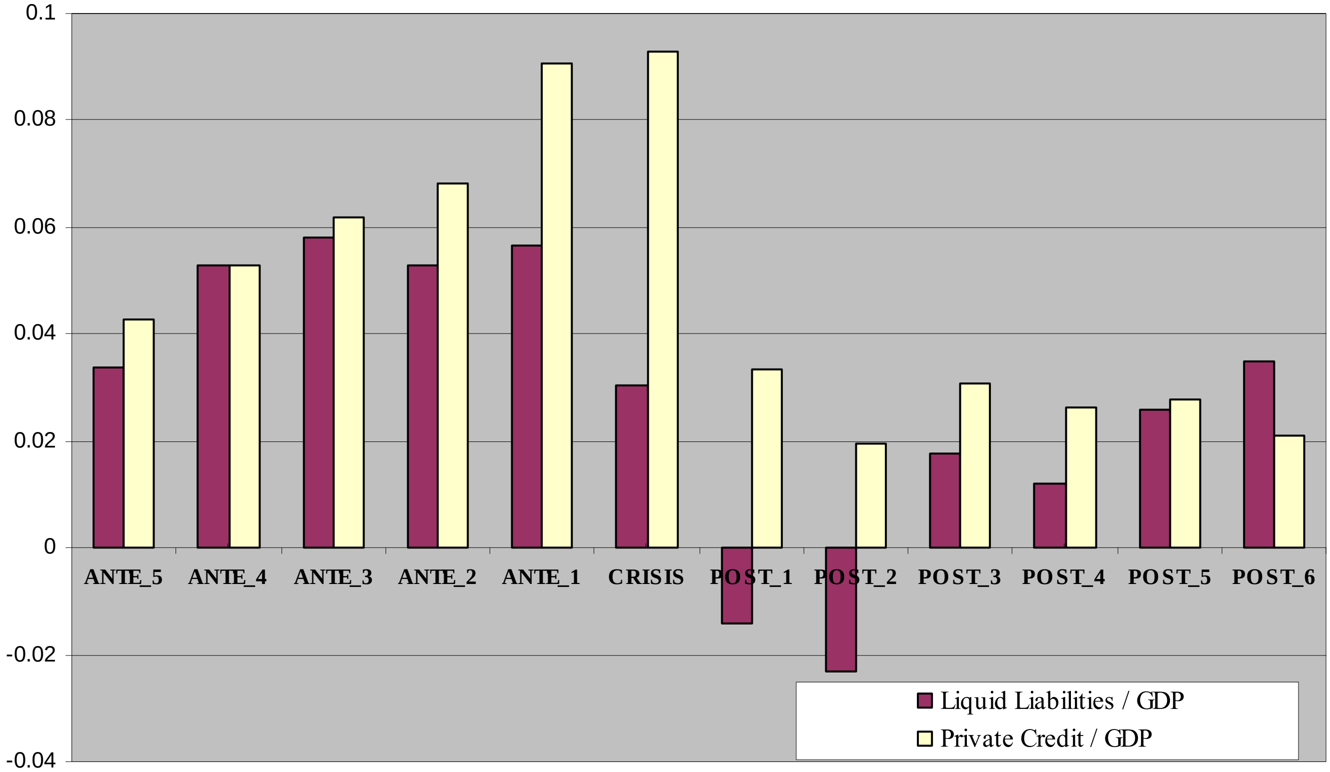

Figure 1b: Growth

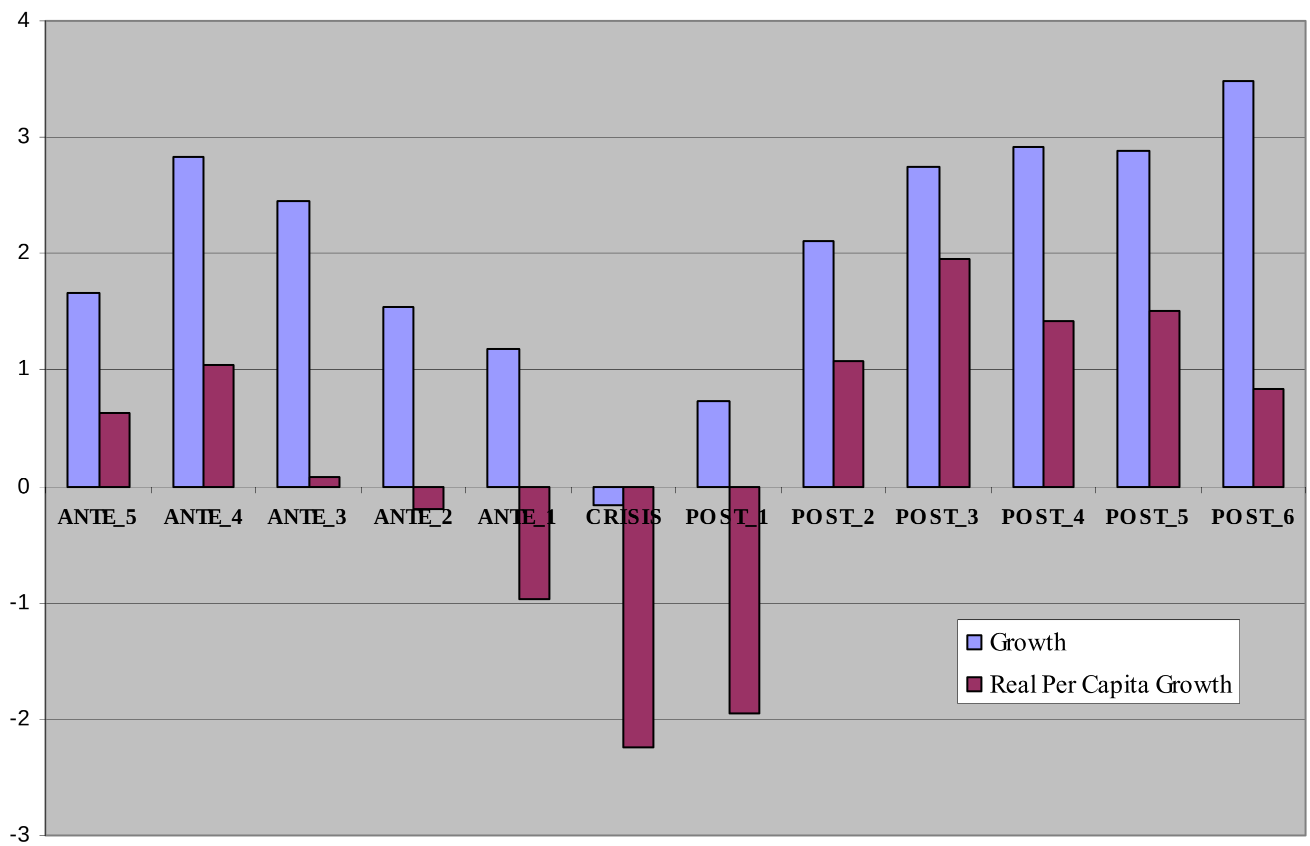

Table 1 Descriptive Statistics for Countries with Crisis Experience

	ANTE CRISIS PERIOD	CRISIS PERIOD	T-test P-Value
	t-5 to the starting year of crisis, t	t+1 to t+6	Ho: ante=crisis
Liquid Liabilities /GDP	0.047578843	0.007509945	0.07
OBS	*48*	*50*	
Private Credit/ GDP	0.066891752	0.027435856	0.06
OBS	*48*	*49*	
Real Per Capita Growth	-0.269641648	0.780450416	0.0157
OBS	*56*	*53*	
Correlation (Liquid Liabilities, Growth)	-0.1072	-0.1208	0.35
OBS	*42*	*40*	
Correlation (Private Credit, Growth)	-0.347	-0.18	0.07
OBS	*42*	*41*	

B. Revisiting the evidence on the growth effects of financial deepening

Working with a large cross-section of countries, King and Levine (1993a, 1993b) find a positive relationship between initial financial intermediation depth and subsequent long-run growth performance. In these and related studies, the long-run growth rate is estimated as the average rate over periods of time as long as 25-30 years. King and Levine use initial measures of financial intermediation (rather than, say, period averages) to be able to conclude that more developed financial systems lead to higher growth. Levine, Loayza, and Beck (2000) address directly the issue of joint endogeneity of financial development through the use of instrumental variables in their growth regressions. They use the countries' legal origin as the "external" instrument for financial depth in their cross-sectional regressions and the lagged observations of all explanatory variables as "internal" instruments in their pooled (cross-country and time-series) regressions. The data panels used by Levine et al. consist of about 74 countries and, for each of them, non-overlapping five-year averages covering the period 1960-95. They use five-year averages, rather than annual observations, to smooth out transitory or business-cycle fluctuations. Confirming previous results, Levine et al. find robust evidence that financial development and depth lead to an improved growth performance.

It is arguable that in most cases, using low-frequency data (such as averages over five or more years) allows the researcher to concentrate on long-run effects. However, in cases of prolonged or deep recessions, such as those associated with financial crises, even averages over long periods may be contaminated by cycle effects. Developing this argument, De Gregorio and Guidotti (1995) present evidence that while in cross-sectional regressions involving a worldwide sample of countries financial intermediation is positively linked with growth, in panel regressions for only Latin American countries, the relationship is negative. They suggest that their results for Latin America may reflect the lasting impact of the repeated financial crises (and associated overlending) that the region has suffered. However, De Gregorio and Guidotti do not offer direct evidence on the role of financial crises in distorting the financial intermediation and growth relationship. Moreover, it is possible that their contrasting results between the worldwide and Latin American samples are actually due to the use of cross-sectional vs. panel-data estimators.

We now analyze how the presence of financial crises modifies the estimated link between measures of financial intermediation and economic growth. For this purpose, we work with the same data and methodology as in Levine, Loayza, and Beck (2000) but allow for, respectively, a banking-crisis and a Latin America effect.

Data and Methodology

We work with a pooled data set consisting of 74 countries and, for each of them, at most 7 non-overlapping five-year periods spanning the years 1960-95. The resulting panel of country and time-period observations is unbalanced. Appendix B lists the countries included in the sample, and Appendix C presents the definitions and sources of the variables included in our empirical model.

We estimate a growth regression using panel data. As standard in the literature, the regression equation is dynamic given that it includes the initial level of per capita output as an explanatory variable. Apart from the measure of financial intermediation, the regression equation considers a set of control variables, including initial per capita output, average secondary school attainment of the adult population, the average ratio of government consumption to GDP, the average inflation rate, and the average black market premium on foreign exchange.

The regression equation to be estimated is the following,

$$y_{i,t} - y_{i,t-1} = (\alpha - 1) y_{i,t-1} + \beta' CV_{i,t} + \delta FD_{i,t} + \mu_t + \eta_i + \varepsilon_{i,t} \quad (1)$$

where, y is the logarithm of real per capita output, CV is a set of control variables, FD is an indicator of financial depth, μ_t is a time-specific effect, η_i is an unobserved country-specific effect, and ε is the error term. The subscripts i,t represent country and time-period, respectively. We assess the banking-crisis and the Latin-America effects by introducing a slope dummy on the financial depth indicator.

The proposed growth regression poses some challenges for estimation. The first is the presence of unobserved period- and country-specific effects. While the inclusion of period-specific dummy variables can account for the time effects, the common methods to deal with country-specific effects ("within" or differences estimators) are inappropriate given the dynamic nature of the regression. The second challenge is that most explanatory variables are likely to be jointly endogenous with economic growth. Then we need to control for the biases resulting from simultaneous or reverse causation. In the following paragraphs we outline the econometric methodology we use to control for unobserved country-specific effects and joint endogeneity in a dynamic model of panel data.

Econometric methodology

We use the Generalized-Method-of-Moments (GMM) estimators developed for dynamic models of panel data that were introduced by Holtz-Eakin, Newey, and Rosen (1988), Arellano and Bond (1991), and Arellano and Bover (1995). Taking advantage of the panel nature of the data, these estimators are based on, first, differencing regressions and/or instruments to control for unobserved effects, and, second, using previous observations of the explanatory variables as instruments (which are called "internal" instruments).

After accounting for the time-specific effects and grouping all explanatory variables in a vector X, we can rewrite equation (1) as follows,

$$y_{i,t} = \alpha y_{i,t-1} + \beta' X_{i,t} + \eta_i + \varepsilon_{i,t} \quad (2)$$

In order to eliminate the country-specific effect, we take first-differences of equation (2),

$$y_{i,t} - y_{i,t-1} = \alpha\left(y_{i,t-1} - y_{i,t-2}\right) + \beta'\left(X_{i,t} - X_{i,t-1}\right) + \left(\varepsilon_{i,t} - \varepsilon_{i,t-1}\right) \tag{3}$$

The use of instruments is required to deal with (i) the likely endogeneity of the explanatory variables, and, (ii) the problem that, by construction, the new error term, $\varepsilon_{i,t} - \varepsilon_{i,t-1}$, is correlated with the lagged dependent variable, $y_{i,t-1} - y_{i,t-2}$. Taking advantage of the panel nature of the data set, the instruments consist of previous observations of the explanatory and lagged dependent variables. Given that it relies on past values as instruments, this method only allows current and future values of the explanatory variables to be affected by the error term. Therefore, while relaxing the common assumption of strict exogeneity, our instrumental-variable method does not allow the *X* variables to be fully endogenous.

Under the assumptions that (a) the error term, ε, is not serially correlated, and (b) the explanatory variables, *X*, are weakly exogenous (i.e., the explanatory variables are assumed to be uncorrelated with future realizations of the error term), the GMM dynamic panel estimator uses the following moment conditions.

$$E\left[y_{i,t-s} \cdot \left(\varepsilon_{i,t} - \varepsilon_{i,t-1}\right)\right] = 0 \quad for\ s \geq 2; t = 3, \ldots, T \tag{4}$$

$$E\left[X_{i,t-s} \cdot \left(\varepsilon_{i,t} - \varepsilon_{i,t-1}\right)\right] = 0 \quad for\ s \geq 2; t = 3, \ldots, T \tag{5}$$

The GMM estimator based on these conditions is known as the *difference* estimator. Notwithstanding its advantages with respect to simpler panel data estimators, there are important statistical shortcomings with the difference estimator. Alonso-Borrego and Arellano (1999) and Blundell and Bond (1998) show that when the explanatory variables are persistent over time, lagged levels of these variables are weak instruments for the regression equation in differences. Instrument weakness influences the asymptotic and small-sample performance of the difference estimator.

Asymptotically, the variance of the coefficients rises. In small samples, Monte Carlo experiments show that the weakness of the instruments can produce biased coefficients.[2]

To reduce the potential biases and imprecision associated with the usual difference estimator, we use a new estimator that combines in a *system* the regression in differences with the regression in levels (developed in Arellano and Bover 1995 and Blundell and Bond 1997). The instruments for the regression in differences are the same as above. The instruments for the regression in levels are the lagged *differences* of the corresponding variables. These are appropriate instruments under the following additional assumption: there should be no correlation between the *change* in the right-hand-side variables and the country-specific effect (which does not preclude from correlation between the levels of these variables and the country-specific effect). This assumption results from the following stationarity property,

$$E\left\lfloor y_{i,t+p} \cdot \eta_i \right\rfloor = E\left\lfloor y_{i,t+q} \cdot \eta_i \right\rfloor \quad \text{and}$$
$$E\left[X_{i,t+p} \cdot \eta_i\right] = E\left[X_{i,t+q} \cdot \eta_i\right] \quad \text{for all } p \text{ and } q \tag{6}$$

The additional moment conditions for the second part of the system (the regression in levels) are:[3]

$$E\left[\left(y_{i,t-1} - y_{i,t-2}\right) \cdot \left(\eta_i + \varepsilon_{i,t}\right)\right] = 0 \tag{7}$$
$$E\left[\left(X_{i,t-1} - X_{i,t-2}\right) \cdot \left(\eta_i + \varepsilon_{i,t}\right)\right] = 0 \tag{8}$$

Thus, we use the moment conditions presented in equations (4), (5), (7), and (8) and employ a GMM procedure to generate consistent and efficient parameter estimates.

Using the moment conditions presented in equations (4), (5), (7), and (8), we employ a Generalized Method of Moments (GMM) procedure to generate consistent

[2] An additional problem with the simple *difference* estimator relates to measurement error: differencing may exacerbate the bias due to errors in variables by decreasing the signal-to-noise ratio (see Griliches and Hausman, 1986).

[3] Given that lagged levels are used as instruments in the differences specification, only the most recent difference is used as instrument in the levels specification. Using other lagged differences would result in redundant moment conditions. (see Arellano and Bover 1995).

estimates of the parameters of interest and their asymptotic variance-covariance (Arellano and Bond 1991, and Arellano and Bover 1995). These are given by the following formulas:

$$\hat{\theta} = (\overline{X}' Z \hat{\Omega}^{-1} Z' \overline{X})^{-1} \overline{X}' Z \hat{\Omega}^{-1} Z' \overline{y} \qquad (9)$$

$$AVAR(\hat{\theta}) = (\overline{X}' Z \hat{\Omega}^{-1} Z' \overline{X})^{-1} \qquad (10)$$

where θ is the vector of parameters of interest (α, β), $\overline{y}$ is the dependent variable stacked first in differences and then in levels, $\overline{X}$ is the explanatory-variable matrix (including the lagged dependent variable, that is, $[y_{t-1}, X]$) stacked first in differences and then in levels, Z is the matrix of instruments derived from the moment conditions, and $\hat{\Omega}$ is a consistent estimate of the variance-covariance matrix of the moment conditions.[4]

The consistency of the GMM estimators depends on whether lagged values of the explanatory variables are valid instruments in the crime-rate regression. We address this issue by considering two specification tests suggested by Arellano and Bond (1991) and Arellano and Bover (1995). The first is a Sargan test of over-identifying restrictions, which tests the overall validity of the instruments by analyzing the sample analog of the moment conditions used in the estimation process. Failure to reject the null hypothesis gives support to the model. The second test examines the null hypothesis that the error term $\varepsilon_{i,t}$ is not serially correlated. As in the case of the Sargan test, the model specification is supported when the null hypothesis is not rejected. In the *system* specification we test whether the differenced error term (that is, the residual of the regression in differences) is second-order serially correlated. First-order serial correlation of the differenced error term is expected even if the original error term (in levels) is uncorrelated, unless the latter follows a random walk. Second-order serial correlation of the differenced residual indicates that the original error term is serially

[4] In practice, Arellano and Bond (1991) suggest the following two-step procedure to obtain consistent and efficient GMM estimates. First, assume that the residuals, $\varepsilon_{i,t}$, are independent and homoskedastic both across countries and over time. This assumption corresponds to a specific weighting matrix that is used to produce first-step coefficient estimates. Then, construct a consistent estimate of the variance-covariance matrix of the moment conditions with the residuals obtained in the first step, and use this matrix to re-estimate the parameters of interest (i.e. second-step estimates). Asymptotically, the second-step estimates are superior to the first-step ones in so far as efficiency is concerned.

correlated and follows a moving average process at least of order one. This would reject the appropriateness of the proposed instruments (and would call for higher-order lags to be used as instruments).

Results

Tables 2 and 3 report the growth regression results. We study how the effect of financial intermediation on growth varies in the presence of financial turmoil by including a slope dummy for countries that have suffered a banking crisis (Table 2). Furthermore, in order to reconsider De Gregorio and Guidotti's findings, we also assess the effect of a slope dummy for Latin American and Caribbean countries (Table 3). Of the 74 countries in the sample, 31 experienced at least one banking crisis and 20 belonged to Latin America and the Caribbean (LAC). All but 3 countries in LAC suffered a banking crisis (see Appendix B for further details). In each case, we work with two indicators of financial intermediation, namely, the ratio of liquid liabilities to GDP and the ratio of domestic credit to the private sector to GDP.

The GMM regression results are presented in Tables 2 and 3. Note that according to both specification tests, Sargan and 2nd-order serial correlation, the null hypothesis of the validity of the moment conditions cannot be rejected.

The estimation results confirm the positive growth effect of larger financial depth. As Table 2 indicates, this effect is significantly positive for the samples of non-crisis and crisis countries. However, as the size and significance of the slope dummy coefficient reveals, the positive growth effect is statistically smaller for crisis than for non-crisis countries. This is true for both indicators of financial intermediation (i.e., liquid liabilities and private domestic credit). In Table 3, we reconsider De Gregorio and Guidotti's results. We agree with them that the growth effect of financial deepening is smaller in Latin American countries than in the rest. However, we find that even for Latin American countries an expansion of financial intermediation, as measured in the frequencies of five-year averages, leads to higher growth rates. Qualitatively, the results obtained with the slope dummies for crisis and LAC countries are similar. Quantitatively, the coefficient on the interactive term for crisis countries is larger than that for LAC countries, which may be due to the fact that Latin America accounts for only about half of all crisis countries.

In summary, the estimated growth effect of financial deepening is smaller, but still positive, in countries that have faced financial crisis, and particularly those in Latin America.[5]

TABLE 2: Financial Intermediation, Crisis Experience and Growth; system estimator

Regressors	Coefficient	Std Error	Coefficient	Std Error
Constant	0.751883	*1.0316*	3.06879	*0.9624*
Log of Initial Income per Capita	-0.204635	*0.1096*	0.10722	*0.1226*
Average year of secondary schooling	0.477162	*0.1463*	0.14471	*0.1519*
Liquid Liabilities	2.086862	*0.1837*		
Liquid Liabilities*Crisis Experience	-0.379457	*0.0414*		
Private Credit			1.43412	*0.0634*
Private Credit*Crisis Experience			-0.26059	*0.0411*
Government size	-1.187689	*0.2865*	-1.90475	*0.2665*
Inflation Rate	0.325441	*0.3941*	-0.39897	*0.3056*
Black Market Premium	-1.980017	*0.09*	-1.18752	*0.0859*
Dummy 71-75	-0.833267	*0.08*	-0.98195	*0.0642*
Dummy 76-80	-0.882677	*0.1251*	-0.96971	*0.1158*
Dummy 81-85	-3.043068	*0.1322*	-2.96185	*0.1672*
Dummy 86-90	-2.074279	*0.1594*	-2.01945	*0.1674*
Dummy 91-95	-2.867901	*0.1776*	-2.77716	*0.1637*
Sargan Test (P-value)	*0.467*		*0.41*	
2nd Order Serial Correlation (P-Value)	*0.836*		*0.642*	
Number of Countries	74		74	
Number of Obsevations	359		359	

[5] The results reported above are obtained using only the closest appropriate lag for each variable in the regression. We could use only one instrument per variable because if we used more, we would run into an overfitting problem (reflected on implausibly large Sargan test statistics with p-values close to 1). Overfitting would occur because the number of instrumental variables is too large compared to the number of available cross-sectional units. In order to assess the robustness of our basic results to the lag structure of the instruments, we need to restrict the set of explanatory variables (to avoid the overfitting problem). We then consider two lags for each variable as instruments, using alternatively the two closest lags to the regression period and the two lags separated by one period from the regression. The results of this exercise are presented in Appendix E. They confirm our basic results, that is, the effect of financial deepening on growth is always positive but significantly smaller in crisis-countries.

TABLE 3: Financial Intermediation,Latin America and Growth; system estimator

Regressors	Coefficient	Std Error	Coefficient	Std Error
Constant	2.074185	0.9213	5.379823	0.9257
Log of Initial Income per Capita	-0.181326	0.0955	-0.036462	0.1106
Average year of secondary schooling	0.592854	0.1141	0.434511	0.1289
Liquid Liabilities	2.098478	0.1586		
Liquid Liabilities*Latin America	-0.203884	0.0498		
Private Credit			1.557448	0.073
Private Credit*Latin America			-0.199361	0.053
Government size	-1.946623	0.1978	-2.665188	0.2506
Inflation Rate	0.363155	0.357	-0.287723	0.2191
Black Market Premium	-1.741312	0.0957	-1.111259	0.0933
Dummy 71-75	-0.923225	0.0941	-1.03786	0.129
Dummy 76-80	-1.070274	0.1002	-1.146228	0.1307
Dummy 81-85	-3.103926	0.1268	-3.131746	0.19
Dummy 86-90	-2.271343	0.1176	-2.261626	0.1375
Dummy 91-95	-3.18211	0.1357	-3.154942	0.1465
Sargan Test (P-value)	0.467		0.461	
2nd Order Serial Correlation (P-Value)	0.836		0.655	
Number of Countries	74		74	
Number of Obsevations	359		359	

III. SHORT- AND LONG-RUN GROWTH EFFECTS OF FINANCIAL DEEPENING

In this section we attempt an empirical explanation of the apparently contradictory effects of financial intermediation on economic activity. This explanation is based on the distinction between cycle and trend changes of financial intermediation and their corresponding effects on output growth. Instead of averaging the data to isolate trend effects, we estimate both long- and short-run effects using annual data in a panel containing a large sample of countries. Our method can be summarized as a panel, error-correction model, where long- and short-run effects are estimated jointly from a general autoregressive distributed-lag (ARDL) model.

We propose this panel error-correction method as an alternative to the traditional method of time averaging for the following reasons. First, while averaging clearly induces a loss of information, it is not obvious that averaging over fixed-length intervals effectively eliminates business-cycle fluctuations. Second, averaging eliminates information that may be used to estimate a more flexible model that allows for some parameter heterogeneity across countries. Third, and most importantly for our purposes, averaging hides the dynamic relationship between financial intermediation and economic activity, particularly the presence of opposite effects at different time frequencies.[6]

A. Methodology

Empirical estimation poses two issues. The first is the need to separate and estimate short- and long-run effects without being able to decompose directly trend and transitory components of growth, financial intermediation, and the other explanatory variables. We treat this issue below in the context of single-country estimation. The second issue is the likely possibility that the parameters in the relationship between financial intermediation and economic activity be different across countries. It can be argued that country heterogeneity is particularly relevant in short-run relationships, given that countries are affected by overlending and financial crises to widely different degrees. On the other hand, we can expect that long-run relationships would be more homogeneous across countries. We discuss below the issue of heterogeneity in the context of multi-country estimation.

Single-country estimation

As said above, we face the challenge to estimate long- and short-run relationships without being able to observe the long- and short-run components of the variables involved. Over the last decade or so, a booming cointegration literature has focused on the estimation of long-run relationships among I(1) variables (Johanssen 1995, Phillips and Hansen 1990). From this literature, two common misconceptions have been derived. The first one is that long-run relationships exist *only* in the context of cointegration of integrated variables. The second one is that standard methods of estimation and inference are incorrect. Pesaran and Smith (1995) and Pesaran and Shin (1999) have argued against both misconceptions, showing how small modifications to standard methods can render consistent and efficient estimates of the parameters in a long-run relationship between both integrated and stationary variables. Furthermore, the methods proposed by Pesaran and co-authors avoid the need for pre-testing and order-of-integration conformability given that they are valid whether or not the variables of interest are I(0) or I(1). The main requirements for the validity of this methodology are that, first, there exist

[6] Similar arguments are made by Attanasio, Scorcu, and Picci (2000) in their cross-country study on the dynamic relationship between saving, investment, and growth.

a long-run relationship among the variables of interest and, second, the dynamic specification of the model be augmented such that the regressors are strictly exogenous and the resulting residual is not serially correlated. For reasons that will become apparent shortly, Pesaran and co-authors call their method "an autoregressive distributed lag (ARDL) approach" to long-run modelling.

As an illustration, consider the following simple bivariate model:

$$y_t = a + by_{t-1} + cX_{t-1} + v_t \tag{1}$$

$$X_t = \gamma + \rho X_{t-1} + \varepsilon_t \tag{2}$$

where y_t, the decision variable, is the per capita GDP growth rate in year t; and X, the forcing variable, represents a set of growth determinants including financial depth and control variables. Furthermore, assume that the residuals (or shocks) have the following distributional properties:

$$\begin{pmatrix} v_t \\ \varepsilon_t \end{pmatrix} iid\left(0, \Sigma\right), \qquad \Sigma = \begin{pmatrix} \sigma_{vv} & \sigma_{v\varepsilon} \\ \sigma_{v\varepsilon} & \sigma_{\varepsilon\varepsilon} \end{pmatrix} \tag{3}$$

The first point to note is that X does not depend on past values of y (beyond its dependence on previous values of X). If a more general process for X were allowed, the long-run relationship between the two variables would not be unique. That is, both variables would be endogenous and additional identification assumptions would be needed to discern between various long-run relationships.[7] Since multiple long-run relationships are beyond the scope of this paper, we restrict the dynamic process for X to be purely autoregressive.

The second point to note is that the existence of a long-run relationship requires the process for y to be stable, which in this simple example entails that $|b|<1$. Notice that once we have restricted the process of X to be purely autoregressive, the existence of a long-run relationship does not rely on whether X is I (0) or I(1); that is, there is no restriction on whether ρ=1. Pesaran, Shin, and Smith (2000) present a test for the null hypothesis that there is no long-run relationship when it is not known *a priori* whether X

[7] See Hsiao (1997) and Pesaran and Shin (1999).

is I(0) or I(1). The test consists on examining the null that b=1 against the alternative that $|b|<1$.

In order to be able to derive the long-run relationship between y and X, we must obtain a dynamic regression equation in which, first, the regression residual is serially uncorrelated and, second, the regressors, X, are *strictly* exogenous (that is, independent of the residuals at all leads and lags.) Given the assumptions on the distributional properties of the residuals ν and ε (equation 3), the requisite that the residuals be serially uncorrelated is met in our simple example. If this were not the case, we would need to augment the lag order in (1) and (2) until the residuals become serially independent (Pesaran and Shin 1999). The second pre-requisite to derive a long-run relationship is, however, not met in our simple example –X is not *strictly* exogenous given that the non-zero correlation between the shocks entails a contemporaneous feedback between y and X. As explained by Pesaran and Shin (1999), the way to control for this contemporaneous feedback is also to augment the dynamic specification in (6). The purpose of augmenting the regression equation is to replace the (correlated) residual ν with a linear predictor based on leads and lags of X and a new residual that by construction is independent of X. In our simple example, we model the contemporaneous correlation between ν_t and ε_t by a linear regression of ν_t on ε_t as follows,

$$\nu_t = \left(\frac{\sigma_{\nu\varepsilon}}{\sigma_{\varepsilon\varepsilon}}\right)\varepsilon_t + \eta_t \qquad (4)$$

where $(\sigma_{\nu\varepsilon}/\sigma_{\varepsilon\varepsilon})$ represents the population coefficient of the regression, and η_t is distributed independently from ε_t.

Substitute the above expression for ν_t into equation (1). Then, using the AR model for X, express ε_t in terms of X_t and X_{t-1}. The ensuing regression equation is an auto-regressive distributed lag model (ARDL) for y from which a long-run relationship can be derived. The resulting ARDL (1,1) for y is given by,

$$y_t = \left(a - \gamma\frac{\sigma_{\nu\varepsilon}}{\sigma_{\varepsilon\varepsilon}}\right) + by_{t-1} + \left(\frac{\sigma_{\nu\varepsilon}}{\sigma_{\varepsilon\varepsilon}}\right)X_t + \left(c - \rho\frac{\sigma_{\nu\varepsilon}}{\sigma_{\varepsilon\varepsilon}}\right)X_{t-1} + \eta_t \qquad (5)$$

Note that the original process for y (equation 1) is now augmented by the inclusion of the additional regressor X_t.

The error-correction model (ECM) implied by the ARDL (1,1) given above can be expressed as,

$$\Delta y_t = -(1-b)\left[y_{t-1} - \left(\frac{a - \gamma \frac{\sigma_{\nu\varepsilon}}{\sigma_{\varepsilon\varepsilon}}}{1-b} \right) - \left(\frac{c + \frac{\sigma_{\nu\varepsilon}}{\sigma_{\varepsilon\varepsilon}}(1-\rho)}{1-b} \right) X_{t-1} \right] + \left(\frac{\sigma_{\nu\varepsilon}}{\sigma_{\varepsilon\varepsilon}} \right) \Delta X_t + \eta_t \qquad (6)$$

Where the expression in brackets is the error-correction term and *(1-b)* is the speed of adjustment.

Therefore, the long-run (steady-state) relationship implied by the dynamic system in equations (1)-(4) is given by,

$$y^* = \left(\frac{a - \gamma \frac{\sigma_{\nu\varepsilon}}{\sigma_{\varepsilon\varepsilon}}}{1-b} \right) + \left(\frac{c + \frac{\sigma_{\nu\varepsilon}}{\sigma_{\varepsilon\varepsilon}}(1-\rho)}{1-b} \right) X^* + \eta^* \qquad (7)$$

or, $y^* = \alpha + \beta x^* + \eta^*$.

The presentation of this simple empirical model serves to highlight the assumptions and properties of the ARDL method proposed by Pesaran and Smith (1995), Pesaran (1997), and Pesaran and Shin (1999) for the estimation of a long-run relationship. The advantage of the method is that standard estimation and inference can be used regardless of whether the regressors are stationary or integrated. The main assumption is that there exist a single long-run relationship between the endogenous and forcing variables.[8] The pre-requisites for consistent and efficient estimation are that the shocks in the dynamic specification be serially uncorrelated and that the forcing variables be strictly exogenous. As we illustrated, the pre-requisites can be met by augmenting sufficiently the lag order of the dynamic regression equation. The resulting equation will generally be an ARDL(p, q) model of sufficiently large lag order.

[8] It is worth noting that this assumption underlies implicitly the various single-equation based estimators of long-run relationships commonly found in the cointegration literature. Without such assumption, these estimators would at best identify some linear combination of all the long-run relationships present in the data.

Multi-country estimation

Our empirical samples below are characterized by time-series (T) and cross-section (N) dimensions of relatively large size. In such conditions, there are a number of alternative methods for multi-country estimation, which allow for different degrees of parameter heterogeneity across countries. At one extreme, the fully heterogeneous-coefficient model imposes no cross-country parameter restrictions and can be estimated on a country-by-country basis -- provided the time-series dimension of the data is sufficiently large. When, in addition, the cross-country dimension is large, the mean of long- and short-run coefficients across countries can be estimated consistently by the unweighted average of the individual country coefficients. This is the "mean group" (MG) estimator introduced by Pesaran, Smith, and Im (1996). At the other extreme, the fully homogeneous-coefficient model requires that all slope and intercept coefficients be equal across countries. This is the simple "pooled" estimator.

In between the two extremes, there are a variety of estimators. The "dynamic fixed effects" estimator restricts all slope coefficients to be equal across countries but allows for different country intercepts. The "pooled mean group" (PMG) estimator, introduced by Pesaran, Shin, and Smith (1999), restricts the long-run coefficients to be the same across countries but allows the short-run coefficients (including the speed of adjustment) to be country specific. The PMG estimator also generates consistent estimates of the mean of short-run coefficients across countries by taking the unweighted average of the individual country coefficients (provided that the cross-sectional dimension is large).

The choice among these estimators faces a general trade-off between consistency and efficiency. Estimators that impose cross-country constraints dominate the heterogeneous estimators in terms of efficiency if the restrictions are valid. If they are false, however, the restricted estimators are inconsistent. In particular, imposing invalid parameter homogeneity in dynamic models typically leads to downward-biased estimates of the speed of adjustment (Robertson and Symons 1992, Pesaran and Smith 1995).

For our purposes, the pooled mean group estimator offers the best available compromise in the search for consistency and efficiency. This estimator is particularly useful when the long run is given by conditions expected to be homogeneous across countries while the short-run adjustment depends on country characteristics such as financial development, institutional quality, and relative price flexibility. Furthermore, the PMG estimator is sufficiently flexible to allow for long-run coefficient homogeneity over only a subset of variables and/or countries.

In view of these considerations, we use the PMG method to estimate a long-run relationship that is common across countries while allowing for unrestricted country heterogeneity in the adjustment dynamics. The interested reader is referred to Pesaran, Shin, and Smith (1999) where the PMG estimator is developed and compared with the MG estimator. Briefly, the PMG estimator proceeds as follows. The estimation of the long-run coefficients is done jointly across countries through a (concentrated) maximum likelihood procedure. Then the estimation of short-run coefficients (including the speed of adjustment), country-specific intercepts, and country-specific error variances is done on a country-by-country basis, also through maximum likelihood and using the estimates of the long-run coefficients previously obtained.[9]

An important assumption for the consistency of our PMG estimates is the independence of the regression residuals across countries. In practice, non-zero error covariances usually arise from *omitted* common factors that influence the countries' ARDL processes. We seek to eliminate these common factors and, thus, ensure the independence condition by allowing for time-specific effects in the estimated regression; this is equivalent to a regression in which each variable enters as deviations with respect to the cross-sectional mean in a particular year.

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[9] The comparison of the asymptotic properties of PMG and MG estimates can be put also in terms of the general trade-off between consistency and efficiency noted in the text. If the long-run coefficients are in fact equal across countries, then the PMG estimates will be consistent and efficient, whereas the MG estimates will only be consistent. If, on the other hand, the long-run coefficients are not equal across countries, then the PMG estimates will be inconsistent, whereas the MG estimator will still provide a consistent estimate of the mean of long-run coefficients across countries. The long-run homogeneity restrictions can be tested using Hausman or likelihood ratio tests to compare the PMG and MG estimates of the long run coefficients. In turn, comparison of the small sample properties of these estimators relies on their sensitivity to outliers. In small samples (low T and N), the MG estimator, being an unweighted average, is excessively sensitive to the inclusion of outlying country estimates (for instance those obtained with small T). The PMG estimator performs better in this regard because it produces estimates that are similar to *weighted* averages of the respective country-specific estimates, where the weights are given according to their precision (that is, the inverse of their corresponding variance-covariance matrix).

B. Data and Results

The sample consists of 49 countries with annual data for the period 1960-97 (see Appendix B for the list of countries included in the sample). Given the procedure's requirements on the time-series dimension of the data, we include only countries that have at least 20 consecutive observations. The dependent variable is the growth rate of GDP per capita. The measures of financial intermediation are liquid liabilities and private domestic credit, both as ratios to GDP. The control variables are the initial level of GDP per capita, government consumption (as ratio to GDP), the volume of trade (as ratio to GDP), and the inflation rate.

Tables 4 and 5 present the results on specification tests and the estimation of long- and short-run parameters linking per capita GDP growth, financial intermediation, and other growth determinants. In Table 4 the measure of financial intermediation is the ratio of private domestic credit to GDP, and in Table 5 it is the ratio of liquid liabilities to GDP. In both tables, we present the results obtained using the pooled mean group (PMG) estimator, which we prefer given its gains in consistency and efficiency over other panel error-correction estimators. For comparison purposes, we also present the results obtained with the mean group (MG) and the dynamic fixed-effects (DFE) estimators.

As outlined in the previous section, the consistency and efficiency of the PMG estimates relies on several specification conditions. The first are that the regression residuals be serially uncorrelated and that the explanatory variables can be treated as exogenous. We seek to fulfill these conditions by including in the ARDL model, three lags of the growth rate, 3 lags of the measure of finance intermediation, and one lag of each control variable. We could not expand the lag structure any further because we would run into problems of lack of degrees of freedom. We chose to use a richer (longer) lag structure for the dependent variable (growth) and the variable of interest (financial intermediation) because our main concern was to characterize their long- and short-run relationships.

The second specification condition is that both country-specific effects and cross-country common factors be accounted for. We control for country-specific effects by allowing for an intercept for each country, and we attempt to eliminate cross-country common factors by demeaning the data using the corresponding cross-sectional means for every period (which is algebraically the same as allowing for year-specific intercepts).

The third condition refers to the existence of a long-run relationship (dynamic stability) and requires that the coefficient on the error-correction term be negative. In the second panel of Tables 4 and 5, we report the estimates for the pooled error-correction coefficient and its corresponding standard error. This coefficient is significantly negative in the PMG estimator (and in dynamic fixed effects), which is evidence that supports the dynamic stability of the model.

The fourth condition is that the long-run parameters be the same across countries. As explained in the econometric methodology section, we can test the null hypothesis of homogeneity through a Hausman-type test; this is based on the comparison between the Pooled Mean Group and the Mean Group estimators. In Tables 4 and 5, we present the Hausman test statistic and the corresponding p-values for the coefficients on each of the explanatory variables and for all of them jointly. When the proxy for financial intermediation is private credit (Table 4), the homogeneity restriction is never rejected, either for individual parameters or jointly. When we use instead liquid liabilities (Table 5), the homogeneity of long-run parameters is not rejected except in the case of the coefficient on the inflation rate.

Regarding the estimated parameters, our analysis focuses on those obtained with the PMG estimator. In the long run, the growth rate of GDP per capita is negatively related to initial income, the size of government, and the inflation rate, and positively related to international trade openness. These are standard results from the empirical growth literature, and it is reassuring that we are able to reproduce them with our methodology.

Most importantly for our purposes, we find that economic growth is positively and significantly linked to the measures of financial intermediation in the long run. On the other hand, the short-run coefficients tell a different story. As explained in the methodology section, short-run coefficients are not restricted to be the same across countries, so that we do not have a single *pooled* estimate for each coefficient. Nevertheless, we can still analyze the *average* short-run effect by considering the mean of the corresponding coefficients across countries. We find that the short-run average relationship between the growth rate of GDP per capita and the measures of financial intermediation appears to be strongly negative in the case of private credit and mildly so in the case of liquid liabilities. Thus, comparing the long- and short-run estimates, we can conclude that the sign of the relationship between economic growth and financial intermediation depends on whether their movements are cyclical or permanent.

Table 4: ARDL(3,3,1,1,1,1); Dependant Variable: Growth; Financial Indicator: Private Credit/GDP
Pooled Mean Group, Mean Group estimators and Dynamic Fixed Effect, controlling for country and time effects
Sample: All Countries 1961-1997

	Pooled Mean Group		**Mean Group**		***Hausman Tests***		**Dynamic Fixed Effect**	
Variabels	Coef.	St.Er.	Coef.	St.Er.	h-test	p-val	Coef.	St.Er.
Long-Run Coefficients								
Private Credit	0.741	0.349	0.032	7.235	0.01	0.92	1.6063	0.9594
Initial Income	-7.042	0.738	-23.06	15.493	1.07	0.3	-3.717	0.9322
Governement Size	-5.359	0.545	-1.76	3.423	1.13	0.29	-2.6075	0.7248
Trade Openness	3.614	0.352	0.966	4.127	0.41	0.52	3.9511	0.6987
Inflation Rate	-3.383	0.411	-3.141	3.805	0	0.95	-2.9602	0.4325
		Joint Hausman Test			6.78	0.24		
Error Correction Coefficients								
Phi	-0.964	0.099	-2.159	0.149			-0.8538	0.0484
Short-Run Coefficients								
Δgrowth(-1)	0.127	0.067	1.878	0.734			0.043	1.6642
Δgrowth(-2)	-0.071	0.04	-1.773	0.232			0.0417	-1.8276
ΔPrivate Credit	-15.236	8.54	-1.784	-8.908			1.6453	-2.1842
ΔPrivate Credit(-1)	6.332	5.768	1.098	-3.827			1.1872	-1.1897
ΔPrivate Credit(-2)	-7.553	6.975	-1.083	-12.859			1.7477	-2.7131
ΔInitial Income	-8.889	3.099	-2.869	-3.764			2.7932	-1.449
Δgovernement	-14.503	2.526	-8.685	3.134			-1.916	1.11
Δtrade	-3.055	1.672	-1.827	-7.938			2.7932	-1.449
Δinflation	-5.06	1.641	-3.084	3.824			1.4129	-2.6074
Inpt	0.022	1.425	0.015	16.332				
No. Countries	48		48				48	
No.Observations	1211		1211				1211	
Avg RBarSq	0.65		0.68				0.68	

Table 5: ARDL(3,3,1,1,1,1); Dependant Variable: Growth; Financial Indicator: Liquid Liabilities/GDP

Pooled Mean Group, Mean Group estimators and Dynamic Fixed Effect, controlling for country and time effects

Sample: All Countries 1961-1997

	Pooled Mean Group		**Mean Group**		***Hausman Tests***		**Dynamic Fixed Effect**	
Variables	Coef.	St.Er.	Coef.	St.Er.	h-test	p-val	Coef.	St.Er.
Long-Run Coefficients								
Liquid Liabilities	1.677	0.526	-4.506	26.511	0.05	0.82	0.3226	1.5346
Initial Income	-8.119	0.529	1.447	11.629	0.68	0.41	-3.1004	0.8602
Governement Size	-0.751	0.502	-6.541	5.889	0.97	0.32	-2.3901	0.7706
Trade Openness	1.077	0.456	10.051	4.393	4.23	0.04	3.9237	0.6802
Inflation Rate	-3.362	0.486	-5.979	13.038	0.04	0.84	-3.1331	0.4465
		Joint Hausman Test			9.5	0.11		
Error Correction Coefficients								
Phi	-0.861	0.084	-1.788	0.149			-0.8406	0.0472
Short-Run Coefficients								
Δgrowth(-1)	0.076	0.054	0.467	0.106			0.0984	0.0379
Δgrowth(-2)	-0.053	0.039	0.097	0.063			-0.0542	0.028
Δliquid_Liabilities	-22.177	8.048	-7.626	25.191			-15.7766	2.8192
Δliquid_Liabilities(-1)	17.716	7.11	4.199	21.24			12.16	2.9951
Δliquid_Liabilities(-2)	-2.588	4.84	-12.56	17.576			-5.7187	2.8335
ΔInitial Income	-8.043	3.008	-7.236	4.025			-4.6441	2.2555
Δgovernement	-13.242	2.868	-5.8	2.862			-1.6355	0.9049
Δtrade	-0.747	2.152	-8.657	2.327			-2.4328	0.938
Δinflation	-6.19	4.176	15.862	5.394			-2.4466	0.5318
Δinflation (-1)	60.921	6.114	119.028	52.686			0.7388	0.8909
Inpt	57.06	5.992	104.47	50.76				
No. Countries	49		49				49	
No.Observations	1235		1235				1235	
Avg RBarSq	0.64		0.68				0.44	

Finally, we consider the question as to whether the negative short-run relationship between growth and financial intermediation can be linked to the occurrence of systemic banking crisis. We address this question by examining the short-run coefficients on financial intermediation for each country in the sample. We separate the countries with significant short-run effects in two groups: those that experienced a systemic banking crisis and those that did not. Figure 2a plots the short-run coefficients for the crisis countries and Figure 2b, for the non-crisis ones. We can see that seventy-five percent of the crisis countries present a negative short-run relationship between growth and financial intermediation, while only forty-four percent of the non-crisis countries do. Therefore, boom-bust credit cycles appear to explain in part the average negative effect of short-run financial intermediation. However, this negative effect appears to occur more generally and can be also linked to experiences of soft-landing after credit booms.[10]

Figure 2a :Short Run Growth Effects of Financial Development
Countries with systemic crisis experience
Liquid Liabilities/GDP

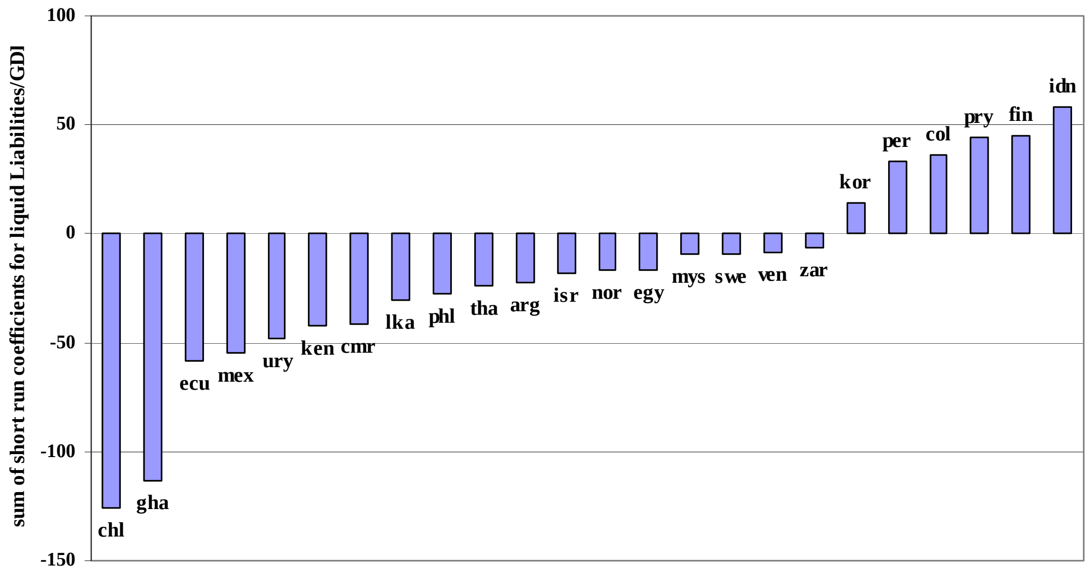
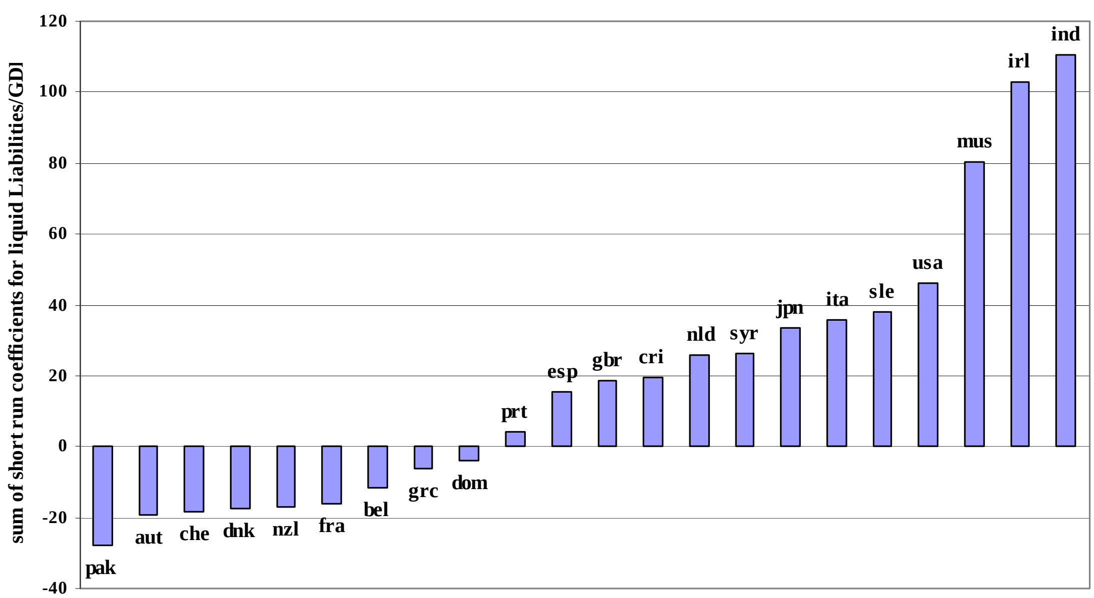


Figure 2b: Short Run Growth Effects of Financial Development
Countries with no systemic crisis experience
Liquid Liabilities/GDP



[10] See Tornell and Westermann (2001) for a model that explains the cycles of credit expansions and contractions by focusing on the dynamics of credit constraints in the non-tradable sector. They conclude that a short-run negative correlation between financial intermediation and growth can reflect not only financial crises but also episodes where lending booms end gradually.

IV. Conclusions

The results in this paper can be summarized as follows.

- The dynamic relationship between economic growth and financial intermediation is negative around financial crises. Furthermore, the positive link between "long-run" economic growth and financial deepening is smaller in countries that have suffered banking crises than in the rest.
- Using recent econometric methods for the estimation of dynamic models using panel data, we find that a positive long-run relationship between financial intermediation and output growth co-exists with a, mostly, negative short-run relationship. We propose this result as an empirical explanation for the apparent contradiction between the crisis literature and the endogenous-growth literature on the effects of financial deepening.

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APPENDIX A:LIST OF SYTEMIC BANKING CRISES*

Country Name	Start	End	Start	End	Start	End
Algeria	1990	1992				
Argentina	1980	1982	1989	1990	1995	1995
Benin	1988	1990				
Bolivia	1986	1987	1994	2000		
Brazil	1990	1990	1994	1996		
Burkina Faso	1988	1994				
Cameroon	1987	1993	1995	1998		
Central African Republic	1988	1999				
Chad	1992	1992				
Chile	1976	1976	1981	1983		
Colombia	1982	1987				
Congo, Rep.	1992	2000				
Cote d'Ivoire	1988	1991				
Czech Republic	1989	1991				
Ecuador	1996	2000				
Egypt, Arab Rep.	1977	1985				
El Salvador	1989	1989				
Estonia	1992	1995				
Finland	1991	1994				
Ghana	1982	1989				
Guinea	1985	1985	1993	1994		
Hungary	1991	1995				
Indonesia	1987	2000				
Israel	1977	1983				
Kenya	1985	1989	1992	1992	1993	1995
Korea, Rep.	1997	2000				
Kuwait	1988	1990				
Latvia	1995	1996				
Lebanon	1988	1990				
Lithuania	1995	1996				
Madagascar	1988	1988	1992	1992		
Malaysia	1997	2000				
Mali	1987	1989				
Mauritania	1984	1993				
Mexico	1995	2000				
Nepal	1988	1988				
Niger	1987	1993				
Norway	1988	1998				
Paraguay	1995	2000				
Peru	1983	1990				
Philippines	1998	2000				
Russian Federation	1995	1995	1998	1998		
Senegal	1988	1991				
Slovak Republic	1991	2000				
Slovenia	1992	1994				
Spain	1977	1985				
Sri Lanka	1989	1993				
Sweden	1991	1994				
Thailand	1997	2000				
Ukraine	1997	1997				
Uruguay	1981	1984				
Venezuela	1994	2000				
Zaire	1991	1992	1994	2000		
Zimbabwe	1995	1995				

Source: Caprio and Klingbiel (1999)

* Here are only listed countries for which we get a precise time period for Banking Crises.

Appendix B

	systemic banking crisis	Latin American and Carribean	GMM Sample	Pooled Mean Group Sample
Algeria	X		X	
Argentina	X	X	X	X
Australia			X	X
Austria			X	X
Belgium			X	X
Bolivia	X	X	X	
Brazil	X	X	X	
Cameroun	X		X	X
Canada			X	X
Central African Republic	X		X	
Chile	X	X	X	X
Colombia	X	X	X	X
Costa Rica		X	X	X
Cyprus			X	
Denmark			X	X
Dominican Republic		X	X	X
Ecuador	X	X	X	X
Egypt	X		X	X
El Salvador	X	X	X	
Finland	X		X	X
France			X	X
Gambia			X	
Germany			X	
Ghana	X		X	X
Great Britain			X	X
Greece			X	X
Guatemala	X	X	X	
Haiti		X	X	
Honduras		X	X	
India			X	X
Indonesia	X		X	X
Iran			X	
Ireland			X	X
Israel			X	X
Italy			X	X
Jamaica		X	X	
Japan			X	X
Kenya	X		X	X
Korea			X	X
Lesotho			X	
Malawi			X	
Malaysia	X		X	X
Mauritius			X	X
Mexico	X	X	X	X
Netherlands			X	X
New Zealand			X	X
Nicaragua		X	X	
Niger	X		X	
Norway			X	X
Pakistan			X	X
Panama		X	X	
Papua New Guinea			X	
Paraguay	X	X	X	X
Peru	X	X	X	X
Philippines	X		X	X
Portugal			X	X
Rwanda			X	
Senegal	X		X	
Sierra Leone			X	X
South Africa			X	X
Spain	X		X	X
Sri Lanka	X		X	X
Sudan			X	
Sweden	X		X	X
Switzerland			X	X
Syria			X	X
Taiwan			X	
Thailand	X		X	X
Togo			X	
Trinidad and Tobago			X	
United States of America			X	X
Uruguay	X	X	X	X
Venezuela	X	X	X	X
Zaire	X		X	X
Zimbabwe	X		X	
total	31	21	75	49

Appendix C: Variables and Sources

Variable	Definition	Original source	Secondary source
Level and growth rate of GDP	Real per capita GDP	World Development Indicators	Loayza et al. (1998)
	Real per capita GDP (for initial GDP in cross-section regressions)	Penn World Tables	
Government size	Government expenditure as share of GDP	World Development Indicators	Loayza et al. (1998)
Openness to trade	Sum of real exports and imports as share of real GDP	World Development Indicators	Loayza et al. (1998)
Inflation rate	Log difference of Consumer Price Index	International Financial Statistics (IFS), line 64	
Average years of schooling	Average years of schooling in the population over 25	Barro and Lee (1996)	
Average years of secondary schooling	Average years of secondary schooling in the population over 15	Barro and Lee (1996)	
Black market premium	Ratio of black market exchange rate and official exchange rate minus one	Pick's Currency Yearbook through 1989 ; and World Currency Yearbook.	
Liquid Liabilities	{(0.5)*[F(t)/P_e(t) + F(t-1)/P_e(t-1)]}/[GDP(t)/P_a(t)], where F is liquid liabilities (line 55l), GDP is line 99b, P_e is end-of period CPI (line 64) and P_a is the average annual CPI.	IFS	
Commercial-Central Bank	DBA(t) / (DBA(t) + CBA(t)), where DBA is assets of deposit money banks (lines 22a-d) and CBA is central bank assets (lines 12 a-d).	IFS	
Private Credit	{(0.5)*[F(t)/P_e(t) + F(t-1)/P_e(t-1)]}/[GDP(t)/P_a(t)], where F is credit by deposit money banks and other financial institutions to the private sector (lines 22d + 42d), GDP is line 99b, P_e is end-of period CPI (line 64) and P_a is the average CPI for the year.	IFS	

Appendix D : 1960-1997 ANNUAL DATA CORRELATION (five year average data correlation in parenthesis)

	com	**lly**	**pc**	**growth**	**inf**	**gov**	**school**	**trade**	**bmp**	**initial**
com	1.00									
lly	0.47 (0.51)	1.00								
pc	0.55 (0.6)	0.84 (0.84)	1.00							
growth	**0.21 (0.33)**	**0.15 (0.22)**	**0.14 (0.2)**	1.00						
inf	-0.2 (0.6)	-0.2 (-0.26)	-0.1 (-0.26)	**-0.2 (-0.29)**	1.00					
gov	0.24 (0.6)	0.37 (0.21)	0.27 (0.24)	**-0.0 (-0.04)**	-0.11	1.00				
school	0.31	0.56	0.56	**0.09 (0.13)**	0.03	0.41	1.00			
trade	0.26 (0.6)	0.16 (0.13)	0.08 (0.09)	**0.05 (0.13)**	-0.16	0.48	0.05	1.00		
bmp	-0.3 (0.6)	-0.1 (-0.03)	-0.2 (0.22)	**-0.1 (-0.2)**	0.26	-0.13	-0.10	-0.21	1.00	
initial income	0.52 (0.6)	0.62 (0.61)	0.55 (0.76)	**0.14 (-0.14)**	-0.11	0.43	0.80	0.08	-0.23	1.00
OBS	2656.00	2509.00	2521.00	2612.00	2577.00	1551.00	2484.00	2620.00	2576.00	2766.00
5 year avg OBS	*359.00*	*359.00*	*359.00*	*359.00*	*359.00*	*359.00*	*359.00*	*359.00*	*359.00*	*359.00*

VARIABLES

com = Commercial Banks Assets /(Central Banks + Commercial Banks Assets)
lly = Liquid Liabilities / GDP
pc = Private Credit/ GDP
growth= real per capita Growth
inf = inflation rate
gov= governement expenditures / GDP
school = average year of secondary education
trade = trade openess
bmp=black market premium
initial income = beginning of the period real per capita income

APPENDIX E : Robustness Check for GMM system estimation in Section II.B

Financial Intermediation, Crisis Experience and Growth

	GMM sytem estimator 4 instruments: t-2		**GMM sytem estimator 8 instruments: t-2,t-3**		**GMM sytem estimator 8 instruments: t-3,t-4**	
Regressors	coef	std error	coef	std error	coef	std error
Initital Income	0.15	*0.23*	0.02	*0.185*	0.09	*0.14*
private credit	1.89	*0.38*	2.11	*0.29*	1.86	*0.23*
private credit*crisis	-0.23	*0.09*	-0.29	*0.05*	-0.2	*0.05*
governement size	-3.04	*0.67*	-3.87	*0.49*	-2.76	*0.45*
Sargan Test						
degree of freedom	*29*		*41*		*41*	
P-Value	*0.198*		*0.25*		*0.48*	
Second Order correlation						
P-Value	*0.12*		*0.12*		*0.125*	
Number of Countries	74		74		74	
Number of Observation	359		359		359	