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Can Dynamic Panel Data Explain the Finance-Growth Link? An Empirical Likelihood Approach

UMUT OGUZOGLU
Department of Economics,University of Manitoba and IZA

THANASIS STENGOS*
Department of Economics, University of Guelph

The short run effect of the financial intermediary development on economic growth is analyzed using an unbalanced panel of 77 countries covering 35 years. Empirical Likelihood (EL) estimation is used and compared to more conventional GMM methods that weight moment conditions equally over the sample. However, if a part of the data is associated with only weak instruments, GMM estimators are subject to considerable small sample bias. EL appropriately re-weights the moment restrictions to deal with that problem. Using EL, we obtain more robust estimates of the effect of financial intermediation on economic growth than GMM.

Keywords: economic growth,financial intermediation, empirical likelihood, dynamic panel data models

1 Introduction

The question of causality between financial structure and economic growth has been a topic of research for a long time. Shumpeter (1912) emphasizes the role of financial intermediaries by defining the banker as, not only a middleman, but also an authority who facilitates the channels for technological innovation. According to this view, a well functioning financial system induces economic growth by evaluating projects, managing risk, monitoring managers, and facilitating transactions. These services allow the reallocation of capital to its highest value use by avoiding issues of moral hazard and adverse selection as well as minimizing transaction costs.

Many development economists, however, have ignored the role of the financial intermediaries as a catalyst for economic growth. According to Robinson (1952), financial instruments evolve as a response to the needs created by economic development. As such, financial development should be seen as an outcome of economic growth not the cause of it. More recently, Lucas (1988) argues that the finance-growth nexus is "badly over-stressed".

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An expanding recent empirical literature aims to shed some light on the above controversy, see Levine (2004) for an excellent survey. King and Levine (1993) employ a cross sectional data from 77 countries to regress three growth indicators on several measures of financial depth while controlling for other factors affecting economic growth. They show that, ignoring causality, financial intermediary development positively affects economic activity and hence leads long-run growth. Levine and Zervos (1998) report results from examining the relationship of stock market liquidity and banking development on growth, capital accumulation and productivity improvements. They find that the former variables positively predict the latter, even after controlling for economic and political factors. Moreover, La Porta et al (2000) and Andrianova, Demetriades and Shortland (2008), show that higher degree of public ownerships of banks, hence lower quality of the financial services, are associated with slower economic growth.

Most recent research uses panel data to cope with endogeneity, omitted variable bias and collinearity which plagues the cross sectional models mentioned above. Levine, Loayza and Beck (2000, hereafter LLB) use two Generalized Method of Moments (GMM) estimators to a macro panel of 74 countries during the 1960-95 period to show that the exogenous component of financial development induces long-run economic growth.

The current paper analyses the effect of exogenous financial intermediary development on economic growth using a dynamic panel data model. Specifications such as the long run model in LLB have been used to model movements from one steady state to another, and also to model the transition effects of various policies, such as financial liberalization. But if we expect diffusion to have a differential impact on growth in the short-run than in the long-run, then we may expect the long run model to be miss-specified. The use of a dynamic model has the advantage that it allows financial development measures to have both a short-run and a long-run impact on growth, which may be expected if full diffusion does not occur immediately.

Dynamic panel data model estimation is often conducted using GMM methods, see Arellano and Bond (1991) and Arellano and Bover (1995), where the lags of the regressors are used as instruments. The main problem with these methods is that GMM estimation weights moment conditions equally over the sample. However, if a part of the data is associated with only weak instruments, GMM estimators are subject to considerable small sample bias and moreover, simulation studies have shown that test statistics based on GMM estimation can be heavily distorted due to the downward bias of asymptotic standard errors, see Imbens, Spady and Johnson (1998). In this paper we will employ Empirical Likelihood (hereafter EL) estimation as an alternative to GMM to cope with these problems. EL, see Owen (1988, 1990, 1991), Qin and Lawless (1994) and Imbens, Spady and Johnson (1998) for a few standard references, offers a theoretical improvement over GMM especially when the moment conditions are weakly defined. In that case EL appropriately re-weights the moment restrictions. The literature on empirical likelihood suggests that EL shares the same first order asymptotic efficiency as GMM while having certain advantages related to higher order asymptotics, see Newey and Smith (2004).

Recent simulation studies have shown that EL based estimation can also have attractive finite sample properties, see Mittelhammer, Judge and Schoenberg (2001) on structural equations, Brown and Newey (2001) and Bond and Windmeijer (2002) on dynamic panel data. Using EL in the context of a dynamic model allows us to obtain more robust estimates of the relationship between financial intermediation and economic growth than those obtained in the recent empirical literature based on conventional GMM, see LLB. The latter display a lot of variability between different model formulations that appear equally well specified according to tests for over-identifying restrictions, whereas this is not the case for EL.

The paper is organized as follows. Section 2 discusses the recent empirical work on the relationship between growth and financial intermediation, section 3 discusses the short run model of LLB, their data and the variables used in their study and ours, section 4 introduces the dynamic model and it describes the GMM and EL estimators and section 5 compares their performance in the context of a small Monte Carlo simulation study. Section 6 presents the empirical results and finally we conclude.

2 Recent Empirical Work

As the search for better theoretical models progressed, so did the search for stronger empirical evidence of the relationship between financial development and growth. King and Levine (1993) investigate whether higher levels of financial development are significantly and robustly correlated with faster current and future rates of economic growth, physical capital accumulation, and economic efficiency improvements. They use four measures of financial development: the ratio of liquid liabilities to GDP, the importance of deposit banks relative to the central bank in allocating domestic credit, issued to non-financial private firms divided by total credit, and credit issued to non-financial private firms divided by GDP. The data spans 80 countries over the period 1960 to 1989 and is taken from Levine and Renelt (1992). King and Levine (1993) present two sets of findings. First, they study the strength of the partial correlation of the period-average levels of the financial development indicators with the average rate of GDP growth, the rate of physical capital accumulation, and the rate of improvement in economic efficiency over the period. Second, they report results of the relationship between the initial level of the financial development indicators and the average level of the aforementioned growth indicators. In both sets of regressions they use period averages (i.e., one data point for each country) and they construct pooled data where the data is constructed according to decades (i.e., three data points for each country). The first series of regressions, studying the contemporaneous associations, is performed using ordinary least squares. They report that higher levels of financial development are positively associated with faster rates of economic growth, physical capital accumulation, and economic efficiency improvements. Similarly, the second set of regressions is also performed using ordinary least squares and they find that the predetermined component of financial development is a good predictor of future growth over the next 10-30 years, future rates of capital accumulation, and improvements in economic efficiency. This work does not, however, confront the potential biases caused by simultaneity or omitted variables, including country-specific effects, as pointed out by LLB. For a study examining the robustness of these estimates, see McCaig and Stengos (2005).

Levine and Zervos (1998) report results from examining the relationship of stock market liquidity and banking development on growth, capital accumulation and productivity improvements. They find that the former variables positively predict the latter, even after controlling for economic and political factors. Furthermore, both financial development indicators enter significantly when used in the same regression. They also find that stock market size, volatility, and international integration are not robustly linked with economic growth. Similar to King and Levine (1993), the investigation uses both period averages and initial period values. Thus, the strong association is not simply due to contemporaneous shocks to both the financial sector and growth. This study does not, however, present any evidence on causality.

In an effort to extract the exogenous component of financial development, and hence introduce results concerning causality, Levine (1998) examines the relationship between the legal system and banking development. He then follows this connection through to long-run rates of per capita GDP growth, capital accumulation, and productivity growth. The results indicate that countries where the legal system emphasizes creditor rights and rigorously enforces contracts have better-developed banks as compared to countries whose legal systems do not. Further results indicate that the exogenous component of banking development – legal origins – is positively and robustly associated with the growth indicators mentioned above. The analysis uses cross-country differences in legal origin, creditor rights, and contract enforcement to identify the exogenous component of banking development. Tests of overidentifying restrictions do not reject the null hypothesis that the instruments are uncorrelated with the error term, providing support for the proposition that the legal origin dummy variables are valid instruments for the financial development indicators. As Levine (1998) notes, using the exogenous component of financial development is a step forward in determining causality, but a dynamic panel setting would be better as it would include the time series dimension.

In a subsequent paper, Levine (1999) presents results using legal and regulatory determinants of financial intermediaries, such as creditor rights indicators, contract enforcement, the risk of governments modifying contracts, and accounting standards, as instrumental variables for various measures of financial development. Results via GMM reveal that the exogenous component of financial development positively influences economic growth and tests of overidentifying restrictions indicate that the data do not reject the hypothesis that the instrumental variables are uncorrelated with the error term. Levine (1999) suggests that the data is consistent with the view that improvements in creditor rights, contract enforcement, and accounting standards further financial development, thereby accelerating growth. In addition, the results are also consistent with the argument that causality runs in both directions; the results do not show that financial development occurs independently of growth, rather that the strong positive association is not due only to simultaneity bias.

LLB extend the previous findings by including private savings rates as a growth indicator by using a dynamic GMM panel estimator, in addition to a pure cross-country instrumental variables estimator. For the dynamic GMM panel estimator, data is averaged over seven 5-year periods. This technique helps to control for biases introduced either by simultaneity or unobserved country-specific effects. The pure instrumental variables estimation technique is plagued by shortcomings, since it does not exploit the time-series dimension of the data. Hence, estimates from a cross-sectional specification may be biased due to omitted country-specific effects, and it does not control properly for the endogeneity of all of the regressors. By comparison, dynamic GMM panel estimation exploits the time series variation in the data, accounts for unobserved country-specific effects, allows for the inclusion of lagged dependent variables as regressors, and controls for endogeneity of all regressors. They find that the level of financial intermediary development exerts a large and positive impact on total factor productivity, which feeds through to overall GDP growth.

All the results that have been discussed so far are based on linear specifications. There has been some evidence in the recent growth literature that there may be nonlinear effects that govern the growth process, especially when it comes to convergence and human capital effects, see Kalaitzidakis et al (2001). Using semiparametric techniques, Ketteni et al (2007) have shown that in the context of a finance growth model similar to the one that we are examining in this paper, the effect of financial intermediation on growth appears to be linear. In our study, we also use a dynamic a linear panel data model as the framework of our analysis.

3 The Data and the Variables

We use the data set used by LLB, where data for 74 countries is collected over the period of 1960-95. The observations for each country is averaged over non-overlapping 5 years periods.

As in LLB, the model for the logarithmic change in GDP for the country i at the time period t can be represented as follows

$$\Delta y_{it} = \beta FINANCE_{it} + \delta CONDITION_{it} + u_{it} \tag{1}$$

where $FINANCE$ is one of the three financial development measures. These variables are Liquid-Liabilities, Commercial-Central Bank and Private Credit. Liquid-Liabilities (LLY) is defined as the liquid liabilities of the financial system (currency plus demand and interest-bearing liabilities of the banks and non-bank financial intermediaries) divided by GDP. Commercial-Central Bank (BCOM) equals the ratio of commercial bank assets divided by the commercial bank plus central bank assets. Private Credit (PRIVO) is the value of credits by financing intermediaries to the private sector divided by GDP. LLY is a size measure and might fail to capture the quality of services given by financial institutions. However, LLY may be also subject to double counting due to deposits of financial institutions into other financial intermediaries. The BCOM variable is constructed on the assumption that commercial banks are more likely to identify efficient investment opportunities by putting greater emphasis on risk management, monitoring and mobilizing their savings than the central bank. Again, this measure of financial development does not perfectly reflect the quality and quantity of services produced by financial intermediaries. Moreover, a commercial bank may also choose to loan only to governments. PRIVO isolates the credit issued to the private sector from that issued to governments, government agencies, and public enterprises. It excludes credits issued by central banks. As with the other two indicators, PRIVO does not directly measure the quality and quantity of financial services offered by financial intermediaries. However, LLB interpret higher levels of PRIVO as indicative of financial intermediary development and they take it to be their preferred indicator.

$CONDITION$ refers to a set of conditioning variables. That may include a simple or a policy-augmented conditioning set, where the former includes the constant, the logarithm of initial income per capita and average years of secondary schooling, while the latter includes in addition to the simple set measures of government size, inflation, the black market exchange rate premium, and openness to international trade. In the conditioning set, the initial income is used to capture the convergence effect and school attainment is used to control for human capital, whereas inflation rate and black market premium are proxies for economic stability and price distortions.

The model given by equation (1), after conditioning on the initial period GDP, y_{i0}, is nested in the more general model (2) which will be introduced in following section by restricting $\gamma = 1$. Even in a typical macro panel where the unit root is a common property, this assumption can be quite restrictive. From an estimation point of view, even when the coefficient of the lagged dependent variable, y_{it-1}, is not our primary concern, allowing for a dynamic process can be crucial for the consistency of the other estimates. Moreover, the process governing the real per capita income may, not surprisingly, be related to the previous period performance of the economy. Therefore, in order to preserve the exogeneity of the $FINANCE$ variables it is important to investigate the process of economic growth in a dynamic framework. Finally, it is important to acknowledge that the development of financial intermediaries itself takes time. In case, where the switch between the pre- and post- financial development steady states does not occur immediately, it is crucial to measure the short run effects on the economy by examining the dynamic model of equation (2) below.

4 Estimating a Dynamic Growth Model

Consider the following equation for a country i at time t.

$$y_{it} - y_{i,t-1} = (\gamma - 1)y_{i,t-1} + \beta' X_{i,t} + \alpha_i + u_{it} \qquad \text{for } i = 1, ..., N \text{ and } t = 1, ..., T \tag{2}$$

where y_{it} is the logarithm of real per capita GDP, X is a set of regressors, α_i is an unobserved country-specific fixed effect and u is the disturbance term. The above model can be expressed as

$$y_{it} = \gamma y_{i,t-1} + \beta' X_{i,t} + \alpha_i + u_{it} \tag{3}$$

Existence of the lagged dependent variable y_{it} makes the classical Least Square Dummy Variable, estimator inconsistent for fixed T, see Nickel (1981) and Judson and Owen (1999)

Among the various estimation techniques proposed to estimate the above model, the GMM estimators of Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998) have attracted most attention. Below we will briefly describe these estimators and we will also introduce the EL approach that we use in this paper as the preferred alternative in estimating these models.

4.1 The differenced GMM estimator

The standard GMM approach due to Arellano and Bond (1991) starts with first differencing equation (2) in order to eliminate the fixed effects. The transformed model takes the following form

$$\Delta y_{it} = \gamma \Delta y_{i,t-1} + \beta' \Delta X_{i,t} + \Delta u_{it} \tag{4}$$

where Δ is the first difference operator.

Since the new error term Δu_{it} is by definition correlated with the lagged dependent variable $\Delta y_{i,t-1}$, one should use instrumental variables. The GMM approach uses all available lags of the dependent and the exogenous variables to form an optimal instrumental variable matrix $Z = [Z_1, ..., Z_N]$. The $(T-2) \times (T-1)(T-2)$ matrix of instruments is constructed according to the following moment conditions

$$\begin{aligned} E(y_{i,t-j}, \Delta u_{it}) &= 0 \quad \text{for } j = 1, ..., t && (5) \\ E(x_{it}, \Delta u_{it}) &= 0 \quad \text{for } t = 1, ..., T && (6) \end{aligned}$$

which can be rewritten as

$$E(Z_i \Delta u_{it}) = 0 \tag{7}$$

where

$$Z_i = \begin{bmatrix} y_{i1}\ x_{i1} ....x_{i3} & 0 & 0 \\ 0 & y_{i1}\ y_{i2}\ x_{i1} ....x_{i4} & 0 \\ 0 & 0 & y_{i1} ...\ y_{i,T-2}\ x_{i1} ....x_{iT} \end{bmatrix} \tag{8}$$

Since condition (6) requires strict exogeneity of the regressors x_{it} , if x_{it} are predetermined, only lagged values can be employed as instruments. We define the sample moment conditions as

$$g_i(\delta) = \frac{1}{N}\sum_{i}^{N} Z_i^T \Delta u_i = 0 \tag{9}$$

The efficient GMM estimator is the solution to

$$\widehat{\delta}_{GMM} = \arg\min(\Delta u^T ZWZ^T \Delta u) \tag{10}$$

where the weighting matrix is defined as,

$$W = (\frac{1}{N}\sum_{i}^{N} Z_i^T \Delta\widehat{u_i}\Delta\widehat{u_i}^T Z_i)^{-1} \tag{11}$$

and $\Delta\widehat{u_i}$ is obtained by a first step consistent estimation of (4).

Simulation studies showed that the GMM estimator that uses the optimal weighting matrix can have poor small sample properties, see Arellano and Bond (1991) and Blundell and Bond (1998). The main problem arises when the observed sample provides only weak instruments, see Bound, Jaeger and Baker (1998). This is the case when either the individual series are close to being random walk or the fixed effects are more variable than the random disturbance, u_{it}. A typical macro data set can be prone to these problems, where the data are highly persistent and as a result the lagged values of the variables are only weakly correlated with the differenced regressors $\Delta y_{i,t-1}$ and $\Delta X_{i,t}$. Furthermore, in empirical growth models, since 5-year averages are used to smoothen out the cyclical patterns of the data, even when the observed sample spans over long time periods, the actual time dimension is quite small something that contributes to the estimation problems mentioned above.

4.2 System GMM

Arellano and Bover (1995) introduce a new estimator, the so called System GMM (SysGMM), to deal with the shortcomings of the standard GMM estimator. The new estimator combines the differenced model (4) and with the regression in levels. The differenced model is instrumented using moment conditions (5)and (6), whereas the level regression utilizes the following

$$E\left[(y_{i,t-s} - y_{i,t-s-1})(\alpha_i + u_{i,t})\right] = 1 \quad \text{for } s = 1 \tag{12}$$

$$E\left[(X_{i,t-s} - X_{i,t-s-1})(\alpha_i + u_{i,t})\right] = 1 \quad \text{for } s = 1 \tag{13}$$

A potential problem with SysGMM is that, the number of moments is often more than the cross sectional dimension of a typical macro panel. In this case the estimator is subject to over-fitting bias and the standard errors are heavily distorted. In addition, SysGMM, as GMM, weights the moment conditions equally over the sample, something that can negatively affect the performance of these estimator in the presence of weak instruments.

4.3 Empirical Likelihood

EL offers itself as a natural alternative to GMM, when estimation relies on using conditional moment restrictions. The main advantage of the technique is to assign probability weights to the moment conditions in order to control their validity. This is particularly important in dynamic panel data models where the data is subject to persistence and hence weak instruments. EL attains the semi-parametric efficiency bound and hence shares the same first order efficiency with GMM. Additionally, Newey and Smith (2004) showed that EL offers additional advantages related to better higher order asymptotics than GMM, since the EL estimator does not share certain components of the second order bias that characterizes GMM estimators. The asymptotic bias of GMM estimator is increasing with the number of over-identifying restrictions, which is not the case with EL.

The EL estimator, maximizes an empirical likelihood distribution subject to certain zero valued moment conditions[1]. The maximization problem can be written as

$$\begin{gathered}\max_{\pi_i} N^{-1}\sum_{i=1}^{N}\ln(\pi_i)\\ \mathit{subject\ to}\ \sum\pi_i g_i(\delta)=0,\\ \sum\pi_i=1,\\ \mathit{and}\ \ \pi_i\geqslant 0\end{gathered} \tag{14}$$

where $\delta = (\gamma\,\beta')$, $g_i(\delta)$ is the set of the moment conditions and π_i are the empirical probabilities. The first restriction ties the data to the model parameters, the second one involves the normalization constraint $\sum\pi_i = 1$ and finally the non-zero condition $\pi_i \geqslant 0$ ensures that the usual probability properties are observed. Unlike GMM, EL treats weights π_i as additional parameters to be estimated, whereas GMM estimators restrict them to be $\pi_i = 1/N$. The Lagrangian for the above maximization problem is

$$L(\pi,\eta,\lambda) \equiv N^{-1}\sum_{i=1}^{N}\ln(\pi_i) - \eta\left(\sum_{i=1}^{N}\pi_i - 1\right) - \lambda^T\sum_{i=1}^{N}\pi_i g_i(\delta) \tag{15}$$

where η and λ are Lagrange multipliers. It can be shown that the solution to the above problem yields $\eta = 1$ and

$$\pi_i^*(\delta,\lambda) = \left[N\left(1+\lambda^T g_i(\delta)\right)\right]^{-1} \tag{16}$$

[1]As a rule, any instruments defined by GMM process can be used by EL estimation. Here $\sum\pi_i g_i = \sum\pi_i Z_i \Delta u_i$.

From equation (16) it is readily seen that the probability weights decrease with an increasing Lagrange multiplier, λ. This allows EL to put less weight on the sample moment conditions when they depart further away from zero. Substituting π_i^* into the objective function yields the empirical log-likelihood function

$$\ln\left[L_{EL}(\delta)\right] = -N^{-1}\sum_{i=1}^{N} \ln\left[\left(1 + \hat{\lambda}(\delta)^T g_i(\delta)\right)\right] \tag{17}$$

where $\hat{\lambda}(\delta)$ has to satisfy the following implicit function

$$\hat{\lambda}(\delta) = \arg\left[N\sum_{i=1}^{N} 1 + \hat{\lambda}(\delta)^T.g_i(\hat{\delta}_{EL})\right]^{-1} g_i(\hat{\delta}_{EL}) = 0 \tag{18}$$

Finally, the EL estimator, $\hat{\delta}_{EL}$, can be obtained as

$$\hat{\delta}_{EL} = \arg\max_{\delta} \ln[L_{EL}(\delta)] \tag{19}$$

The estimation of EL parameters $\hat{\delta}_{EL}$ and $\hat{\lambda}(\delta)$ using the implicit functions (18) and (19) can be computationally cumbersome even when the panel dimension is moderate. A practical remedy is, first to maximize the empirical log-likelihood function over the Lagrange multiplier λ for a given consistent estimate for δ to obtain a profile empirical likelihood. Finally, the profile empirical likelihood is maximized over δ to obtain the final estimate, $\hat{\delta}_{EL}$, see Kitamura (2001).

4.4 Test of Overidentifying Restrictions

In a dynamic panel data model, the number of instruments increases geometrically. It is common practice to drop the earliest lags of the instruments in order to facilitate the estimation and omit redundant variables from the instrument matrix. The validity of this subset of restrictions is examined by a test of Over Identifying Restrictions (OIR), where the null hypothesis is that there is no correlation between the additional instruments and the differenced error terms.

The OIR test based on minimized GMM criterion is given by the *J test*

$$J(\hat{\delta}_{G2}) = \bar{g}(\hat{\delta}_{G2})W(\hat{\delta}_{G1})\bar{g}(\hat{\delta}_{G2}) \tag{20}$$

where $\hat{\delta}_{G1}$ and $\hat{\delta}_{G2}$ are the one and two step GMM estimators respectively and $\bar{g}(.)$ is the sample averages of the moment conditions mentioned earlier. When the moment conditions are valid, the test statistics $NJ(\hat{\delta}_2)$ has an asymptotic chi-square distribution with $m - k$ degrees of freedom where m denotes the number of over-identifying restrictions and k is the number of model parameters. The OIR test is found to over reject the correct null hypothesis severely compared to its nominal size. This problem arises due to severe downward bias in the estimated asymptotic standard errors of the GMM estimator, see Arellano Bond (1991).

A very informative by-product of Empirical Likelihood estimation allows us to construct an OIR test statistics which is the first order equivalent to the *J test* presented above. This likelihood ratio type test is twice the difference between unrestricted empirical likelihood , $-n\log(n)$, and the maximized empirical likelihood of the model given in equation (15). Hence, the test statistic is

$$OIR^{EL} = LR_n = \sum 2\ln(1 + \hat{\lambda}' g(\hat{\delta}_{EL})) \tag{21}$$

Recent simulation studies, see Imbens et al (1998), showed that the OIR^{EL} test based on Empirical Likelihood have better small sample performance that the GMM based $Jtest$.

5 Monte Carlo Evidence

Below we will present a small Monte Carlo simulation study that compares the bias and root mean square error (RMSE) performance of GMM and EL using artificial data sets that mimic the characteristics of the growth data that we use. The DGP design follows Kiviet (1995) and can be summarized as follows.

The dependent variable is generated according to

$$y_{it} = \alpha_i + \gamma y_{it-1} + x_{it}^T\beta + u_{it}, \qquad u_{it} \sim N(0, \sigma_u^2) \tag{22}$$

where the x_{it} are formed by the following AR(1) process

$$x_{it} = \rho x_{it-1} + \zeta_{it}, \zeta_{it} \sim N(0, \sigma_\zeta^2). \tag{23}$$

Kiviet (1995) defines a signal to noise ratio σ_s^2 and shows that it can be calculated from the other parameters as follows

$$\sigma_s^2 = \beta^2\sigma_\zeta^2\left[1 + \frac{(\gamma+\rho)^2}{1+\gamma\rho}[\gamma\rho - 1] - (\gamma\rho)^2\right]^{-1} + \frac{\gamma^2}{1-\gamma^2}\sigma_u^2$$

The signal to noise ratio controls the information supplied by x_{it} in order to explain y_{it}. The higher σ_s^2, the more useful the x_{it} becomes to the model.

Additionally the vector of fixed effects α is drawn from $N(0, \sigma_\alpha)$. The standard deviation of the fixed effects σ_α is determined by

$$\sigma_\alpha = \mu\sigma_u(1 - \gamma)$$

The parameter μ is used to control relative variance of fixed effect with respect to the residual variance σ_u^2. When μ is equal to 1, the impact of both shocks are the same.

In order to mimic the macro growth data at our disposal and to form an environment where the data is highly persistent and therefore the instruments are only weakly defined, we choose the simulation parameters as follows. The data for y_{it} and x_{it} are generated to be close to random walk ($\gamma = 0.8$ and $\rho = 0.9$ or 0.5), σ_s^2 alternates between 2 and 8 and μ takes the values 1 and 5. The time dimension of the panel is allowed to alternate between 5 and 7, while the cross sectional dimension fixed at 200. Also x_{i0} and y_{i0} are set to zero and the first 50 observations are discarded before choosing the appropriate sample. Finally, 500 replications are conducted for the simulations.

The results are discussed by computing the bias and the RMSE of the different estimators. Tables 1 and 2 report the bias and RMSE of one- and two-step GMM estimators alongside the performance of the EL estimator.

The one-step GMM estimator (hereafter GMM1), is obtained by setting the weighting matrix in (10) to $W = (\frac{1}{N}\sum_i^N Z_i^T H Z_i)^{-1}$, where H is a $T-2$ square matrix which has twos on the main diagonal, minus ones on the first sub-diagonals and zeros otherwise. Here, H is used to deal with the $MA(1)$ error term of the first-differenced model (4). The efficient GMM estimator, GMM2, is computed by using GMM1 as an initial first step consistent estimator in the definition of W in equation (11).

We can see that when the data is generated to mimic a macro panel with high persistency problems EL outperforms GMM in all cases in terms of absolute bias and in about ninety percent of cases in terms of MSE. The performance differences are most visible when we generate highly persistent data, by limiting the information supplied by x_{it}, by setting $\sigma_s^2 = 2$ and letting the variance of the fixed effects to be larger than the error variance by choosing $\mu = 0.5$

6 Results from Macro Panel

In this section we present the results from the dynamic growth model presented above in section 4, based on the formulation of equation (3)[2]. Tables 3 to 8 present the coefficient estimates of the different $FINANCE$ variables, LLY, BCOM and PRIVO, alongside their p-values for significance and the OIR test statistics. For each financial development measure (LLY, BCOM and PRIVO) the regressions including simple and policy conditioning sets are carried out separately. The regressions are repeated including time dummies. Note that time dummies, apart from their usual role of capturing deterministic trends in the data, serve as exogenous instruments when they are included into the model. For GMM we report both the efficient GMM2 and the System GMM (SysGMM) estimates.

Table 3 reports the results for Liquid Liabilities (LLY) using the simple conditioning set. The short run effect of an exogenous change in LLY on growth is statistically significant and

[2]LLB used the formulation given in equation (2), whereas we use equation (3) as the basis of our estimation. The results from formulation (2) are qualitatively similar to those obtained using (3), except that in certain cases convergence was more difficult to achieve both for SysGMM and EL.

economically large. EL estimates of Liquid Liabilities (LLY) are highly significant and positive. GMM estimation underestimates this effect and rejects the validity of instruments, when time dummies are not included and for GMM2 also in the case when time dummies are included. The OIR test based on the EL procedure does not reject the null hypothesis of zero correlation between the instruments and the errors of the model in either case. The parameter estimates form GMM2 suggest a negative relationship between human capital and growth, whereas the opposite is true for EL and also for SysGMM when time dummies are included. The LLY estimate is only significant for GMM2 if time dummies are excluded.

Table 4 presents the results when the policy conditioning set is included. Again we distinguish between the cases where time dummies are included or not. Both GMM and EL coefficients are significant for LLY and both the OIR^{EL} and J tests confirm the validity of the instruments for the case when time dummies are included. However, for EL, when time dummies are not included the OIR^{EL} test suggests that there is misspecification in the choice of instruments. Inclusion of time dummies changes dramatically the results for EL estimation, where the LLY coefficient increases substantially. Note that the effect of human capital is again negative for both sets of GMM estimates when no time dummies are present and it becomes positive for SysGMM when time dummies are included. It is positive for EL. Even though, the J-test suggests that there is no instrument misspecification in either case, the GMM parameter estimates differ, with some variables changing signs and significance levels. Including time dummies as part of the model seems to be improving the results from a specification point of view for EL as it is evident from the OIR^{EL} p-values. On the other hand, even though there is no sign of misspecification according to the J-test, the variability of results between the two cases suggests a lack of robustness and hence the presence of misspecification not captured by the J-test for both sets of GMM2 and SysGMM estimates.

The effect of Private Credit variable (PRIVO) is presented in Table 5 when we only allow for a simple conditioning set, with and without the time dummies. Inclusion of time dummies seems to produce plausible estimated relationships for both EL and GMM2. In that case, the latter produces larger estimates for the role of private credit on economic growth than either SysGMM or EL. However, SysGMM produces a negative effect of human capital, something that differs both from EL and GMM2. The estimates of human capital are both positive for both EL and GMM2, in contrast to the results from LLY when only EL produced positive estimates. The results for PRIVO improve when policy conditioning variables are included into the regression as seen in Table 6. The OIR^{EL} test suggests that the relationship is misspecified, when time dummies are excluded. The J-test statistics for both sets of GMM estimates on the other hand do not display any signs of misspecification, yet for the two cases both sets of the GMM coefficient estimates jump around in terms of sign and significance and are not robust. Note for example, that the SysGMM estimate of the effect of human capital on growth is negative and significant when no time dummies are present and turns positive when the latter are present with a p-value of 0.07. The OIR^{EL} test suggests that the formulation with the time dummies is well specified and the results obtained in that case seem quite reasonable. The J-test is unable to distinguish between the two cases of not including and including the time dummies, yet the GMM estimates are themselves not robust between the two cases. Therefore, when the moment restrictions are appropriately weighted as it the case with EL, the PRIVO results with the policy conditioning set can be viewed with confidence, whereas the same is not true for the standard GMM methods.

Table 7 presents the results for BCOM with the simple conditioning. Both the OIR^{EL} and the J-test suggest that the time dummies should be included. In that case, the EL and GMM2 results suggest that the BCOM does not have a significant effect on growth, whereas the SysGMM estimates produce a significant and positive effect. Table 8 presents the results when we use the policy conditioning set, with and without the time dummies. EL is correctly specified when time dummies are included and in that case the results show that BCOM has a large positive effect on economic growth and this effect is highly statistically significant. On the other hand GMM estimation does not show any misspecification according to the J-test, yet the parameter estimates are clearly not robust between the two cases for both sets of estimates. In fact for GMM2, the coefficient on BCOM becomes negative and insignificant when time dummies are included, whereas the SysGMM estimates for human capital changes sign between the two cases.

In general the picture that emerges from EL estimation suggests that results based on conditioning sets augmented with time dummies are on the whole reliable estimates of the effects of the financial intermediaries variables on growth. On the other hand, the results from GMM for either GMM2 or SysGMM seem quite unreliable, jumping around between different models which according to the J-test are supposed to be well specified. Using EL we have found a positive effect on growth for all three variables. However the LLY is nearly twice as much as BCOM and four times as large as PRIVO. Our results do not produce the same sizeable effects that were obtained in LLB, although we do obtain statistically significant estimates using EL in well specified formulations. When interpreting the effect of financial intermediaries on growth, one has to be careful to identify a correctly specified model that produces these results and from what we have seen in our estimates, there is a lot of variation between different specifications depending on the conditioning and instrument sets. Overall, EL provides a useful method to overcome the problems that plague GMM in dynamic panel models and offers a robust method to distinguish between the different measures of financial intermediaries with regard to their effect on growth.

7 Conclusions

The current paper analyses the effect of exogenous financial intermediary development on economic growth using a dynamic panel data model. Dynamic panel data model estimation is often conducted using the GMM procedure of Arellano and Bond (1991), where the lags of the regressors are used as instruments. The main problem with this method is that the GMM estimation weights moment conditions equally over the sample. However, if a part of the data is associated with only weak instruments, GMM estimators are subject to considerable small sample bias. Moreover, test statistics based on GMM estimation can be heavily distorted due to the downward bias of asymptotic standard errors. In this paper we employ EL estimation as an alternative to GMM to cope with these problems. Using EL in the context of a dynamic panel model allows us to obtain more robust estimates of the relationship between financial intermediation and economic growth than those obtained in the recent empirical literature based on conventional GMM. The latter display a lot of variability between different model formulations based on different conditioning and instrument sets. Using GMM makes these formulations appear equally well specified according to tests for over-identifying restrictions. This is not the case for EL, where we are able to distinguish between well-specified and misspecified model specifications.

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Table 1: Average Absolute Bias , GMM and EL Estimators

ρ=0.5						ρ=0.9					
GMM1	GMM2	EL	T	μ	$sigma_s^2$	GMM1	GMM2	EL	T	μ	σ_s^2
0.1182	0.1191	0.0591	5	1	2	0.1309	0.1333	0.0741	5	1	2
0.0286	0.0272	0.0069	5	1	8	0.0927	0.0955	0.0582	5	1	8
0.3196	0.344	0.125	5	5	2	0.365	0.3975	0.1871	5	5	2
0.0911	0.1001	0.0299	5	5	8	0.2093	0.2256	0.1047	5	5	8
0.0332	0.0384	0.0237	7	1	2	0.0407	0.0543	0.0074	7	1	2
0.0226	0.0175	0.0056	7	1	8	0.0303	0.0375	0.0021	7	1	8
0.1257	0.1542	0.0216	7	5	2	0.1668	0.1882	0.0328	7	5	2
0.0418	0.0363	0.0001	7	5	8	0.1	0.1216	0.0304	7	5	8

Table 2: RMSE , GMM and EL Estimators

ρ=0.5						ρ=0.9					
GMM1	GMM2	EL	T	μ	σ_s^2	GMM1	GMM2	EL	T	μ	σ_s^2
0.1563	0.1672	0.1256	5	1	2	0.1692	0.1773	0.1339	5	1	2
0.0733	0.0834	0.0771	5	1	8	0.1286	0.1295	0.1054	5	1	8
0.3887	0.4321	0.3185	5	5	2	0.4322	0.4757	0.3975	5	5	2
0.1307	0.1572	0.1454	5	5	8	0.2554	0.275	0.174	5	5	8
0.0599	0.0591	0.0585	7	1	2	0.0715	0.0739	0.0548	7	1	2
0.0446	0.0403	0.0372	7	1	8	0.0561	0.0564	0.0466	7	1	8
0.152	0.1875	0.1597	7	5	2	0.1955	0.2128	0.1409	7	5	2
0.0726	0.0764	0.0968	7	5	8	0.1256	0.1554	0.087	7	5	8

Table 3: Liquid Liabilities with Simple Conditioning Set

Time Dummies	Not Included			Included		
	GMM2	SysGMM	EL	GMM2	SysGMM	EL
GDP_{t-1}	0.68801	1.062541	0.61893	0.81225	0.995582	0.89921
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Secondary Education	-0.0206	-0.309211	0.08399	-0.1284	0.019553	0.55386
	(0.8248)	(0.0000)	(0.4187)	(0.3797)	(0.8715)	(0.4187)
Liquid Liabilities	0.30426	0.129994	0.64917	0.09043	0.096132	0.47142
	(0.0001)	(0.0008)	(0)	(0.2612)	(0.0034)	(0.0000)
OIR	0	0.04	0.1592	0.004	0.27	0.0751

Note: The OIR results refer to the p-values of the $J - test$ under the GMM columns and of the OIR^{EL} under the EL column.

Table 4: Liquid Liabilities with Policy Conditioning Set

Time Dummies	Not Included			Included		
	GMM2	SysGMM	EL	GMM2	SysGMM	EL
GDP_{t-1}	0.61887	1.040505	0.33165	0.89172	0.953817	0.81728
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Secondary Education	-0.0229	-0.243359	0.17498	-0.0788	0.058803	0.3712
	(0.7371)	(0.0017)	(0.0433)	(0.5285)	(0.3707)	(0.1116)
Liquid Liabilities	0.29594	0.155837	0.53144	0.21056	0.210444	0.909
	(0.0000)	-(0.0072)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Government Size	0.02298	-0.049967	-0.121	0.02607	-0.03506	0.05023
	0.73459	0.4169	0.26573	0.63233	-0.4836	0.70332
Opennes to Trade	0.03494	-0.062524	0.25197	-0.019	-0.03323	0.0737
	(0.3824)	(0.1419)	(0.0007)	(0.6068)	(0.3691)	(0.5285)
Inflation	0.21643	0.03026	0.69812	0.05839	0.146357	0.10432
	(0.0112)	(0.7552)	(0.0000)	(0.4697)	(0.0539)	(0.5483)
Black Market Premium	-0.0479	-0.153461	0.129	0.00854	-0.04157	0.145
	(0.0776)	(0.0023)	(0.0097)	(0.7537)	(0.1289)	(0.0513)
OIR	0.125	0.426	0.0034	0.129	0.962	0.6014

Note: The OIR results refer to the p-values of the $J-test$ under the GMM columns and of the OIR^{EL} under the EL column.

Table 5: Private Credits with Simple Conditioning Set

Time Dummies	Not Included			Included		
	GMM2	SysGMM	EL	GMM2	SysGMM	EL
GDP_{t-1}	0.6211	1.0713	0.5735	0.6648	1.0046	0.8398
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Secondary Education	0.0932	-0.4042	0.4005	0.2401	-0.0081	0.0372
	(0.2039)	0.0000	0.0000	(0.0740)	(0.9398)	(0.8013)
Private Credits	0.1412	0.0971	0.0638	0.2069	0.1019	0.1141
	0.0000	(0.0008)	(0.0792)	(0.0001)	(0.0061)	(0.0363)
OIR	0.0160	0.0280	0.0000	0.3130	0.3720	0.2060

Note: The OIR results refer to the p-values of the $J-test$ under the GMM columns and of the OIR^{EL} under the EL column.

Table 6: Private Credits with Policy Conditioning Set

Time Dummies	Not Included			Included		
	GMM2	SysGMM	EL	GMM2	SysGMM	EL
GDP_{t-1}	0.5633	1.0076	0.6664	0.8122	0.9522	0.8653
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Secondary Education	0.0942	-0.1043	0.2206	0.2746	0.1235	0.2049
	(0.0451)	(0.0449)	(0.0005)	(0.0062)	(0.0706)	(0.0658)
Liquid Liabilities	0.1533	0.0711	0.2157	0.1464	0.1131	0.1210
	(0.0000)	(0.0130)	(0.0000)	(0.0027)	(0.0000)	(0.0000)
Government Size	0.0574	-0.0948	-0.0835	-0.0730	-0.0681	-0.0310
	(0.2212)	(0.0917)	(0.1870)	(0.1547)	(0.2594)	(0.7440)
Opennes to Trade	0.0305	-0.1189	-0.1435	-0.0842	-0.0060	-0.1847
	(0.3223)	(0.0054)	(0.0041)	(0.0232)	(0.8615)	(0.0356)
Inflation	0.0738	-0.1979	0.1786	-0.0002	0.0136	-0.1057
	(0.3103)	(0.0110)	(0.1050)	(0.9991)	(0.8610)	(0.4729)
Black Market Premium	-0.0051	-0.1451	0.1680	0.0230	-0.0406	0.0290
	(0.8373)	(0.0025)	(0.0041)	(0.6406)	(0.2652)	(0.7175)
OIR	0.1420	0.4610	0.0000	0.7020	0.7510	0.2000

Note: The OIR results refer to the p-values of the $J - test$ under the GMM columns and of the OIR^{EL} under the EL column.