“Financial development and economic growth nexus: another look at the panel evidence from different geographical regions”

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Financial development and economic growth nexus: another look at the panel evidence from different geographical regions

Abstract

This paper re-examines the causality issue on financial development and economic growth from a panel data perspectives using the system generalized method of moments (GMM) technique developed by Arellano and Bover (1995), and Blundell and Bond (1998). Focusing on developing countries in four main geography regions (Africa, Asia, Europe and Western Hemisphere), the main finding of the results reveals that although there exist evidence supporting the other views including the "demand following" as well as non-causal relation between the economic growth and the financial deepening, these supports are not as strong as the "supply leading" hypothesis.

Keywords: finance-growth nexus, Africa, Asia, Europe, Western Hemisphere, GMM.
JEL Classification: O11, O16, O53.

Introduction

Throughout the years, a major focus of attention in macroeconomic literature has been to identify empirically alternative schemes to promote economic growth. A great majority of these analysts believe that financial deepening is a catalyst for economic growth. Influenced to a large extent by the rapid and spectacular deepening in the scale and complexity of the financial system of advance economies, the policy makers in developing countries have now made financial strengthening a priority with the expectation that this will contribute significantly to economic performance. In facts, it is commonly believed that the technological development in England during the late 18th century was the driving force behind the industrial revolution and modern economic growth.

The recognition of a significant positive relationship between financial development and economic growth can be traced back at least to the work of Schumpeter (1912). Presenting such view, include Goldsmith (1969), Mckinnon (1973) and Shaw (1973). Such "financial structuralist" view suggest that a widespread network of financial institutions and a diversified array of financial instruments will have a beneficial effect on the saving investment and hence, on growth.

The rapidly expanding "endogenous growth" literature also tend to placed center attention on the significant role of financial development (e.g., information collecting and analyzing, risk sharing, liquidity provision) in improving economic growth. Empirical studies in this spirit include the work of Bencivenge and Smith (1991), Greenwood and Javanovic (1990), as well as Pagano (1993) suggesting that financial intermediate have positive effect on economic growth.

The supply leading phenomena, as in Goldsmith (1969), McKinnon-Shaw and the endogenous growth literature has been dubbed the financial-led growth hypothesis, are popular among developing countries as a means to promote development. Such financial-led hypothesis, however, evoked criticism. Originally put forward by Robinson (1953), who has questioned such one-way causality, that financial development follows rather than lead economic growth – "where enterprise leads finance follows" (Robinson, 1953, p. 86). Such "demand following" hypothesis, postulate the passive response of financial development to a growing economy. As the real-side of the economy expanse, this will intensified the need for more financial services, leading to the growth of financial services and thus, led to economic growth (Demetriades and Hussein, 1996; Ireland, 1994).

Apparently, these are two opposite patterns of causal relationship between financial development and economic growth, each with striking different policy implication. A third view comprising the combination of demand leading and supply hypothesis, which postulates the two variables, is mutually causal (Greenwood and Smith, 1997; Al-Yousif, 2002).

Interestingly, there is another view that denies any reliable causal relationship between financial deepening and economic growth is mutually independent (Stern 1989; Lucas, 1988). Lucas (1988), for instance, claimed that economists have generally overstressed the role of financial development in economic growth.

The remainder of the paper is organized as follows. Section 1 presents the relevant literature. Section 2 described the data used follow by the discussion of the system GMM causality tests employed. The empirical results are reported in Section 3. Finally, in the last Section we make our concluding remarks.

1. Review of related literature

Apparently, there exist different steams of thought on the relationship between the financial development and economic growth. Methodologically, there have been several approaches to examine the nature and the direction between financial development and economic growth. In the literature, it can be observed that there has been a large number of studies focus on the cross-sectional analysis, which aim in determining whether cross-sectional variation in financial development can explain cross-country variation in economic growth patterns. These studies generally found positive cross-section correlations between the financial development and economic growth. But this does not settle the causality issue: it should be noted that high and positive correlation between financial development and economic growth reported in many of the previous studies does not necessarily imply causality (see Levine and Zervos, 1996; Al-Yousif, 2002). In fact, there is possibility that two variables could be highly correlated, yet causally independent (Granger, 1986). Others studies, attempt to address the causality issue in the cross-section context (King and Levine, 1993a, 1993b). However, the empirical interpretation is subjected to several limitations pertaining to the nature of cross-sectional analysis techniques employed in the study (see Demetriades and Hussein, 1996).

On the other hand, empirical causality evidence based on time series in developing economies remains relatively scarce. This can be possibly ascribed to the scarcity of sufficiently long time series national account data in developing economies. Several studies attempt to mitigate such problem by using quarterly data. For example, Gupta (1984) utilizes data on industrial production as a proxy for the level of economic development. Nevertheless, as far as the time series analysis concern, the span of data is much more important than the number of observations (see Campbell and Perron, 1991).

While data limitations prevent a rigorous examination of the growth-financial nexus using either cross sectional or the time series observation, it is possible to analyze the issue using panel data approach. The present study re-examines the causality issue from a panel data perspectives using the system GMM technique developed by Arellano and Bover (1995), and Blundell and Bond (1998), focusing on the four main geography region in the developing countries. Previous studies by Fase (2001) suggest that the development of financial system has greater impact on growth in a developing country than in developed economies.

2. Methodology

Following the common practice in the literature, the economic growth is measure by real gross domestic product (RGDP in first differences). As for the proxy for financial development, the ratio of domestic credit to GDP is used. Based on the IMF dataset, a panel dataset with a number of developing countries, focusing on four main geography regions (depending on the availability of data), can be constructed (see Appendix B, Table 5 for the selection of countries in the sample). The availability data allow forming an unbalanced panel with 6-9 annual observations over the period of 1990-1998.

To explore the causal relationship between financial deepening and economic growth, this study uses the GMM panel estimates proposed by Arellano and Bover (1995), and Blundell and Bond (1998) to extract consistent and efficient estimates of the role of financial deepening in economic growth in developing countries.

Considered a time series-stationary VAR model as in Holtz-Eakin et al. (1988, 1989):

$$y_t = \alpha_0 + \sum_{i=1}^{m} \alpha_i y_{t-i} + \sum_{i=1}^{m} \beta_i x_{t-i} + \eta_i + \nu_{it} \qquad i = 1,...,N;\ t = 1,...,T\ ,$$

$$x_t = \delta_0 + \sum_{i=1}^{m} \delta_i y_{t-i} + \sum_{i=1}^{m} \gamma_i x_{t-i} + \mu_i + u_{it} \qquad i = 1,...,N;\ t = 1,...,T\ , \qquad (1)$$

where y is the RGDP, and x is the domestic credit share of GDP. N countries (indexed by i) are observed over T periods (indexed by t). μ_i and η_i are unobservable individual effect. The number of periods T is short (fixed) and the number of individuals N is large[1]. It is convenient to treat the individual specific effect as fixed effect, because the lagged variables are predetermined but not strictly exogenous[2].

The complication of equation (1) is the joint presence of the lagged dependent variable and the individual-specific effect given the possible correlation between these variables. In this context, Hsiao (1986) shows that including an individual effect together with

[1] When the number of cross sectional units (N) is much larger than the number of T periods, the emphasis on the time series properties of the series can be attenuated (Holtz-Eakin et al., 1988).

[2] Since T is fixed and there is independence in the cross-sectional dimension for the residuals terms, the time-specific effects can be control by including year dummies in the regressions.

lagged dependent variable generates biased estimates for a standard LSDV (least squares dummy variable) estimator especially when N is much larger than T.

A common practice in the literature to take the first differences of equation (1), which eliminated the individual effect.

$$\begin{aligned} \Delta y_t &= \sum_{i=1}^{m} \alpha_i \Delta y_{t-i} + \sum_{i=1}^{m} \beta_i \Delta x_{t-i} + \Delta v_{it} \qquad i = 1,...,N;\ t = 2,...,T\ , \\ \Delta x_t &= \sum_{i=1}^{m} \delta_i \Delta y_{t-i} + \sum_{i=1}^{m} \gamma_i \Delta x_{t-i} + \Delta u_{it} \qquad i = 1,...,N;\ t = 2,...,T\ . \end{aligned} \tag{2}$$

Still, the dependence of differenced residual terms, Δv_{it} on the $v_{i,t-1}$ in the first differenced model (2) implies that the pooled OLS estimates are inconsistent, and the use of instrumental variables are required in such case[1]. For the panel data estimation, Anderson and Hsiao (1981, 1982) observed that lags of the endogenous variables are valid instruments. This is the first-difference two-stage least squared (2SLS) estimator that proposed by Anderson and Hsiao (1982).

As this remain the case, when $T > 3$, the 2SLS is over-identified. Also, if the errors at the levels are serially uncorrelated, the errors in differences are moving average of order one (MA (1))[2]. As such, the 2SLS is not asymptotically efficient even if the complete set of available instruments is used for each equation and the disturbances are homoskedastic.

The GMM, developed by Hansen (1982), provide a convenient framework for obtaining asymptotically efficient estimator in this context. Hansen (1982) and White (1982) showed that by optimally weighting the distance between the sample and population moments, with the weights being the inverse of the covariance matrix of the sample moments, this can improve the efficiency over the 2SLS estimates.

Assuming the disturbances term have the familiar error component structure in which:

$$E(\eta_i) = 0;\ E(v_{it}) = 0;\ E(v_{it}\eta_i) = 0 \text{ for } i = 1,\ldots,N \quad t = 2,\ldots,T \tag{3}$$

and

$$E(v_{it}v_{is}) = 0 \text{ for } i = 1,\ldots,N \text{ and } \forall\ t \neq s\ . \tag{4}$$

The standard assumption concerning the initial conditions of dependent variable:

$$E(y_{it}v_{it}) = 0 \text{ for } i = 1,\ldots,N,\ t = 2,\ldots,T. \tag{5}$$

Together, equations (3), (4), (5) implying the following $m = 0.5(T-1)(T-2)$ moment restrictions $y_{i,t-s}\Delta v_{it} = 0$ which can be written more compactly as:

$$E[Z_i^{'}\Delta v_{iT}] = 0 \text{ for } i = 1,2,\ldots,N, \tag{6}$$

where $Z_i^{'}$ is the instrumental matrix for the first differences with equation (2):

$$Z_i = Z_{di} = \begin{pmatrix} y_{i1} & y_{i2} & \cdots & y_{ip} & 0 & 0 & \ldots & 0 & \ldots & 0 & 0 & \ldots & 0 \\ 0 & 0 & \ldots & 0 & y_{i1} & y_{i2} & \cdots & y_{i(p+1)} & \cdots & 0 & 0 & \ldots & 0 \\ . & . & . & . & . & . & . & . & & . & . & & . \\ . & . & . & . & . & . & . & . & & . & . & & . \\ 0 & 0 & \ldots & 0 & 0 & 0 & \ldots & 0 & \cdots & y_{i1} & y_{i2} & \cdots & y_{i(T-2)} \end{pmatrix},$$

where the matrix consist of $T-m-1$ rows and $\sum_{j=p}^{T-2} j$ columns[3], and $\Delta v_i = (\Delta v_{i3}, \Delta v_{i4},..., \Delta v_{iT})^{'}$.

These are the moment restriction exploited by the standard first difference GMM estimator. If the residual term are not serial correlated with each other, then, for time $t = p + 2$, $(y_{i1}, y_{i2}, \ldots, y_{ip})$ are correlated with y_{ip+2}, therefore can be used as a valid instruments. Similarly, $(y_{i1}, y_{i2}, \ldots, y_{i,T-2})$ can be used in the first differenced equation for period $t = T$.

Based on these moment conditions, the GMM estimator minimizes the quadratic distance $\Delta v^{'} z_d W_N z_d^{'} \Delta v$ for some weighted matrix. This gives the GMM estimators as:

[1] As in Holtz-Eakin et al. (1988, 1989) the analysis is performed estimating each equation of model (2) separately. For illustration purpose, the following discussions will based on the growth equation in model (2), the same hold, *mutatis mutandis*, for the financial development equation in model (2).

[2] If the error at the levels are MA(k), then, the disturbances in differences are MA(k+1).

[3] If these are regressor other than lagged endogenous variables uncorrelated with individual effect and the error terms, these regressor can be used as instruments together with the above Z_i.

$$\hat{\beta}_d = \left[\left(\sum \Delta x_i^{i} Z_{di}\right) \mathrm{W}\left(\sum_i Z_{di} \Delta x_i\right)\right]^{-1} \left(\sum_i \Delta x_i^{'} Z_i^{d}\right) W \left(\sum_i Z_i^{dt} \Delta y_i\right), \quad (7)$$

where Δ is the difference operator, x_i is a data matrix containing the time series of lagged dependent variables, the lagged x's and the time dummies, W is the weighted matrix. Alternative choices for the weights W give rise to a set of GMM estimators based on the moment condition (6), all of which are consistent for large N and finite T, but differ in their asymptotic efficiency.

Under the assumptions that the disturbances are homoskedastic through time, i.e., if $E(v_{it}^2) = \sigma_i^2$ for $t = 2,\ldots, T$, the first differences model implies that an asymptotically equivalent GMM estimator obtained in one-step using the weight matrix

$$W_{1N} = \left(\frac{1}{N} \sum Z_{di}^{'} H_i Z_{di}\right)^{-1}, \quad (8)$$

where

$$H = \begin{pmatrix} 2 & -1 & . & . & . & & 0 \\ -1 & 2 & & & & & 0 \\ . & . & & & & & . \\ . & . & & & & & . \\ . & . & & & & & -1 \\ 0 & 0 & . & . & . & -1 & 2 \end{pmatrix}$$

H is a (T–2) square matrix with 2's on the main diagonal, -1's on the first off-diagonals and zero elsewhere.

If v_{it} are heteroskedastic, a two-step estimator can be estimated using:

$$H_i = \Delta \hat{v}_i^{*} \Delta \hat{v}_i^{'}, \quad (9)$$

where $\hat{v}_i^{*}$ are one-step residuals, which can be express as below:

$$W_N = \left[\frac{1}{N} \sum_{i=1}^{N} (Z_i^{'} \Delta \hat{v}_i \Delta \hat{v}_i^{'} Z_i)\right]^{-1}, \quad (10)$$

where the $\Delta \hat{v}_i$ are consistent estimates of the first differenced residual obtained from a preliminary consistent estimator.

Nevertheless, for the first differences GMM estimates, the absence of information about the parameters of interest in the levels of variables results in loss of what sometimes is very substantial part of the total variation in the data. Particularly when the time series are persistent and the numbers of time series are small, the first differences GMM estimator is poorly behave, in terms of bias and imprecision[1]. Under these conditions, large finite sample biases can be occur when the instrumental variables are weak.

Moreover, studies have showed that instrumental variables estimates in first differences equation can be subject to serious finite sample biases when the correlation between the available instrumentals with endogenous variables becomes weak, i.e., when the lagged levels of the series are only weakly correlated with the subsequent first differences (Alonso-Borrego and Arellano, 1999; Blundell and Bond, 1998)[2] .

Arellano and Bover (1995), Blundell and Bond (1998) show that this biases can be dramatically reduced when the additional moment conditions relative to the equation in levels are considered. The system GMM estimator exploits an assumption about the initial conditions to obtain moment conditions that remain informative even for persistent series and have been shown to perform well in simulation.

In order to fully exploit these instruments, the equations in first differences and equations in levels corresponding to the periods $p + 2,\ldots,T$ are stacked as system equations for GMM estimations as follows similar to equation (7).

The level moment conditions used can be expressed as $E(Z_{1i}^{'} v_i) = 0$, where Z_{li} is:

$$Z_i^{l} = \begin{pmatrix} \Delta y_{i(p+1)} & 0 & . & . & 0 \\ . & & . & & . \\ . & & . & . & . \\ . & & . & & . \\ 0 & & . & . & . \; \Delta y_{i(T-1)} \end{pmatrix}.$$

Instead of Δy_i, the stacked vector ($\Delta y_{i(m+1)},\ldots,$ $\Delta y_{iT}, Y_{i(m+2)},\ldots, y_{iT}$) is used. For Δx_i are now be replaced by the stacked vector $\Delta x_i^{+} = (\Delta x_{i3},\ldots,\Delta x_{iT},$

[1] These features are typically present in the growth models as RGDP is a highly persistent series.

[2] The instruments used in the standard first-differences GMM estimator become less informative in two important cases. One, when the series are close to random walks (Blundell and Bond, 1998); and two, as the variance of the individual effect increase relative to the variance of u_{it}. In both cases the time series y_{it} becomes highly persistent and lagged levels provide weak instruments for the subsequent first differences.

$x_{i(m+2)},\dots,x_{iT}$), the system moment condition can be expressed as $E(Z_s^{'}q_i) = 0$, where $q_i = \begin{pmatrix} \Delta u_i \\ u_i \end{pmatrix}$ and the matrix of instrument is now, $Z_{si}^{+} = \begin{pmatrix} Z_{di} & 0 \\ 0 & Z_{li} \end{pmatrix}$ for such system of equations in first differences and levels, the one-step estimates uses the weighting matrix, $H_{si}^{+} = \begin{pmatrix} H_{di} & 0 \\ 0 & I_i \end{pmatrix}$, where H_i^d = weighting matrix for the first differences estimator, I_i is an identity matrix with dimension $T-2$[1].

Whilst the two-step estimator uses:

$$H_i^* = \hat{v}_i^* \hat{v}_i^{*'} . \tag{13}$$

Though the one-step is asymptotically inefficient relative to two-step, even if the disturbance are homoskedastic, simulation suggested that inference based on the one-step may be more reliable than two-step, even in moderately large sample (Blundell and Bond, 1998).

Clearly, the system GMM estimator is a combination of GMM differed estimator and a GMM levels estimator; with an additional set of equations in levels with suitably lagged first-differences as instruments. This combination is linear for the system estimator, which is given by:

$$\hat{\beta}_s = \gamma\hat{\beta}_d + (1-\gamma)\hat{\beta}_l , \tag{14}$$

where $\hat{\beta}_d$ and $\hat{\beta}_l^p$ are the fist-differenced and levels estimator, respectively and

$$\gamma = \frac{\Delta y^{'} Z_d (Z_d^{'} Z_d)^{-1} Z_d^{'} \Delta y}{\Delta y^{'} Z_d (Z_d^{'} Z_d)^{-1} Z_d^{'} \Delta y + y^{'} Z_l \, (Z_l^{'} Z_l\,) Z_l \, y} =$$

$$= \frac{\hat{\pi}_d^{'} Z_d^{'} Z_d \hat{\pi}_d}{\hat{\pi}_d^{'} Z_d^{'} Z_d \hat{\pi}_d + \hat{\pi}_l^{'} Z_l^{'} Z_l \, \hat{\pi}_l} ,$$

where $\hat{\pi}_d$ and $\hat{\pi}_l$ are the OLS estimates of the first stage regression coefficients. For the system GMM estimator, although the levels of y_{it} dependent variable are necessarily correlated with the individual-specific effects η_i, Δy_{it} are not correlated with η_i, permitting lagged differences to be used as instrumentals in the levels equations. As an empirical matter, the validity of these additional instruments can be tested using standard Sargan tests of over-identifying restrictions, or using difference Sargan or Hausman comparisons between the first-differenced GMM and system GMM results (see Arellano and Bond, 1991).

Despite the validity of the set of instrumental variable, the consistencies of the GMM estimator also depend on the assumption of no serial correlation in the residual terms. The $m1$ and $m2$ tests for the absence of first and second order serial correlation in the differences residuals (i.e., $\hat{v}_{it} - \hat{v}_{i,t-1}$), respectively. If the disturbances in levels are not serially correlated, then there should be evidence of significant negative first order serial correlation in the differenced residuals.

Using these instruments and following the estimation strategy outlined by Blundell and Bond (1998), the coefficients for the lagged dependent variables and predetermined variables can be estimated for the purpose of causality tests. The test of whether x cause y is simply a test of the joint hypothesis that $\beta_1 = \beta_2 = \dots = \beta_m$ are all equal to zero. If this null hypothesis is accepted, then it means that x does not cause y.

The validity of the over identifying restrictions can be tested using a two-step robust Sargan-Hansen test. The tests on the model in first differences can be express as:

$$SH = N^{-1}\left(\sum_i^N \Delta\hat{v}_i^{'} Z_i^d\right) A_N \left(\sum_i^N Z_i^{d'} \Delta\hat{v}_i\right). \tag{15}$$

SH is asymptotically distributed Chi-square under the null that the over identifying restrictions are valid with degree of freedom equal to the number of over identifying restriction.

For system estimator, similar test can be performed. A test for the validity of level moment condition that are utilized by the system estimator is then obtained as the difference between SH_s and SH_d:

$$Dif\text{-}SH = SH_s - SH_d. \tag{16}$$

And the *Dif-SH* is asymptotically chi-squared distributed with $L_s - L_d$ degrees of freedom under the null that level moment conditions are valid.

Alternatively, the validity of instrumentals' set for equation in levels can be tested using the Hausman type tests proposed in Arellano (1993), which can be computed by including another set of regressors that take the value zero in the equations in first differences, and reproduce the levels of the right hand side variables for the equation in levels. The test statistic is then a Wald test of the hypothesis that these additional regressors are jointly zero[2].

[1] For unbalanced panel, I_i is an identity matrix equal to the number of levels equations observed for individual *i*.

[2] See Arellano and Bond (1991) and Arellano (1993) for full details of these test procedures.

3. Results and discussions

As in Holtz-Eakin et al. (1988; 1989) the analysis is performed estimating each equation of model (2) separately. For the choice of lag length, *p*, the appropriate specification is an important issue especially in short panels, otherwise misleading results on causality may be obtained. According to Holtz and Eakin et al. (1988), the lag length should be less than 1/3 of the total time period; other wise, the covariance matrix cannot correctly estimated due to over-identification problem. Initially, a VAR (3) model is specified, so that 5 observations per individual are available for the estimation. A Wald test on the joint significant of the regressor is then being performed.

The system dynamics panel estimates for the four main developing regions are reported in Tables 1 to 4 (see Appendix A), respectively[1]. The reported results are one-step estimator, for which inference based on the asymptotic variance matrix has been found to be more reliable then the two-step estimator[2]. It is worth pointing out that the GMM standard errors are asymptotically robust to time series or cross-sectional heteroskedasticity of unknown type. Hence, this does not require the assumption of homoskedasticity across time or individual. Before drawing any inference from the panel causality tests, one must ensure the consistency of the GMM estimator; which relies on the validity of the instrumental variable and the assumption that the error terms does not exhibit serial correlation.

Clearly, the m1 and m2 tests of serial correlation in the first differences residuals are in both cases consistent with the maintained assumption of no serial correlation in the residual terms. The Sargan-Hansen test does not reject the validity of the overidentifying restriction[3]. Moreover, both the Sargan-Hansen and Arellano's version of the Hausman test do not reject the validity of the addition moment condition used in the levels equations, suggesting that the unobservable country specific effect is uncorrelated with the differences of the regressors.

A quick glance on the Wald statistic in Table 1 (see Appendix A) on both growth and financial equation reveal that, after controlling for problems associated with lagged dependent variables and weak instrumental, country-specific effects, endogeneity, and potential problem associated with lagged dependent variables and weak instrumentals, the empirical evidence suggest that for the countries in the Africa region, the financial deepening and economic growth are mutually not causally related. Meanwhile, as in Tables 2 and 3, the exist causality runs from financial development to growth, suggesting financial deepening of developing countries in the Asian and Europe region may contribute to the more general process of economic development, thus supporting the old Schumpeterian hypothesis. On the other hand, developing economics in the Western Hemisphere region provides evidence supporting the "demand leading" view.

Apparently, although there exist evidence supporting the other views including the demand leading and the view of no causal relation between the economic growth and the financial deepening, however, these support are not as strong as the supply-leading hypothesis, on balance, most of the evidence seems favor of the view that finance is a leading sector in the process of economic development. This is not particularly surprising: for emerging economies without mature entrepreneurial experience, financial intermediates will be more important.

Conclusion

Theoretically reasoning and empirically evidence, the literature on the relationship between the economic growth and financial development overwhelmingly suggest as positive, first-order relationship between the two. Nevertheless, empirical studies on the issue of causality between the financial development and economic growth, however, remain sparse (see Pagano, 1993). Financial development may simply be a leading indicator, rather than an underlying cause of economic growth. Providing evidence on causality has important implications. It will help policy makers design reforms that indeed promote growth enhancing financial sector development, otherwise, if the opposing thesis is the correct description of reality, then the unnecessary emphasis on financial deepening will divert attention away from other, perhaps more, urgent policy options to spur economic growth.

This paper re-examines the causality issue from a panel data perspectives using the system GMM technique developed by Arellano and Bover (1995), and Blundell and Bond (1998) to conduct the causality test. The panel dataset involved developing countries of 4 main regions: Africa, Asia, Europe and Western Hemisphere over the period of 1990-1998. Differs from previous studies on the panel causality test developed by Holtz-Eakin et al. (1988), the system GMM employed in this study include initial conditions as additional instrumentals to improve estimation accuracy.

[1] GMM results for Asia is adapted from Habibullah and Eng (2006).

[2] If the residuals are not only serially uncorrelated but also homoskedastic, the first-step estimate is asymptotically equivalent to the two-step estimator.

[3] The Sargan are reported based on the minimized values of the associated two-step GMM estimator.

The main finding of the results consistent with the "financial structuralist" view suggests that a widespread network of financial institutions and a diversified array of financial instruments will have a beneficial effect on economic growth. Although there are evidence supporting the other views including the demand following and the view of no causal relation between the economic growth and the financial deepening, these supports are not as strong as the supply leading hypothesis.

The findings in the present study suggest there is much room for further study. While there exist a clear empirical link exist between financial development and economic growth, yet, there is still limited knowledge on policies to support of growth promoting financial systems.

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Appendix A

Table 1. GMM estimates of panel causality tests (Africa)

Dependent variable	Growth	Finance
CONSTANT	0.0297 (2.0191)**	-0.0894 (-3.2158)***
GROWTH (-1)	1.2389 (4.4800)***	1.5928 (5.6437)***
GROWTH (-2)	-0.6415 (-1.5796)	-0.4634 (-1.4778)
GROWTH (-3)	0.3689 (1.8554)*	
FIN (-1)	0.0092 (0.1201)	0.2611 (1.7668)*
FIN (-2)	-0.0631 (-0.4153)	-0.2618 (-1.8073)*
FIN (-3)	0.0351 (0.3677)	
m1 (*p*-value)	-1.715 (0.086)	-1.767 (0.077)
m2 (*p*-value)	1.428 (0.153)	1.090 (0.276)
Sargan-Hansen [d.f] (*p*-value)	17.2368[22] (0.750)	12.9087[48] (0.999)
Sargan Difference [d.f] (*p*-value)	2.9995[8] (0.9343)	1.0602[10] (0.9997)
Hausman-Arrelano (*p*-value)	1.8023 (0.4061)	0.4721 (0.7897)
Causality	2.4317	3.3016
Wald test	(0.488)	(0.192)
Instrumental variables:		
Differenced equation	All lagged *y* and *x* dated *T*-5 and earlier	All lagged *y* and *x* dated *T*-4 and earlier
Level equation	Δx_{t-4} and Δy_{t-4}	Δx_{t-3} and Δy_{t-3}

Notes: t-statistics are in parenthesis. Standard errors and test statistic are asymptotically robust to heteroskedasticity. Time dummies were included in all equations. m1 and m2 are test for first- and second-order serial correlation in the first-differenced residuals, asymptotically distributed as N (0,1) under the null of no serial correlation. Argan-Hansen test is a test of over-identifying restriction. Sargan-Hansen Difference is a nested test for the additional instruments variables of the level equation. Hausman-Arellano test is a Hausman type test for the absence of mean independence, and more generally, for the instruments' set for the equation in levels.

Table 2. GMM estimates of panel causality tests (Asia)

Dependent variable	Growth	Finance
CONSTANT	-0.1048 (-1.4607)	0.2082 (2.5047)**
GROWTH (-1)	0.75405 (2.0510)**	0.5406 (2.4806)**
GROWTH (-2)	-0.5976 (-1.4829)	0.1564 (1.3777)
GROWTH (-3)	0.79463 (1.3176)	0.1705 (0.7893)
FIN (-1)	-0.0828 (-0.7756)	-0.5491 (-1.6132)
FIN (-2)	0.50935 (2.1179)**	-0.5735 (-1.4255)
FIN (-3)	-0.206 (-0.8796)	1.0752 (2.1643)**

Table 2 (cont.). GMM estimates of panel causality tests (Asia)

Dependent variable	Growth	Finance
m1 (*p*-value)	-1.809 (0.076)	-2.067 (0.039)
m2 (*p*-value)	0.497 (0.620)	-1.519 (0.129)
Sargan-Hansen [d.f] (*p*-value)	1.8924[32] (0.999)	5.8436[32] (0.999)
Sargan Difference [d.f] (*p*-value)	0.0764[8] (0.9999)	0.0238[8] (0.9999)
Hausman-Arrelano (*p*-value)	1.40059 (0.496)	2.7159 (0.257)
Causality	8.3171	5.7759
Wald test	(0.040)	(0.123)
Instrumental variables:		
Differenced equation	All lagged *y* and *x* dated *T*-4 and earlier	All lagged *y* and *x* dated *T*-4 and earlier
Level equation	Δx_{t-3} and Δy_{t-3}	Δx_{t-3} and Δy_{t-3}

Notes: As per Table 1 above.
Source: Habibullah and Eng (2006).

Table 3. GMM estimates of panel causality tests (Europe)

Dependent variable	Growth	Finance
CONSTANT	-0.0458 (-0.4623)	0.2082 (2.5047)**
GROWTH (-1)	1.2125 (5.8502)***	0.5406 (2.4806)**
GROWTH (-2)	-0.4219 (-3.4174)***	0.1564 (1.3777)
GROWTH (-3)	0.1103 (1.1957)	0.1705 (0.7893)
FIN (-1)	0.0216 (1.1668)	-0.5491 (-1.6132)
FIN (-2)	0.0335 (2.4200)***	-0.5735 (-1.4255)
FIN (-3)	0.0189 (1.2901)	1.0752 (2.1643)**
m1 (*p*-value)	-2.034 (0.042)	-2.067 (0.039)
m2 (*p*-value)	-0.054 (0.957)	-1.519 (0.129)
Sargan-Hansen [d.f] (*p*-value)	1.4903[22] (0.999)	5.8436[32] (0.999)
Sargan Difference [d.f] (*p*-value)	1.1112[8] (0.9974)	0.0238[8] (0.9999)
Hausman-Arrelano (*p*-value)	1.0236 (0.5994)	2.7159 (0.257)
Causality	7.2227	1.0089
Wald test	(0.065)	(0.604)
Instrumental variables:		
Differenced equation	All lagged *y* and *x* dated *T*-5 and earlier	All lagged *y* and *x* dated *T*-4 and earlier
Level equation	Δx_{t-4} and Δy_{t-4}	Δx_{t-3} and Δy_{t-3}

Notes: As per Table 1 above.

Table 4. GMM estimates of panel causality tests (Western Hemisphere)

Dependent variable	Growth	Finance
CONSTANT	0.0184 (2.6262)***	-0.5255 (-4.5520)***
GROWTH (-1)	1.5865 (11.7613)***	2.8772 (8.7728)***

Table 4 (cont.). GMM estimates of panel causality tests (Western Hemisphere)

Dependent variable	Growth	Finance
GROWTH (-2)	-0.6015 (-4.5688)***	-1.0839 (-2.0996)**
GROWTH (-3)		-0.4778 (-1.4733)
FIN (-1)	-0.0149 (-1.4950)	1.4384 (0.6108)
FIN (-2)	0.0138 (1.6283)	0.3875 (0.1127)
FIN (-3)		-1.6196 (-1.2892)
m1 (*p*-value)	-2.316 (0.021)	-1.759 (0.079)
m2 (*p*-value)	1.287 (0.198)	0.017 (0.986)
Sargan-Hansen [d.f] (*p*-value)	10.9110[48] (0.9999)	13.0850[32] (0.9987)
Sargan Difference [d.f] (*p*-value)	2.6856[12] (0.9973)	8.3978[24] (0.9986)
Hausman-Arrelano (*p*-value)	0.7147 (0.6995)	1.4824 (0.4765)
Causality	2.7020	9.8128
Wald test	(0.259)	(0.020)
Instrumental variables:		
Differenced equation	All lagged *y* and *x* dated *T*-4 and earlier	All lagged *y* and *x* dated *T*-4 and earlier
Level equation	Δx_{t-3} and Δy_{t-3}	Δx_{t-3} and Δy_{t-3}

Notes: As per Table 1 above.

Appendix B

Table 5. Selected countries in the sample

Africa	Asia	Europe	Western Hemisphere
Burkina	Bangladesh	Cyrus	Argentina
Cameroon	India	Hungary	Barbados
Center Africa	Indonesia	Malta	Belize
Ethiopia	Korea	Poland	Bolivia
Kenya	Lao	Turkey	Chile
Madagascar	Malaysia	Bulgaria	Columbia
Mali	Myanmar	Romania	Costa Rica
Morocco	Nepal	Estonia	Dominica
Niger	Pakistan	Armenia	Dominican Republic
Senegal	Philippines	Czech republic	Ecuador
Sierra Leone	Singapore	Kazakhstan	El Salvador
Seychelles	Sri Lanka	Latvia	Granada
Swaziland	Thailand	Lithuania	Haiti
Tunisia		Macedonia	Honduras
Zimbabwe		Russia	Jamaica
		Slovak republic	Mexico
		Slovenia	Nicaragua
			Panama
			Paraguay
			Peru
			St. Lucia
			St. Vincent
			Suriname
			Trinidad
			Venezuela