Does Composition of Government Spending Matter to Economic Growth?

Bingxin Yu
Postdoctoral Fellow
Development Strategy and Governance Division
International Food Policy Research Institute
2033 K ST NW, Washington DC 20006 USA
Tel: 1-202-862-8114, Email: b.yu@cgiar.org

Shenggen Fan
Division Director
Development Strategy and Governance Division
International Food Policy Research Institute
2033 K ST NW, Washington DC 20006 USA
Tel: 1-202-862-5677, Email: s.fan@cgiar.org

Anuja Saurkar
Research Analyst
Development Strategy and Governance Division
International Food Policy Research Institute
2033 K ST NW, Washington DC 20006 USA

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Abstract

This paper assesses the impact of the composition of government spending on economic growth in developing countries. We use a dynamic GMM model and a panel data set for 44 developing countries between 1980 and 2004. We find that the various types of government spending have different impact on economic growth. In Africa, human capital spending contributes to economic growth whereas in Asia, capital formation, agriculture and education has strong growth promoting effect. In Latin America, none of government spending items has significant impact on economic growth. Our results are robust regardless of model specifications and instruments chosen.

Key Words

Government expenditure, growth, GMM

JEL code

H5, O1, C232

DOES COMPOSITION OF GOVERNMENT SPENDING MATTER TO ECONOMC GROWTH?

1. Introduction

The role of government spending in promoting economic growth and poverty reduction has been intensely debated among various scholars (Aschauer, 1989; Barro, 1990; Tanzi and Zee, 1997; Fan, Hazell and Thorat, 2000). Most of these studies either treat *total* government spending as one variable or only include one type of spending in their models, which could obscure the underlying economic dynamics by aggregation.

Only a few studies attempted to link different types of government spending to economic growth. Based on a simple OLS regression of GDP growth rate over five government expenditure variables, Landau (1986) concluded that government expenditure of education, defense and capital development had a weak or even no impact on economic growth. Castles and Dowrick (1990) used the shares of disaggregated government spending in health, education and social transfers in GDP to explain economic growth. They found that social transfers and education had a positive effect on growth. Devarajan, Swaroop, and Zou (1996) also used shares as explanatory variables in assessing the impact of different types of government spending on economic growth and they did not find any significant link. There are two potential problems associated with composition or share approaches applied to disaggregate data. First, government spending or its composition could also be a result of economic growth and there is a need to control for endogeneity or reverse causality. Second, it is often the case that potential model misspecification problem occurs when the composition or share of different government spending is used as the independent variable in determining economic growth.

Nowadays the issues on government spending are of special policy relevance, since they are directly related to the impact of government investment on economic growth and poverty reduction in a global scope. In order to achieve the Millennium Development Goals (MDGs), developing countries and the international development community are intensifying their efforts by increasing and redirecting resources in order to achieve development objectives. Thus, the key questions need to be answered include: whether government spending affects growth and therefore poverty reduction? How should resources be allocated among different sectors such as agriculture, infrastructure, health and education to achieve the stated objectives of growth and poverty reduction?

The purpose of this paper is to analyze differential impacts of government spending in developing countries using a dataset that includes 44 developing countries over 1980-2004. We address the potential problems presented in previous studies by applying generalized method of moments (GMM) on disaggregate public investment data.

2. Conceptual Framework and Empirical Econometric Model

In this study, we use the production function as our analytical framework to link economic growth to different types of government expenditures. A production function is a physical relationship between inputs and output. In our case, aggregate national GDP is used as total output and is used as the dependent variable, while the explanatory variables include labor, gross capital stock, and capital stock of various government expenditures.

$$GDP_{it} = f(LABOR_{it}, K_{it}, KGE_{it}, Z_{it}) \qquad (1)$$

where i represents country and t denotes year. GDP_{it} is aggregate national GDP, $LABOR_{it}$ total economically active population, and K_{it} gross capital stock. KGE_{it} is a capital stock vector constructed from current and past government spending, which is further disaggregated into $KAGEXP_{it}$ representing stock of government spending in the agricultural sector, $KEDEXP_{it}$ representing stock in the education sector, $KHEXP_{it}$ representing stock in the health sector, $KTCEX_{it}$ representing stock in the transportation and telecommunication sector, $KSSEXP_{it}$ representing stock in the social security sector, and $KDEXP_{it}$ representing stock in the defense sector. We include year dummies to proxy for Z and to control for other factors not included in the model and to prevent the most likely form of cross-country correlation, contemporaneous correlation.

Usually stocks cannot be observed directly, and we use the following procedure to construct a stock series from capital formation or various sector investment:

$$K_t = I_t + (1-\delta)\mathrm{K}_{\mathrm{t-1}} \tag{2}$$

Where K_t is the capital stock in year t, I_t is gross capital formation or sector investment in year t, and δ is the depreciation rate. Although the depreciation rate may vary by country, we simply assume a 10 percent for all the countries. To obtain initial values for the capital stock, we use a procedure similar to Kohli (1978):

$$K_{1980} = \frac{I_{1980}}{(\delta + \mathrm{r})} \tag{3}$$

Equation (3) implies that the initial stock in 1980 (K_{1980}) is gross capital formation or investment in 1980 (I_{1980}) divided by the sum of real interest rate r and depreciation rate δ.

We choose a dynamic model with lagged dependent variables to estimate the production function based on a panel data set. It allows sufficient information about the whole time period and individual heterogeneity in investigation of dynamic relationships and obtaining consistent parameter estimates (Bond, 2002). Several econometric difficulties arise using this approach. First, since government expenditure variables on the right hand side could also be a function of GDP, special attention is required to avoid or minimize the estimation bias caused by this endogeneity. Second, any variable series included in the analysis might not be stationary, i.e., unit roots exist. Thirdly, the estimation processes are complicated and can easily generate invalid estimates. In this study, a generalized method of moments (GMM) estimator is used to estimate production function based on a dynamic panel data model, taking both endogeneity and dynamic panel bias into consideration.

Let us assume that there are N countries observed over T periods, and *i* indexes country and *t* the time period. The model to be estimated is specified as:

$$y_{it} = \alpha_0 + \sum_{e=1}^{m} \alpha_e y_{i,t-e} + \sum_{k=1}^{n} \beta_k x_{i,t-k} + \lambda_t + \eta_i + u_{it} \qquad (4)$$

$$E(\eta_i) = E(u_{it}) = E(\eta_i u_{it}) = 0 \qquad i=1,\ldots,N; \quad t=m+2,\ldots,T;$$

where *y* is GDP, *x* is a set of independent variables (labor, gross capital stock, and sector stocks), all in logarithmic form, α 's and β 's are parameters to be estimated, λ_t is time dummies. Here the disturbance term has two orthogonal components: the stochastic individual effects η_i and the idiosyncratic shocks u_{it} , and the lag lengths *m* and *n* are sufficient to ensure that u_{it} is a stochastic error. While it is not essential that *m* equals *n*, we follow typical practice by assuming that they are identical.

Expressed in matrix, the (T-m) equations for individual *i* in equation (4) could be written as

$$Y_i = W_i\delta + \phi_i\eta_i + u_i \qquad i=1,\ldots,N \tag{5}$$

where δ is a parameter vector including the α 's and β 's, and W_i is a data matrix containing the time series of the lagged dependent variable *y*'s, *x*'s and the time dummies, ϕ_i is a vector of ones to capture individual endogeneity.

After certain transformation of equation (5), i.e., in level, first difference, combinations of first differences and levels, etc. Assuming we could find a set of suitable instrumental variables Z_i (which may or may not be entirely internal), and H_i is a possibly individual specific covariance matrix of the transformed errors, the linear GMM estimators of δ is computed as

$$\hat{\delta} = [(\sum_i W_i^{*'} Z_i) A_N (\sum_i Z_i^{'} W_i^{*})]^{-1} (\sum_i W_i^{*'} Z_i) A_N (\sum_i Z_i^{'} Y_i^{*}) \tag{6}$$

where weighting matrix $A_N = (\frac{1}{N}\sum_i Z_i^{'} H_i Z_i)^{-1}$, and W_i^* and Y_i^* denote some general transformation of W_i and dependent variable Y_i .

Lagged dependent variables are endogenous to the individual effects in the error term in equation (5), causing dynamic panel bias. Arellano and Bond (1991) proposed a method to estimate a dynamic panel difference model using all suitably lagged endogenous (and predetermined) variables as instruments in generalized method of moments (GMM) technique, called difference GMM. In principle, efficient GMM exploits a different number of instruments in each time period. Difference GMM avoids the trade-off between instrument lag depth and sample depth in 2SLS by including separate instruments for each time period.

Following their approach, equation (4) is thus transformed into first difference equation

$$\Delta y_{it} = \sum_{e=1}^{m} \alpha_e \Delta y_{i,t-e} + \sum_{k=1}^{n} \beta_k \Delta x_{i,t-k} + \Delta \lambda_t + \Delta u_{it} \tag{7}$$

At time *t*, if u_{it} are not serially correlated with each other, lagged dependent variables ($y_{i1}, y_{i2}, ..., y_{i,t-2}$) are uncorrelated with Δy_{it} and therefore can be used as valid instruments for difference Equation (7) at time *t+2*.

Despite all the advantages, difference transformation has its own weakness: it might destroy the long-term relationship in the data and leave just short-term impact (Hsiao, 1986; Munnel, 1992). As a result, the difference GMM procedure was criticized for efficiency loss and serious finite sample biases when the instruments used are weak (Blundell and Bond, 1998, 1999). As Blundell and Bond (1998) demonstrated in simulations, if dependent variable is close to a random walk, difference GMM performed poorly because past levels conveyed little information about future changes and thus lagged levels were weak instruments for differenced variables. Blundell, Bond and Windmeijer (2000) also suggested that this could be a concern for the multivariate difference GMM estimators when the individual series were highly persistent.

The solution is to find instruments orthogonal to the individual fixed effects η_i, instead of purging them. If there are instruments available that are uncorrelated with the individual effects, these variables can naturally work as instruments for the equations in levels. Usually this implies a set of moment conditions relating to the difference equations and an additional set of moment condition relating to the level equations. Arellano and Bover (1995) considered the simple mean-stationary AR(1) model, in which the differences ($\Delta y_{i3},...,\Delta y_{it}$) was uncorrelated with the individual effects η_i and thus could be used as instruments in the levels equation (4) .

Arellano and Bond (1998) and Blundell and Bond (1998) therefore proposed to use an extended system estimator that uses lagged differences as instruments for equations in levels, in addition to lagged levels as instruments for equations in first difference. In other words, we "stack" both difference and level equations together for estimation, doubling observations, and this new approach is called system GMM. The system GMM formula still treat the system as a single equation estimation problem since the same linear functional relationship still applies to both difference and level equations. When combined together, the system GMM estimator is shown to have dramatically reduced finite-sample bias and increased efficiency associated with the basic difference GMM estimator, and it is robust to any patterns of heteroskedasticity and cross-correlation models (Bond, 2002).

A crucial assumption for the validity of the GMM estimates is the exogeneity of the instruments. If the estimation system is overidentified, a test statistic for the joint validity of the moment conditions (identifying restrictions) falls out of the GMM framework and it is reported in Sargan/Hansen test. Sargan/Hansen statistics can also be used to detect the validity of a subset of instruments by a difference in Sargan tests. The Sargan difference test compares the Sargan/Hansen test statistic for all instruments with a subset of instruments. This difference of statistic follows an asymptotic chi-square distribution under the null of validity of a subset of instruments, with degrees of freedom equal to the difference in the number of instruments (Arellano and Bond, 1991).

The GMM estimator is consistent only if there is no second-order serial correlation in the idiosyncratic error term of the first difference equations. Arellano and Bond (1991) developed a z test for serial correlation which would render some lags invalid as instruments. In general, we restrict the instrument set to deeper lag if serial correlation is revealed. If the disturbances are not serially correlated, there should be evidence of significant negative first-order autocorrelation in differenced residuals and no evidence of second-order autocorrelation in the differenced residuals. If autocorrelation exists, some lags could be invalid instruments and deeper lags are needed.

3. Data

Most of the data used in this study are from the World Bank and IMF. Total government expenditures and its composition are from the International Monetary Fund's Government *Finance Statistics (GFS) Yearbook* sectors. We concentrate on six sectors, namely agriculture, defense, education, health, social security, and transportation and communication.

To convert expenditures, denominated in current local currencies, into international dollar aggregates expressed in base year (2000), prices were first deflated from current local currency expenditures to a set of base year prices using each country's implicit GDP deflator. We then used 2000 exchange rates measured in 2000 purchasing power parity reported by the World Development Indicators (World Bank, 2006) to convert local currency expenditures measured in terms of 2000 prices into a value aggregate expressed in terms of 2000 international dollars.

We included 44 developing countries from three regions in our analysis, partly reflecting the availability of data and partly because these countries are important in their own right while representing broader rural development throughout all developing countries. In 2004, these countries account for more than 80 percent of GDP of total developing countries.

Figure 1 shows the trends in public expenditure. The top three expenditures for Africa in 2004 were education, defense and health. Education, health and defense were the top three expenditure for Asia. Social security spending ranked at the top for Latin America with agriculture at the bottom. That Africa and Latin America spend so little on transportation and communications is discouraging: the share gradually declined in Africa from 11 percent in 1980 to 6 percent in 2004. The decline was even sharper in Latin America, from 7 percent in 1980 to 2 percent in 2004.

4. Estimation results

Before, we estimate our dynamic panel model, we conduct unit root tests for key variables in the estimation. As a first step, we perform Dickey-Fuller generalized least squares test for each individual country proposed by Elliott, Rothernberg and Stock (1996). This test is preferred by many time series econometricians to the Dickey-Fuller or Phillips-Perron test due to its robustness. Three panel unit root tests, namely, Levin-Lin-Chu test (2002), Im-Pesaran-Shin test (2003), and Hadri Lagrange Multiplier test (2000), are also conducted. The results for both individual country and pooled panel cross-country tests cannot reject the null of a presence of unit root. For all variables, the panel tests constructed after those individual statistics suggest the series considered as a panel are stationary. Having established the order of integration of the panel data series, the study proceeds with the estimation of the dynamic model, as described in section 2.

Following Roodman's (2007) suggestion, first we conducted a grid search to identify the optimal instruments and lag length. Sargan statistic is generally robust in lag length, but varies significantly across different instrument set. Table 1 reports p values from Sargan difference tests for the validity of a subset of instruments, at lag 3-5. Only lags three and higher are used to provide valid instruments because there is evidence suggesting the idiosyncratic errors are not i.i.d. For the purpose of this study, results from both difference GMM and system GMM estimators are included.

The top panel of Table 1 lists p values of GMM estimation for each variable entering the instrument matrix along with lagged dependent variable, as Z_i in (6), and we fail to reject the null hypothesis of valid instrument for each variable alone. Based on economics and the purpose of our study, different subsets of instruments are carefully chosen and Sargan difference tests are reported in the lower panel of Table 1. The results confirm our previous guess of excess instruments. It is found that public expenditure for productive purpose (including expenditures in capital, labor, health, education, agriculture, and transportation and communication) are jointly valid instruments for the estimation in most cases. In addition, non-productive public expenditures (including expenditures in defense and social security) are not valid instruments.

The purpose of this paper is to study the composition of government expenditure and its impact on economic growth, and we first look at expenditure in aggregate levels. GMM estimators are represented in Table 2. The coefficients of total non-capital expenditure are not significant in any case, while gross capital formation contributed to growth in Africa and Asia.

The result clearly demonstrates the shortcoming of using only aggregate expenditure in analyzing the relationship between investment and growth. In addition, inferences derived from aggregate numbers could be misleading since tremendous differences among various sector expenses are masked. Coefficients for labor are relatively stable, especially in system GMM equations, indicating a robustness of our functional form. The number of observations and instruments are also reported, where the number of instruments are far less than the number of observations to avoid overfitting and biased estimates.

Based on Sargan difference test in Table 1, we will estimate the dynamic production function (4), using a subset of productive investments (labor, capital formation, agriculture, education, and health expenditure) as instruments. The first two columns of Table 3 report results from the whole sample of the countries. Coefficients of labor, capital formation, education, and social security are statistically significant and of the expect sign in system equation. The elasticity of GDP with respect to labor is 0.79. The elasticities of GDP with respect to education spending are positive (0.59) and significant, indicating the highest return from investment in human capital. The coefficients of agriculture and health spending are insignificant. The coefficient of the defense spending variable is insignificant in difference equation but negative and statistically significant in system equations, implying that this type of spending is an opportunity cost for other productive investments to growth. The social security spending is significant and of the expected sign in both equations. Transportation and telecommunication spending variables are negative in both GMM estimations, but only statistically significant in system equation.

The pooled analysis may cover large regional variation in the effects of various spending on growth. In Table 4, we report results for both difference GMM and system GMM results for Africa, Asia and Latin America. Indeed, they show large regional differences. For example, elasticities of GDP with respect to capital formation range from 0.41 in Africa to 0.77 in Asia. In Africa, 1 percent additional investment in education and health collectively will contribute to .57 percent growth. Defense is significant, but the causality relationship requires further investigation. However, the coefficients of investment in infrastructure and social security are negative and statistically significant when the system GMM is used. In Asia, capital accumulation stimulated economic growth, as indicated by the positive and significant signs of the coefficients. Investment in agriculture and education also contribute to its economic growth. The negative and significant signs of health expenditure seem puzzling. In Latin America, both agriculture and defense are negatively associated with growth, requesting further investigation. Only health expenditure is positive and significant. Coefficients for infrastructure are negative in Africa but marginally positive in both Asia and Latin America, which could be attributed to the poor maintenance low rural accessibility in the continent.

Sargan tests accept difference equations but reject system equation, indicating that the additional instruments for level equations might be invalid. In system GMM, Sargan difference tests for the full set of instruments for the level equations, as well as the subset based on the lagged depended variables are also included. The joint validity of lagged dependent variables is not rejected in difference equations but in system equations, which is consistent from Sargan difference tests of GMM instruments for levels. This confirms that the instruments in level equations are probably endogenous to GDP growth and thus become invalid instruments.

The AR(1) and AR(2) tests for serial correlation show that there exist negative first-order correlations and no evidence of second-order autocorrelation in the differenced residuals. This assures the consistency of the GMM estimators (Arrelleno and Bond, 1991).

Robustness tests are also performed (not reported here). Basically, we examine the behavior of the coefficient estimates and overidentification tests when we decrease the number of instruments. If a coefficient systematically loses significance as the instrument count falls, this should raise worries about overfitting. We choose the a small instrument set for GMM estimation and our estimates are relatively robust regardless of model selection and the number of instruments.

5. Major findings

This paper provides new empirical evidence of the impact of different government spending in developing countries. Using the GMM instrument variable estimator to control for endogenity, we find the performance of government spending in economic growth is mixed. In Africa, government spending in human capital were particularly strong in promoting economic growth. In Asia, capital, agriculture, and education expenditure promotes economic growth. In Latin America, none of the government spending items has any significant impact on economic growth. This may be because of omitted variables such as governance and institutions.

Several lessons can be drawn from this study. First, various types of government spending have differential impacts on economic growth, implying greater potential to improve efficiency of government spending by reallocation among sectors. Second, governments should reduce their spending in unproductive sectors such as defense. Third, among all regions, Africa should increase spending in agriculture, particularly on production-enhancing investments such as agricultural R&D. This type of spending not only yields high returns to agricultural production, but also has a large impact on poverty reduction since most of the poor still reside in rural areas and their main source of livelihood is agriculture.

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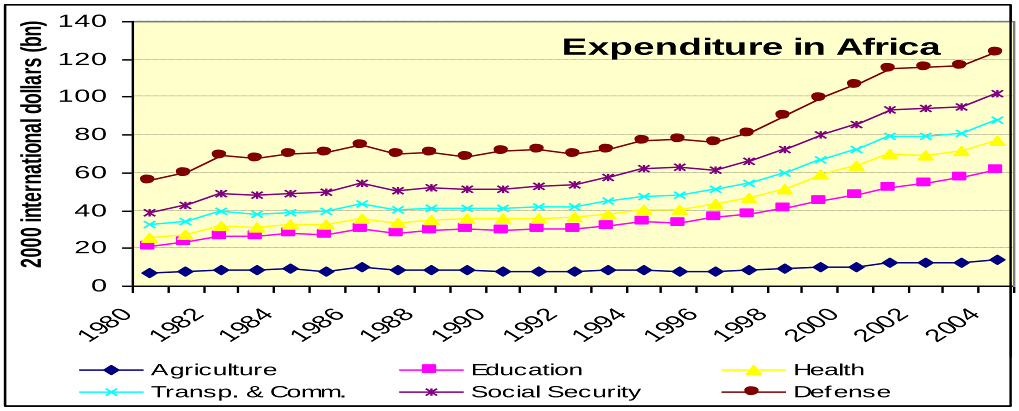
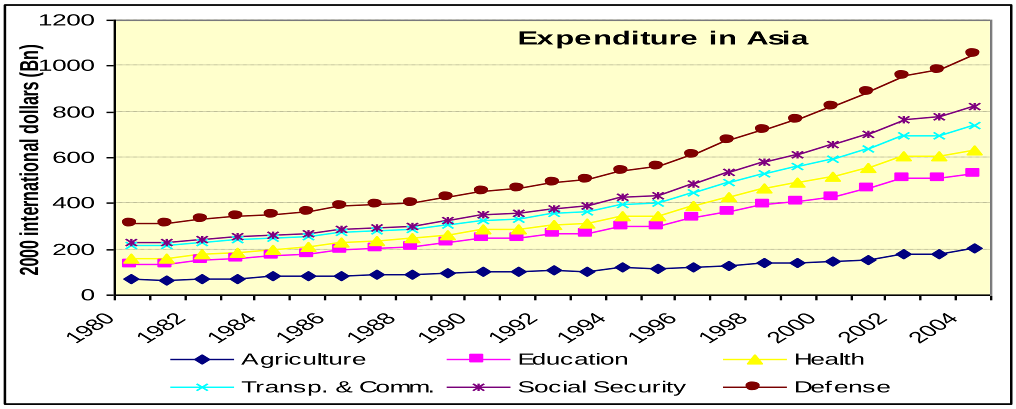
Figure 1: Trends of Government Spending in Developing Countries





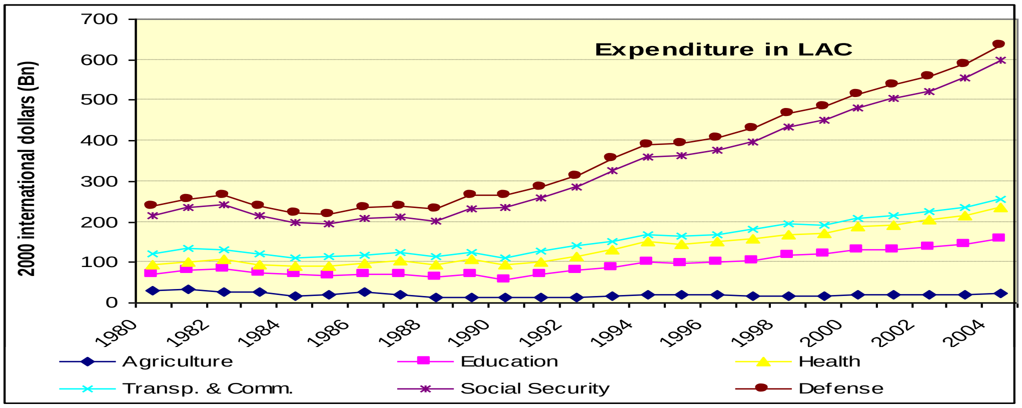


Table 1. P-values from Sargan difference tests for validation of a subset of instruments.

	Pooled		Africa		Asia		LAC	
	difference	system	Difference	system	difference	system	difference	system
Single variable								
labor	0.56	0.07	0.49	0.93	0.22	0.00	0.27	0.37
capital formation	0.05	0.97	0.89	0.04	0.90	0.35	0.33	0.50
agriculture exp	0.01	0.00	0.90	0.06	0.14	0.70	0.81	0.48
education exp	0.02	0.03	1.00	0.36	0.37	0.03	0.37	0.46
health exp	0.02	0.02	1.00	0.38	0.46	0.03	0.73	0.56
defense exp	0.98	0.00	0.67	0.05	0.56	0.47	0.10	0.23
social security exp	0.65	0.00	0.68	0.35	0.82	0.77	0.53	0.02
trans. & comm. exp	0.66	0.00	0.99	0.00	0.75	0.11	0.67	0.07
Combination of variables								
labor + capital formation (L+K)	0.04	0.39	0.82	0.09	0.57	0.00	0.25	0.56
L+K+agriculture exp	0.51	0.00	0.99	0.00	0.10	0.26	0.93	0.61
L+K+ag+education exp	0.77	0.00	0.97	0.22	0.90	0.05	0.00	0.16
L+K+ag+health exp	0.57	0.00	0.95	0.00	1.00	0.00	0.04	0.12
L+K+ag+education + health exp	0.86	0.00	0.98	0.00	0.37	0.01	0.02	0.23
L+K+ag+trans. & comm. exp	0.69	0.18	0.96	0.00	0.27	0.02	0.80	0.04
L+K+ag+trans. & comm. + edu exp	0.92	0.00	0.98	0.00	0.37	0.02	0.02	0.02
L+K+ag+trans. & comm. + health exp	0.82	0.00	0.98	0.00	0.41	0.01	0.02	0.03
L+K+ag+trans. & comm. + edu + health exp	0.94	0.00	1.00	0.00	0.62	0.01	0.08	0.00
L+K+ag+defense + social security + ag exp	0.80	0.00	0.98	0.00	0.57	0.02	0.03	0.01
L+K+defense + social security exp	0.51	0.00	0.99	0.00	0.14	0.18	0.95	0.00

Note: Report based on Sargan statistics estimated from collapse instruments set with lags 3-5.

Table 2. GMM estimated GDP Function using only aggregate total expenditure

	Pooled		Africa		Asia		LAC	
	difference	system	Difference	system	difference	system	difference	system
GDP_{-1}	0.167	0.366	0.080	0.354	0.807	0.816	0.624	1.000
	(0.4)	(0.09)*	(0.4)	(0.1)	(0.0)***	(0.0)***	(0.1)	(0.0)***
labor	-2.232	0.343	1.053	0.067	1.726	0.036	1.179	-0.011
	(0.4)	(0.05)**	(0.5)	(0.3)	(0.4)	(0.2)	(0.3)	(0.8)
capital formation	-0.348	0.180	-0.087	0.481	0.283	0.105	-0.002	0.023
	(0.2)	(0.2)	(0.4)	(0.03)**	(0.06)*	(0.05)**	(1.0)	(0.4)
total exp	0.127	0.064	0.045	0.086	0.179	0.027	0.340	0.000
	(0.5)	(0.2)	(0.5)	(0.2)	(0.3)	(0.2)	(0.3)	(1.0)
p-value of Sargan difference tests								
GMM lagged dep. variables	0.55	0.00	0.17	0.41	0.72	0.00	0.92	0.30
GMM instruments for levels		0.00		0.00		0.00		0.04
Sargan test	6.77	86.16***	11.68	53.88***	2.87	33.48***	5.35	17.87
AR1 test	-0.66	-2.78***	-0.89	-2.32**	-0.42	-1.82*	-0.020	-2.35**
AR2 test	-0.039	-1.38	0.057	-0.38	-1.01	-2.44	-1.44	-1.97
No. observations	958	1002	364	381	242	253	352	368
No. IV	34	41	34	39	34	39	34	39

Note: Asterisk (*) (**) and (***) indicate significance at the 10, 5 and 1 percent level, respectively.

Table 3. GMM estimated GDP Function

	Pooled		Africa		Asia		LAC	
	difference	system	Difference	system	difference	system	difference	system
GDP$_{-1}$	0.043	0.382	-0.037	0.28	0.78	0.87	0.81	1.02
	(0.6)	(0.00)***	(0.6)	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***
Labor	0.044	0.49	-0.335	0.53	-0.603	0.015	1.173*	-0.023
	(1.0)	(0.00)***	(0.9)	(0.00)***	(0.5)	(0.5)	(0.09)	(0.6)
Capital form. exp	0.023	0.254	-0.057	0.069	0.20	0.10	0.063	0.016
	(0.8)	(0.00)***	(0.6)	(0.2)	(0.00)***	(0.00)***	(0.5)	(0.3)
Agriculture exp	0.196	-0.016	-0.152	-0.098	-0.074	0.04	-0.047*	0.007
	(0.4)	(0.5)	(0.2)	(0.4)	(0.6)	(0.03)**	(0.10)	(0.4)
Education exp	-0.085	0.365	-0.171	0.22	0.42	-0.019	0.031	-0.020
	(0.7)	(0.00)***	(0.8)	(0.04)**	(0.00)***	(0.6)	(0.5)	(0.4)
Health exp	-0.328	-0.046	0.230	0.19	-0.32	-0.07	0.07	0.015
	(0.3)	(0.3)	(0.8)	(0.02)**	(0.00)***	(0.02)**	(0.05)*	(0.2)
Defense exp	0.506	-0.332	0.31	0.33	-0.100	0.04	-0.40	-0.005
	(0.6)	(0.00)***	(0.00)***	(0.00)***	(0.6)	(0.00)***	(0.00)***	(0.8)
Social security exp	0.32	0.17	0.196	-0.38	-0.047	0.006	-0.063	-0.005
	(0.04)**	(0.00)***	(0.5)	(0.00)***	(0.4)	(0.7)	(0.3)	(0.6)
Trans. Comm. exp	-0.064	-0.182	-0.104	-0.14	0.117	0.006	0.086	0.004
	(0.6)	(0.00)***	(0.7)	(0.06)*	(0.1)	(0.7)	(0.1)	(0.9)
p-value of Sargan difference tests								
GMM lagged dependent variables	0.05	0.00	0.83	0.00	0.40	0.05	0.33	0.42
GMM instruments for levels		0.00		0.00		0.00		0.04
Sargan test	14.38	79.67***	1.79	34.93***	7.29	32.61***	11.18	23.77*
AR(1)	1.76*	-5.38***	0.91	-3.23**	-0.73	-3.85***	-0.73	-4.18***
AR(2)	1.07	0.32	-0.045	0.66	-0.49	-2.25**	0.089	-2.45**
No. observations	968	1012	374	391	242	253	352	368
No. IV	40	49	40	47	40	47	40	47

Note: Asterisk (*) (**) and (***) indicate significance at the 10, 5 and 1 percent level, respectively.