Robust Determinants of Growth in Asian Developing Economies: A Bayesian Panel Data Model Averaging Approach

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Abstract

This paper investigates the determinants of growth in the Asian developing economies. We use Bayesian model averaging (BMA) in the context of a dynamic panel data growth regression to overcome the uncertainty over the choice of control variables. In addition, we use a Bayesian algorithm to analyze a large number of competing models. Among the explanatory variables, we include a non-linear function of inflation that allows for threshold effects. We use an unbalanced panel data set of 27 Asian developing countries over the period 1980–2009. Our empirical evidence on the determinants of growth suggests that an economy's investment ratio and trade openness are positively correlated to growth, whereas government consumption expenditure is negatively correlated. Further, our empirical results indicate a substantial probability that inflation impedes economic growth when it exceeds 5.43%. We also find no evidence of conditional convergence or divergence.

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1   Introduction

Some countries grow faster than others. Why does this happen? Many empirical studies have focused on this issue by regressing the observed GDP per capita growth rate on a number of explanatory variables (e.g., Kormendi and Meguire, 1985; Grier and Tullock, 1989; Romer, 1990; Barro, 1991; Aghion and Howitt, 1992; Sala-i-Martin, 1997a, b; Hall and Jones, 1999; Durlauf and Quah, 1999; Temple, 1999; Fernandez et al., 2001a, b; Sala-i-Martin et al., 2004). However, the number of potential regressors suggested by competing growth theories is large, with the potential problem of over-parameterization (see, for example, Koop and Tole, 2004b). For this reason it is not recommended to include all the potential regressors in a model.

On theoretical grounds, researchers have not reached a consensus on the set of explanatory variables that have an effect on growth. Furthermore, there is a myriad of possibilities in the empirical literature. For example, Sala-i-Martin (1997a, b) considers 59 potential regressors, whereas Fernandez et al. (2001a) consider 41 and Sala-i-Martin et al. (2004) had 67 potential regressors.

Previous empirical growth studies have proposed different econometric techniques to address the issue of model uncertainty, that is, the uncertainty regarding which factors explain the growth differences across countries. Typically, researchers have to deal with a large number of empirical growth models, each one consisting of a different combination of explanatory variables. Each of these models has some probability of being the "true" model. Bayesian model averaging (BMA) is a widely accepted technique to overcome the problems associated with the selection of a single model, and has been used in many recent empirical growth studies. This method was popularized in the growth literature by the seminal works of Fernandez et al. (2001a, FLS henceforth) and Sala-i-Martin et al. (2004, SDM henceforth). Since then, it has been applied in several growth empirical studies (e.g., Ciccone and Jarocinski, 2010; Moral-Benito, 2010, 2012; Koop et al., 2012; León-González and Montolio, 2012) and other areas of economics (e.g., Koop and Tole, 2004a; Chen et al., 2011).

Most previous empirical studies using BMA dealt only with the model uncertainty that results from different choices of control variables. However, as noted by Caselli et al. (1996), the failure to account for country-specific fixed effects and the endogeneity of regressors might

render cross-country growth regression estimates inconsistent. These problems might arise from measurement errors, omitted variable bias, and simultaneous effects. However, the econometric techniques to solve these problems need to rely on a choice of instruments and exogeneity restrictions. This adds another layer of difficulty to the model selection problem. To take this into account, Koop et al. (2012; henceforth KLS) and León-González and Montolio (2012; henceforth LM) extended the BMA approach to consider the additional dimensions of model space.

Many of the empirical growth models mentioned above take into account model uncertainty on the assumption of a linear relationship between growth and its determinants. However, evidence shows that some of the growth determinants might have an effect on growth non-linearly. For instance, inflation (e.g., Fischer, 1993; Khan and Senhadji, 2001; Bick, 2010; Yilmazkuday, 2011), government size, the number of years the economy has been open, and initial income per capita (e.g., Crespo-Cuaresma and Doppelhofer, 2007; Yilmazkuday, 2011) might have a non-linear effect on growth.

Therefore, in this study, we consider a non-linear function that allows for a threshold in the impact of inflation on growth. By following the BMA methodology in KLS and LM, we take into account model uncertainty over the set of controlling regressors in a dynamic panel data growth regression. Since we have a large model space in our empirical application, we compute by using the reversible-jump Markov Chain Monte Carlo (RJMCMC) algorithm suggested by KLS.

In this paper, we use an unbalanced panel data set covering 27 Asian developing countries over the period 1980–2009 and consider 14 explanatory variables. In order to eliminate business cycle fluctuations, we take two-year averages, and thus, the actual number of time observations is halved. Since we include fixed effects in the estimation, we do not include time-invariant regressors. Therefore, the number of explanatory variables we use is smaller than that used in other BMA applications in a cross-section context.

The rest of the paper is organized as follows. Section 2 briefly discusses the econometric framework of this study. The data and details of the variables are described in Section 3. Section 4 presents the estimation results of the econometric model and its findings. In Section 5, we

compare our results with those from other estimation methods. Finally, in Section 6, we conclude the paper.

2 Econometric Framework

In our basic model setup, we use a simultaneous equations model (SEM) with dynamics in a panel data framework. This allows us to control for individual fixed effects and simultaneity. First, we define the main structural equation as follows:

$$g_{it} = \gamma' h_{it} + \beta' x_{it} + \mu_i + u_{it} \tag{1}$$

where i denotes the cross-sectional dimension (for $i = 1, \ldots, N$), t is the time dimension (for $t = 1, \ldots, T$), g_{it} is the gross domestic product (GDP) per capita growth rate for country i at time t, h_{it} denotes an $M \times 1$ vector of endogenous regressors[1] for country i at time t, x_{it} represents a $k_{1j} \times 1$ vector of exogenous explanatory variables for country i at time t (see Table 1 for a description of the variables), μ_i indicates the unobserved individual heterogeneity, and u_{it} is the error term with zero mean and no serial correlation. The sub-index j in k_{1j} denotes the model, and it implies that the number of exogenous regressors in each model could be different. Regarding the dimension of h_{it}, we fix it as M for all models, but allow gamma to have zero elements. Thus, in practice, we can have a different number of endogenous regressors in each model.

2.1 Fixed-Effect Elimination

In the first phase of the estimation method, we need to eliminate the unobserved country-specific fixed effects. For that purpose, we should apply forward orthogonal deviation (FOD) transformation to the dynamic equation (1). This transformation is preferred to first-differencing transformation because it does not introduce serial correlation in the error term. FOD transformation subtracts the average of all future available observations. Therefore, the formula for transforming a variable, u_{it}, is given by

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[1] In our empirical application, we have only one endogenous variable, the initial level of GDP per capita. Thus, h_{it} is 1×1.

$$u_{it}^* = \sqrt{\frac{T-t}{T-t+1}}\left[u_{it} - \frac{1}{(T-t)}\left(u_{i(t+1)} + \cdots + u_{iT}\right)\right] \tag{2}$$

By applying this procedure to equation (1), we obtain

$$g_{it}^* = \gamma' h_{it}^* + \beta' x_{it}^* + u_{it}^* \tag{3}$$

where $t = 1, \ldots, T-1$ (therefore, we lose one observation). This transformation ensures that if $Var(u_{it}) = \sigma^2 I_T$ with no serial correlation, then we also have $Var(u_{it}^*) = \sigma^2 I_{T-1}$ with no serial correlation. Moreover, as noted by LM, this transformation can also be explained from a Bayesian perspective. The transformation comes from integrating out the fixed individual effects from the posterior density by using a flat prior.

2.2   Solving the Endogeneity Problem

Equation (3) cannot be estimated with ordinary least squares (OLS) estimation because there is a correlation between h_{it}^* and u_{it}^*. In our empirical application, h_{it} contains only the initial GDP per capita level. Even if we assume that h_{it} is uncorrelated with u_{it}, it is clear that the transformation induces a correlation between h_{it}^* and u_{it}^*. To solve this problem, we use instrumental variables. In particular, we use the Bayesian analogue of the two-stages-least-squares (2SLS) estimator as suggested by LM (2012). Then, the system of equations containing auxiliary equations for h_{it}^* can be defined as follows:

$$g_{it}^* = \gamma' h_{it}^* + \beta' x_{it}^* + u_{it}^*$$
$$h_{it}^* = \Pi_x x_{it}^* + \Pi_z z_{it} + v_{it}^* \tag{4}$$

where z_{it} is a $k_{2j} \times 1$ vector of predetermined instruments and the error terms u_{it}^* and v_{it}^* are normally distributed with zero mean and mutually uncorrelated across the cross sections and over time. That is, $E\left(u_{it}^*, v_{js}^*\right) = 0$ for either $i \neq j$ or $t \neq s$ or both. We assume that the variables x_i and z_i are exogenous; thus,

$$E\left(x_{it}^*, \begin{bmatrix} u_{it}^* \\ v_{it}^* \end{bmatrix}'\right) = 0 \text{ and } E\left(z_{it}, \begin{bmatrix} u_{it}^* \\ v_{it}^* \end{bmatrix}'\right) = 0 \tag{5}$$

The predetermined instruments are typically constructed using lags of h_{it}. Hence, as an instrument for the transformed initial GDP per capita level, h_{it}^*, we use the untransformed value

(h_{it}). Although we can use further lags as instruments, no clear guidelines exist on the optimal number of instruments. Using Monte Carlo simulation, Roodman (2009) proposed that increases in the instrument count tend to raise the estimate of a parameter. Windmeijer (2005) reports that reducing the instrument count by a certain amount lowers the average bias of the interest parameter, whereas LM (2012) shows that models using nearer lags as instruments have larger posterior probability. For this reason, we use only one instrument in our estimation, h_{it}. The moment condition associated with this instrument is

$$E\left(u_{it}^*, h_{i,t}\right) = 0 \quad \text{for } t = 1, \dots \dots, \text{T} - 1 \tag{6}$$

The dimensions of parameter matrices (Π_x, Π_z, β) differ over model space. Following KLS, the model space in our empirical application includes all the just-identified and over-identified models verifying the restriction $k_{2j} \geq \text{M}$. Further, we assume that the coefficient matrix of the instruments (Π_z) has full rank. Therefore, the model space consists of models that differ on the following aspects:

- ✓ Variables in x_{it}: x_{it} is a subset of a larger group of potential exogenous regressors denoted by X, which are not allowed to be instruments. Therefore, there is uncertainty over the dimensions of x_{it} and β.

- ✓ Set of instruments: Although this technique can consider models with a different set of instruments in principle, in our application, all the models use the same instrument, that is, h_{it}. Therefore, we do not consider uncertainty over the set of instruments.

- ✓ Exogeneity restrictions: Although, in principle, some of the covariances between the error terms $(u_{it}$ and $v_{it})$ can be restricted to zero, in our setup, we have only one endogenous variable (initial GDP per capita level), which we are certain must be treated as endogenous. Therefore, in our setup there is no uncertainty over exogeneity restrictions.

- ✓ Restrictions on coefficients of endogenous or predetermined regressors: Some of the coefficients of γ might be restricted to zero. In our case, γ is a scalar parameter. In some models, it will be restricted to zero. A zero value of γ implies that there is neither conditional convergence nor conditional divergence among countries.

As shown in KLS, the model space consists of $2^{2M} N^A$ number of models, with N^A taking the form

$$N^A = \sum_{j=M}^{k_2^T} 2^{k_1^T + k_2^T - j} \, C_j^{k_2^T} \tag{7}$$

where k_1^T denotes the total number of potential regressors in X, k_2^T the total number of potential instruments, and $C_j^{k_2^T}$ the combinatorial number. In our empirical analysis, we have only two endogenous regressors including the dependent variable ($M = 2$), 1 instrument ($k_2^T = 1$) and 13 exogenous variables ($k_1^T = 13$). Thus, the number of models can be calculated[2] as 2^{14}.

2.3 Bayesian Model Averaging Approach in Panel Data

A basic strategy for model selection is to choose the most plausible model H_j, specifically, the one with the highest posterior model probability, $p(H_j|Y)$. Posterior model probability is defined as

$$p(H_j|Y) = \frac{f(Y|H_j)\, p(H_j)}{\sum_{r=1}^{K} f(Y|H_j) p(H_j)} \tag{8}$$

where Y represents all the observed data, $f(Y|H_j)$ is the marginal likelihood of model H_j, and $p(H_j)$ is the prior probability that model H_j is true; $K = 2^{2M} N^A (= 2^{14})$ is the total number of models such that the summation takes place over the whole model space. Thus, equation (8) implies that the posterior probability of model H_j is proportional to the prior model probability times the marginal likelihood of the model. The marginal likelihood of model H_j can be given by

$$f(Y|H_j) = \int f(Y|\theta, H_j) p(\theta)\, d\theta \tag{9}$$

where θ denotes the unknown parameters of model H_j, $p(\theta)$ is the prior for parameter θ under model H_j, and $f(Y|\theta, H_j)$ is the likelihood of that model.

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[2] Note that although the direct application of the formula gives 2^{15} models, we have only 2^{14} models because we do not allow h_{it}^* to be treated as exogenous.

However, selecting the model with the highest probability ignores the problem of model uncertainty since it disregards the models that also have some positive probability of being true. BMA solves this problem by calculating the weighted average over all the models such that the weights are proportional to the posterior probabilities of the models.

The inference for θ can be constructed on the basis of the posterior distribution

$$f(\theta|Y) = \sum_{j=1}^{K} f(\theta|H_j, Y)\, p(H_j|Y) \tag{10}$$

Equation (10) shows that the full posterior distribution of θ is the weighted average of the posterior distribution under each model, where the weights are proportional to the posterior model probabilities, $p(H_j|Y)$. BMA allows for computing the probability of including a regressor, which is the probability that the regressor has a non-zero coefficient:

$$p(x_{it}|Y) = \sum_{j=1}^{K} I(x_{it}|H_j)\, p(H_j|Y) \tag{11}$$

where x_{it} is an explanatory variable and $I(x_{it}|H_j)$ is an indicator function that takes the value 0 if the coefficient of x_{it} is restricted to zero under model H_j and 1 otherwise. Furthermore, the posterior mean of θ can be calculated from the posterior distribution in equation (10) as

$$E(\theta_i|Y) = \sum_{j=1}^{K} E(\theta_i|Y, H_j)\, p(H_j|Y) \tag{12}$$

From expression (12), we see the posterior mean for θ as a weighted average of the posterior means under each model.

Implementation of the BMA procedure presents three challenges. First, we need to choose the prior model probabilities $p(H_j)$ and the prior for parameters $p(\theta|H_j)$. In our empirical study, we assume that all the models exhibit equal prior probabilities, implying that the prior over the model space is uniform: $p(H_1) = p(H_2) = \cdots = p(H_K) = \frac{1}{K}$. With regard to choice of priors for parameters, we follow the same setup as in LM. Second, the marginal likelihood $f(H_j|Y)$ depends on an integral that cannot be solved analytically. This can be calculated only through a

computationally intensive numerical approach. Finally, the model space in our empirical application contains approximately 2^{14} models, which is computationally challenging. To overcome these challenges, we apply the RJMCMC algorithm developed by KLS as a computational strategy. This algorithm iteratively obtains values for models (H_j) and parameters (θ). Given the arbitrarily fixed initial values for (θ, H_j), we can use the generated values as a sample from the posterior of (θ, H_j) after an adequate number of iterations. With this sample, we can compute the quantities of interest, such as the posterior probabilities of models and confidence intervals for parameters.

3   Data and Variables

Tables 1 and 2 in the appendix show the lists of variables used in our growth regression, with definitions, data sources, and some descriptive statistics. Our dataset spans the period 1980–2009 for 27 Asian developing countries (see Table 3 for the list of countries), and we extend the dataset used by Vinayagathasan (2013) by adding some more explanatory variables. Since the values for school enrollment in primary and secondary education are missing, our dataset is unbalanced. However, this does not affect the methodology that we use. To allow for the threshold effects of inflation, we build on Vinayagathasan (2013), who used a dynamic panel threshold growth regression approach (Kremer et al., 2009) and estimated the threshold level as 5.43%. Accordingly, in the set of explanatory variables, we include the following two inflation-related variables:

$$inf\_low = inflation*d_I$$

$$inf\_high = inflation*d_I$$

where d_I is a binary indicator that takes the value of 1 when inflation is below the threshold and 0 otherwise. Therefore, the coefficient of inf_low gives the impact when inflation is below the threshold level and the coefficient of inf_high gives the impact when inflation is above the threshold level.

Several studies estimate the determinants of growth by taking the averages of four-year periods (e.g., LM, 2012; Chen et al., 2011), five-year periods (e.g., Bick, 2010; William and Wacziarg, 2004; Gylfason and Herbertsson, 2001), and ten-year periods (e.g., Moral-Benito,

2010). However, in this paper, the number of countries is comparatively small because we focus only on Asian countries. Therefore, to maximize the number of observations, we use non-overlapping two-year period averages.

4   Estimation Results

In order to carry out BMA analysis, we run the RJMCMC algorithm for 300000 iterations after discarding the initial 10000 values. To check the convergence of the algorithm, we calculate the "total visited probability"[3] (TVP), as shown in George and McCulloch (1997) and LM (2012), and obtain a value close to 1 (0.999), which indicates good convergence. Furthermore, we run the model many more times with randomly drawn initial values and obtain almost the same results.

As shown in Table 4, the exogenous regressors with a posterior probability of inclusion close to 1 are investment ratio, trade openness, secondary school enrollment rate, and population. The estimated coefficient of the investment ratio is clearly positive, because a 95% credible interval does not include 0 and the posterior probability that the coefficient is positive is close to 1. Although the 95% credible intervals for trade openness and population[4] do contain the value 0, both of them have a substantial posterior probability of being positive (65.4% and 73.8%, respectively). However, the posterior probability that the coefficient of secondary education is positive is only 52.2%, indicating that the sign cannot be clearly established (that is, the probability that the coefficient is positive is almost the same as the probability that it is negative). Government consumption expenditure has a high posterior probability of inclusion (85.1%), and as Table 4 shows, the probability that government consumption has a negative impact on growth is also 85.1%. Finally, the regressor "inflation above threshold level" (inf_high) has a probability of around 53.6% of having a non-zero impact on growth; the probability of having a negative impact is approximately 53.3%. This indicates a substantial probability that the impact of inflation on growth is negative whenever inflation is beyond the threshold value of 5.43%. On the other hand, since the posterior inclusion probability of inflation below the threshold (inf_low)

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[3] Total visited probability is an estimate of the fraction of the total posterior probability mass visited by the chain (for more details, see LM 2012).

[4] However, our sample includes China and India, and this might have an impact on the estimated coefficient. When we carry out BMA analysis without these two countries, the posterior inclusion probability of population becomes almost 0, while the other results are very similar to our main findings (available upon request). Therefore, China and India seem to play a significant role in explaining the positive impact of population on growth.

is almost 0, we can conclude that any inflation below the threshold value has no impact on growth. These conclusions are consistent with Vinayagathasan (2013), who analyzed a similar dataset using GMM estimation.

The remaining regressors (growth rate of population, terms of trade, labor force participation rate, primary school enrollment rate, price level of investment goods, and population density) have very small probabilities of inclusion. Thus, they do not seem to explain the economic growth of the Asian developing countries. However, the impact of these variables might be country specific.

In sum, the investment ratio of an economy is positively associated with its growth rate whereas government consumption expenditure is negatively correlated. Evidence also indicates that trade openness stimulates economic growth. Further, substantial evidence shows that inflation hurts economic growth when it is beyond the threshold value of 5.43% but does not have any significant effect on growth below that level.

Recall that we have treated the "initial level of GDP per capita" as an endogenous regressor. As shown in Table 5, the posterior probability of including the initial level of GDP per capita is only 17.2%, implying that the probability that its coefficient is 0 is as high as 82.8%. This indicates that countries are conditionally neither converging nor diverging. That is, if the other growth determinants are constant, the initial value of GDP will not be important. To understand this, note that each country has a different resource endowment, but we control for this by including the fixed effects. This could be the reason why we find no conditional convergence or divergence. Although the neoclassical growth model (Solow model; Solow, 1956) proposes conditional convergence, LM (2012) finds that countries are conditionally neither converging nor diverging when using the whole sample with fixed effects.

5   Comparison with Other Estimation Methods

In the previous section, we considered initial income as a predetermined regressor and controlled for country fixed effects. For a comparative study, let us first carry out a more basic BMA analysis, assuming that all the regressors are exogenous in a pooled regression context, with no

fixed effects[5]. The results obtained vary in three different aspects (see Table 6). First, the regressors population density and labor force participation rate, which showed a very small probability of inclusion, become significant and positively correlated to growth with a higher posterior inclusion probability (93.2% and 67.2%, respectively). Second, the probability of inclusion of regressors "trade openness" and "government consumption expenditure" decreased from nearly 1 to close to zero. Finally, inflation above the threshold level became insignificant, with a probability of inclusion close to zero. With respect to similarities, the investment ratio and population are positively correlated to growth, with a probability of inclusion close to 1 in both cases.

In addition to the basic BMA analysis, we carry out a comparative study by using estimation methods that allow for endogeneity and/or fixed effects but not model uncertainty, such as the Generalized Method of Moment (GMM: Arellano and Bond, 1991), Fixed Effect (FE: Wooldridge, 2010, chapter 10), and the bias-corrected Least Square Dummy Variable (LSDVC: Judson and Owen, 1999) estimators. The results show that one of the regressors that was earlier found significant with our main BMA analysis, secondary school enrollment rate, now became insignificant. Further, the effect of the threshold variable (inflation above the threshold level) on growth is significant and negative in all the three cases (see Table 7). Moreover, as in the main BMA analysis, the GMM estimator also finds that population and trade openness are vital factors to determine the growth rate, whereas the FE and LSDVC estimators do not find so. Fourth, government consumption expenditure is significant and negatively correlated to the growth rate according to the GMM and FE estimators but not according to the LSDVC estimator. Finally, the investment ratio, which was found significant with our main BMA approach, is also found significant with these three approaches.

While the standard BMA analysis did not take into account endogeneity or fixed effects, the three approaches, GMM, FE, and LSDVC, do not consider the issue of model uncertainty. However, our main BMA analysis considered the issues of model uncertainty, endogeneity, and fixed effects simultaneously.

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[5] The analysis was carried out with the R software and the "BMA R package" of version 3.15.1.

6   Conclusions

The existing empirical studies have used various techniques to account for model uncertainty in growth regressions. Among these techniques, BMA analysis was widely used and is presently the most prominent approach to overcome model uncertainty in the empirical growth literature. In this paper, we used a recent technique to carry out BMA analysis in the context of a dynamic panel data model with fixed effects. Only a few empirical growth studies have considered these issues in their model setup. Furthermore, our study is novel in that we allow for a threshold level such that inflation has an impact on economic growth and we focus on Asian countries.

Our empirical evidence on the determinants of growth has found three variables, namely, investment ratio, trade openness, and government consumption expenditure, to have a significant impact on growth. We also found that the countries are conditionally neither converging nor diverging because the probability of their coefficient of initial income being zero is as high as 82.8%.

In addition, we found that any inflation above the threshold level of 5.43% has a negative impact on growth with a 53% probability. Although this probability is not as high as for the other determinants of growth, we consider its size to be sufficiently high to warn the policy makers in Asia about the potentially damaging effect of inflation on growth. However, one limitation of this study is that we did not distinguish between expected and unexpected inflation or look into the impact of inflation volatility. We leave this subject matter for future research.

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Table 1: Data Description and Source(s)

Variables	Description and Source	Source(s)
y	GDP per capita growth rate in purchasing power parity (PPP) 2005 constant prices	PWT 7.0
log_initial	GDP per capita from previous period in PPP 2005 constant prices (in Log)	PWT 7.0
inv	Annual percentage change of GDP per capita dedicated to investment in PPP 2005 constant prices	PWT 7.0
inf[6]	Average percentage change of CPI for the year	EW
gpop	Annual growth rate of population	WDI
open	Share of export plus import in percentage of GDP in 2005 constant prices	PWT 7.0
tot	Export value divided by import value (2000 = 100)	WDI
lfpr	Percentage of total population between ages 15 and 65	WDI
gce	Government consumption share of GDP per capita converted in PPP 2005 constant prices	PWT 7.0
prim	Gross enrollment rate in primary education (% of total enrollment regardless of age)	WDI[7]
secnd	Gross enrollment rate in secondary education (% of total enrollment regardless of age)	WDI
pi	Price level of investment in PPP 2005 constant prices	PWT 7.0
pop	Total population in million	WDI
popdn	People per sq. km of land area	WDI

Note: PWT represents Penn World Table, EW denotes Economy Watch, and WDI indicates World Development Indicator.

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[6] In order to allow for threshold effects, we enter inflation into the model in the form of two regressors, (i) inflation below the threshold level and (ii) inflation above the threshold level (see Section 3 for the details).

[7] Since the school enrollment rate data for certain periods for some of the Asian countries are not available in the World Development Indicator data base, we collected the data of primary school enrollment ratio for Bangladesh for 1996–2004 from *http://www.igs-bracu.ac.bd/UserFiles/File/archive_file/Working%20paper.pdf* and for 2005–2009 from *http://www.indexmundi.com/facts/bangladesh/school-enrollment*. The primary school enrollment ratio of Vietnam for 2002–2009 was collected from *http://www.indexmundi.com/facts/vietnam/school-enrollment*. We collected the secondary school enrolment ratio of Bhutan for the periods of 1981, 1988, and 1994 from the Asian Economic Outlook. The primary school enrollment ratio of Saudi Arabia for the periods 1980, 1985, 1990, 1991, 1995, and 2004 was collected from *http://www.tradingeconomics.com/saudi-arabia/school-enrollment-primary-percent-gross-wb-data.html*, and the secondary school enrollment ratio for the periods of 1980, 1985, 1990, 1991, and 1995 was collected from *http://www.tradingeconomics.com/saudi-arabia/school-enrollment-secondary-percent-gross-wb-data.html*.

Table 2: Summary Statistics of Full Sample

Variable	Observation	Mean	Std. Dev.	Min	Max
y	345	2.837	4.944	-22.28	20.56
log_initial	345	3.737	0.575	2.805	5.176
log_infl	345	0.498	1.067	-7.439	2.046
infl	345	8.148	12.33	-6.439	111.2
inv	345	28.05	11.16	5.605	67.92
gpop	345	2.616	2.271	-5.966	18.06
open	345	90.87	55.84	7.776	386.6
tot	345	82.65	23.72	25.76	192.9
lfpr	345	64.42	9.918	42.50	84.05
gce	345	10.14	5.397	2.747	39.24
prim	345	99.05	16.87	34.43	151.3
secnd	345	59.46	24.95	4.512	99.77
pi	345	51.89	28.75	10.69	259.6
pop	345	1.21e+8	2.97e+8	159278.5	1.33e+9
popdn	345	733.1	2575.29	3.928	18743.9

Source: Author's calculations based on data from Penn World Table (PWT 7.0), Economy Watch, and World Development Indicator. All the statistics are in two-year arithmetic averages over the period 1980–2009.

Table 3: List of Countries and Summary Statistics for Inflation and Growth Rate

Region	Country	id	T_i	Mean		
				Inflation	Log of inflation	Growth rate of GDP per capita
South Asia	Bangladesh	2	13	8.096	0.862	2.392
	Bhutan	3	11	7.319	0.811	5.039
	India	7	15	8.078	0.881	4.083
	Maldives	15	9	4.978	0.155	6.172
	Nepal	16	12	9.095	0.912	1.757
	Pakistan	18	8	8.735	0.892	2.769
	Sri Lanka	23	10	11.986	1.055	3.487
East Asia	China	4	15	5.697	0.358	8.614
	Hong Kong	6	11	3.855	-0.226	4.211
	Macao	13	8	17.077	0.463	6.646
South East Asia	Indonesia	8	15	9.472	0.498	3.433
	Laos	12	15	33.110	0.740	4.538
	Malaysia	14	15	3.178	0.416	3.615
	Papua New Guinea	19	11	7.987	0.869	-0.032
	Philippines	20	15	9.684	0.877	1.129
	Thailand	25	15	3.899	0.310	4.172
	Vietnam	27	8	13.984	0.648	5.820
Western Asia	Bahrain	1	15	1.661	-0.459	-0.469
	Cyprus	5	15	4.065	0.546	2.750
	Iran	9	12	18.764	1.239	2.314
	Jordan	10	15	5.262	0.526	0.697
	Kuwait	11	15	3.528	0.341	0.048
	Oman	17	15	2.023	-0.634	2.126
	Qatar	21	15	4.211	0.514	3.155
	Saudi Arabia	22	7	2.660	-0.130	1.020
	Syria	24	15	12.010	0.587	1.308
	United Arab Emirates	26	15	4.747	0.628	-0.658

Source: Author's calculations based on data from the sources of Penn World Table (PWT 7.0) for growth rate of GDP per capita and Economy Watch for inflation rate over the period 1980–2009. T_i is the number of observations per country.

Table 4: BMA Estimation for Coefficients of Exogenous Variables

Variable	Probability	2.50%	97.50%	Mean	Positive
inv	0.995	0.0228	0.1853	0.1091	0.988
inf_low	0.006	0.0000	0.0000	0.0001	0.003
inf_high	0.536	-2.5416	0.0000	-0.8280	0.003
gpop	0.005	0.0000	0.0000	-0.0004	0.001
open	0.996	-0.0231	0.0262	0.0039	0.654
tot	0.311	-0.0456	0.0000	-0.0077	0.014
lfpr	0.281	0.0000	0.4973	0.0971	0.281
gce	0.851	-0.6262	0.0000	-0.3514	0.000
prim	0.051	-0.0318	0.0000	-0.0016	0.008
secnd	1.000	-0.0878	0.0538	-0.0019	0.522
pi	0.012	0.0000	0.0000	-0.0002	0.001
pop	1.000	-1.8e-8	2.1e-8	4.6e-9	0.738
popdn	0.069	-6.9e-6	0.0006	1.9e-5	0.043

Note: The column *Probability* gives the posterior probability that the coefficient is different from zero. The following two columns give the lower and upper bounds of a 95% credible interval. The column *Mean* gives the posterior mean of the coefficient. The column *Positive* gives the posterior probability that the coefficient is positive.

Table 5: BMA Estimation for Coefficient of Endogenous Regressor

Variable	Probability	2.50%	97.50%	Mean	Negative
Initial	0.172	-12.369	32.045	8.7462	0.036

Note: The column *Probability* gives the posterior probability that the coefficient is different from zero. The following two columns give the lower and upper bounds of a 95% credible interval. The column *Mean* gives the posterior mean of the coefficient. The column *Negative* gives the posterior probability that the coefficient is negative.

Table 6: BMA Estimation Results of Equation (4), Treating All Explanatory Variables as Exogenous and with No Fixed Effects.

Variable	Probability	Mean	SD
log_initial	34.30	-0.5528	0.8270
inv	100.0	0.1056	0.0244
inf_low	0.000	0.0000	0.0000
inf_high	1.100	-0.0066	0.0819
gpop	11.60	-0.0276	0.0741
open	0.000	0.0000	0.0000
tot	60.60	-0.0173	0.0165
lfpr	67.20	0.0468	0.0394
gce	0.000	0.0000	0.0000
prim	6.800	-0.0018	0.0081
secnd	67.70	-0.0269	0.0212
pi	0.000	0.0000	0.0000
pop	95.70	2.28e-9	1.1e-9
popdn	93.20	2.81e-4	1.21e-4

Note: Column 1 indicates the posterior inclusion probability of a variable entering the model as an exogenous regressor, column 2 denotes the posterior mean of the coefficient, and column 3 represents the standard deviation of parameters. The number of observations is 345.

Table 7: One-Step System GMM, FE, and LSDVC Estimation Results of Equation (4)

Variables	System GMM		FE		LSDVC	
log_initial	-9.995	(-1.44)	-2.480	(-0.83)	-7.877*	(-1.77)
inv	0.116*	(1.78)	0.148***	(4.05)	0.122**	(2.51)
Inf_low	-0.223	(-0.70)	0.034	(0.90)	-0.029	(-0.09)
Inf_high	-1.474*	(-1.75)	-1.440**	(-2.42)	-2.257***	(-2.89)
gpop	0.047	(0.13)	-0.063	(-0.42)	0.095	(0.53)
open	0.062**	(2.61)	0.010	(1.01)	0.017	(0.94)
tot	-0.029	(-1.17)	-0.024*	(-1.71)	-0.008	(-0.44)
lfpr	0.522**	(2.51)	0.327***	(2.89)	0.301*	(1.87)
gce	-0.360**	(-2.35)	-0.404***	(-3.50)	-0.258	(-1.47)
prim	-0.071	(-1.09)	-0.015	(-0.52)	-0.040	(-0.89)
secnd	0.002	(0.05)	0.001	(0.04)	0.051	(1.28)
pi	-0.001	(-0.90)	-0.009	(-0.77)	-0.004	(-0.32)
pop	2.4e-8**	(2.15)	1.1e-8	(1.48)	1.21e-8	(1.25)
popdn	0.001	(0.90)	-0.0002	(-0.32)	-0.001	(-0.23)
y.L1					0.244***	(3.72)
Observation	299		345		265	

Note: t-statistics are given within parenthesis; *** indicates $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.