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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 is positively correlated to growth, whereas government consumption expenditure and terms of trade are negatively correlated. We also find evidence of a nonlinear relationship between inflation and economic growth, that is, inflation impedes economic growth when it exceeds 5.43% but does not have any significant effect on growth below that level.

Keywords: Determinants of Growth, Bayesian Model Averaging, Panel Data Model, Inflation Threshold.

JEL Classification: O40, E31, C11, C23

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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.

Researchers have not, on theoretical grounds, 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. Endogeneity problems might arise as a consequence of 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 the model space.

Many of the empirical growth models mentioned above take into account model uncertainty while assuming 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.

Review of past empirical works reveals that no study has examined the determinants of growth in the context of Asian developing countries using Bayesian Model Averaging. Moreover, we allow some variables to interact with economic growth in a nonlinear manner. In particular, among the explanatory variables we include a nonlinear function of inflation that allows for threshold effects. These are the novelties in this paper.

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 carry out the computations 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:

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

where i denotes the cross-sectional dimension (for $i = 1, \dots, \mathrm{N}$), t is the time dimension (for $\mathrm{t} = 1, \dots., \mathrm{T}$), $\mathrm{g_{it}}$ is the gross domestic product (GDP) per capita growth rate for country i at time t, h_{it} denotes an $\mathrm{M} \times 1$ vector of endogenous regressors for country i at time t, x_{it} represents a $\mathrm{k_{1j}} \times 1$ 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 $\mathrm{k_{1j}}$ 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 keep it constant across models but allow the vector γ 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 apply the forward orthogonal deviation (FOD) transformation to the dynamic equation (1). This transformation is preferred to the first-differencing transformation because it does not introduce serial correlation in the error term. The FOD transformation subtracts the average of all future available observations. Therefore, the formula for transforming a variable, u_{it}, is given by:

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

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 arises from integrating out the fixed individual effects from the posterior density if a flat prior is used for the individual effects.

2.2 Solving the Endogeneity Problem

Equation (3) cannot be estimated with the ordinary least squares (OLS) method because there is a correlation between h_{it}^{*} and u_{it}^{*}. In our empirical application h_{it} contains, among other regressors, the initial GDP per capita level (log_initial). Even if we assume that log_initial in period *t* is uncorrelated with u_{it}, it is clear that the transformation induces a correlation between the transformed log_initial 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) and Limited-Information-Maximum-Likelihood (LIML) estimators as suggested by LM (2012). Then, the system of equations containing auxiliary equations for h_{it}^{*} can be defined as follows:

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

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, $E(u_{it}^{*} v_{js}^{*}) = 0$ for either $i \neq j$ or $t \neq s$ or both. We assume that the variables x_{it} and z_{it} are strictly 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 ($log\_initial_t^{*}$), we use the contemporaneous untransformed value ($log\_initial_t$). For the other endogenous regressors we use the first untransformed lag as an instrument. Although we can use further lags as instruments, no clear guidelines exist on the optimal number of instruments. Using Monte Carlo simulation, Roodman (2009) found that increases in the instrument count tend to artificially raise the estimate of a parameter. Windmeijer (2005) reports that reducing the instrument count by a certain amount lowers the average bias of the parameter of interest, whereas LM (2012) shows that models using nearer lags as instruments have larger posterior probability. For this reason, we use only one instrument per potentially endogenous variable in our estimation. 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 $k_{2j} \geq M$ (M is the number of endogenous variables). 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: Because we are using the minimum amount of instruments necessary for identification, all the models use the same set of instruments. Therefore, we do not consider uncertainty over the set of instruments.
- ✓ Exogeneity restrictions: Some of the covariances between the error terms (u_{it} and v_{it}) can be restricted to zero. Therefore, we consider models that impose different exogeneity restrictions on the potentially endogenous regressors. However, all the models that we consider treat log_initial as endogenous, because as mentioned earlier, the transformed value of log_initial is correlated with the transformed error term.
- ✓ Restrictions on coefficients of endogenous or predetermined regressors: Some of the coefficients of γ might be restricted to zero. However, in our empirical application we do not allow for zero restrictions on the coefficient of log_initial, as we think that this regressor should always be in a growth model. We do allow for zero restrictions on the coefficients of other endogenous regressors.

In our case, the number of models in the model space is $K = 2^{2(\mathrm{M}-1)}2^{k_1^T}$, where k_1^T denotes the total number of potential regressors in X.

2.3 The Bayesian Model Averaging Approach

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

$$\mathrm{p}(\mathrm{H_j}|\mathrm{Y}) = \frac{f(\mathrm{Y}|\mathrm{H_j})\ \mathrm{p}(\mathrm{H_j})}{\sum_{\mathrm{r}=1}^{\mathrm{K}} f(\mathrm{Y}|\mathrm{H_j})\mathrm{p}(\mathrm{H_j})} \tag{6}$$

where Y represents all the observed data, $f(Y|H_j)$ is the marginal likelihood of model H_j, $p(H_j)$ is the prior probability that model H_j is true, and K is the total number of models, such that the summation takes place over the whole model space. Thus, equation (6) 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 is given by

$$f(\mathrm{Y}|\mathrm{H_j}) = \int f(\mathrm{Y}|\theta, \mathrm{H_j})\mathrm{p}(\theta|\mathrm{H_j})\ \mathrm{d}\theta \tag{7}$$

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

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 model posterior probabilities.

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

$$f(\theta|\mathrm{Y}) = \sum_{\mathrm{j}=1}^{\mathrm{K}} f(\theta|\mathrm{H_j}, \mathrm{Y})\ \mathrm{p}(\mathrm{H_j}|\mathrm{Y}) \tag{8}$$

Equation (8) 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, $p(H_j|Y)$. The BMA approach allows for computing the posterior probability of including a regressor, which is the posterior probability that the regressor has a non-zero coefficient:

$$p(x_{it}|Y) = \sum_{j=1}^{K} I(x_{it}|H_j)\, p(H_j|Y) \tag{9}$$

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 (8) as

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

From expression (10), we see that the posterior mean for θ is 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 used random prior probabilities of models and a hyper-prior on the parameter g following the same setup as in Ley and Steel (2009, 2012) and in LM. Further, as a robustness check, we assume that all the models exhibit equal prior probabilities, implying that the prior over the model space is uniform: $p(H_1) = p(H_2) = \cdots = p(H_K) = \frac{1}{K}$ and fix the parameter g equal to the sample size. 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 a large amount of 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 $(\theta,\ H_j)$, 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[1]. 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:

$inf\_low = inflation * d_I$

$inf\_high = inflation * (1 - d_I)$

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 captures the impact of inflation when inflation is below the threshold level and the coefficient of inf_high captures the impact of inflation when inflation is above the threshold level.

Given the availability of data in the panel context and while following the lead of existing empirical works (e.g., Sala-i-Martin, 1997a, b; FLS; SDM; Moral-Benito, 2010, 2012) that identify the factors that significantly correlate with growth, we consider the following set of growth determinants that are most relevant from a policy-makers' perspective.

- ✓ Initial income: The neoclassical growth model predicts a negative coefficient on the initial level of per-capita GDP—that is, if we keep constant other determinants of growth, then less advanced economies will grow at a faster rate, catching up with the more advanced economies at the rate specified by the magnitude of the coefficient (e.g. Sørensen and Whitta-Jacobsen (2005, p. 153)).

[1] Since most of the countries have at least one missing data for the school enrolment rate, attempting to construct a balanced-panel would result in too few countries being available.

- ✓ Investment: In the neoclassical growth theory, the ratio of investment to output denotes the rate of saving. This model reveals that a higher saving rate increases the output per effective worker at the steady-state level and thereby increases the rate of growth for a given GDP value (e.g. Moral-Benito, 2010, 2012).
- ✓ Inflation rate: Since the seminal work of Fischer (1993), many authors have considered growth models in which the inflation rate has a nonlinear impact. For example, Huyben and Smith (1998, 1999) illustrate that inflation hampers economic growth by impeding the financial sector resource reallocation, but only if the level of inflation exceeds a certain critical value. Thus, in this paper, we allow inflation to be entered as a nonlinear function that allows for threshold effects on economic growth.
- ✓ Population growth: In exogenous growth models (e.g. the general Solow model) the steady state level of income per person decreases with population growth (e.g. Sørensen and Whitta-Jacobsen (2005, p. 140)). However, in R&D based semi-endogenous growth models, population growth affects positively the growth rate of technology, increasing economic growth (e.g. Sørensen and Whitta-Jacobsen (2005, p. 271)). Therefore, the sign of the impact of population growth on economic growth depends on the theoretical model used.
- ✓ Trade openness: Economies' external environments or trade regimes are captured by the degree of openness, as measured by exports plus imports as a percentage of GDP. It is often argued that a greater level of openness affects growth positively.
- ✓ Terms of trade: Many studies consider movements in the terms of trade, measured by changes in the relative prices of exports and imports, crucial growth factors. The most common finding among these studies is that the terms of trade affect economic growth positively.
- ✓ Labor force participation rate: We proxy the labor force participation rate by the proportion of population that is in the working age group (i.e. age between 15 and 65). A higher proportion of population in the working age group might increase per capita income growth by decreasing the dependency ratio.
- ✓ Government consumption expenditure[2]: Since the seminal work of Barro (1991), several researchers have considered the share of government consumption as a measure of the

[2]One of the variables in this paper is investment ratio (% GDP per capita), which includes both private and government investment. Hence, we did not include government investment as a separate explanatory variable.

distortion in the economy. Although the ratio of government consumption to GDP does not affect private productivity directly, it might decrease saving and growth via a distortion effect from the government expenditure program or taxation (e.g. Moral-Benito, 2010).

- ✓ School enrollment rate: Since the seminal study by Lucas (1988), several studies have broadened the concept of capital, with the inclusion of human capital in addition to physical capital. Many empirical studies use education as a proxy for the quality of human capital (e.g., Barro, 1991; FLS; SDM); thus, we consider the school enrollment rate in primary and secondary education[3] as a proxy for this.
- ✓ Price level of investment: Since the seminal work by Agarwala (1983), many authors have come to consider the investment price as a proxy for price distortions in the economy (e.g., Barro, 1991; Easterly, 1993; Moral-Benito, 2010). It is often argued that price distortions have a negative impact on economic growth; hence, following Barro (1991), we consider the price level of investment as a proxy for price distortions.
- ✓ Population: Aghion and Howitt (1992) and Romer (1990) each explain the benefits of a large economic scale by using an endogenous growth model. Particularly, if there is a substantial set-up cost for adapting or inventing new products or production techniques at the country level, then larger economies would perform better on this basis. Many authors include a country's population to examine the country-wide scale effect (e.g. Moral-Benito, 2010).
- ✓ Population density: There are several arguments about the impact of population density on the economy. First, low but growing population densities facilitate a more productive agriculture sector and greater specialization and exchange within society (Boserup, 1965). Most planners argue that the rising population density is beneficial to the economy, because "there are economies of density in the production of certain services" (Ladd, 1992 p. 274). On the other hand, Ladd (1992) argues that a higher population density might increase crime, which would in turn increases public safety costs.

[3] The United Nations Educational, Scientific and Cultural Organization (UNESCO), describes 'Gross Enrollment Ratio' as the total enrollment within a country "in a specific level of education, regardless of age, expressed as a percentage of the population in the official age group corresponding to this level of education." An elementary formula used by most countries to calculate the Gross Enrollment Ratio is to divide the number of individuals who are actually enrolled in schools by the number of children who are of the corresponding school enrollment age (see, http://en.wikipedia.org/wiki/Gross_enrolment_ratio). Therefore, the gross enrolment ratio can be greater than 100% as a result of grade repetition and entry at ages younger or older than the typical age at that grade 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; Hauk and Wacziarg, 2009; 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. As a robustness check, we also carried out the analysis using five-year period averages, because this transformation could wash up the business cycle more effectively.

4 Estimation Results

In order to carry out BMA analysis, we run the RJMCMC algorithm for 800000 iterations after discarding the initial 10000 values[4]. Repeated estimation with randomly chosen initial values gave the same results, indicating good convergence of the algorithm.

We first carried out the BMA analysis by assuming that all regressors, except log_initial, are exogenous (Table 4). The first panel of Table 4 shows the BMA estimates of exogenous regressors, the second panel of Table 4 reports the estimate of the coefficient of log_initial and the last panel shows the estimates of the dummy variable coefficients. According to this output, the exogenous regressors with a posterior probability of inclusion close to 1 are investment ratio, terms of trade, 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. The estimated coefficient of the terms of trade is clearly negative since the posterior probability that the coefficient is positive is close to 0 and a 95% credible interval does not include 0. This finding is similar to Samami et al. (2011) who suggested that the terms of trade volatility has often been negatively correlated with economic growth in commodity dependent developing countries whereas it is positively correlated with growth in oil exporting countries. Note that our sample includes developing countries from the Asian region, and most of the economies have more imports than exports, so this could be the reason that an increase in the terms of trade has a negative impact on growth. The posterior probability that the coefficient of secondary education is positive is only 9.34%,

[4]The analysis was carried out using GAUSS software on an Intel Core CPU with 3.33 GHz processor speed, which takes approximately 16 hours to run 800000 iterations.

indicating that secondary education has a negative impact on growth with probability 91.6%. This could be for three reasons: (i) the enrolment rate includes grade repetition, which delays entering into the labor force, (ii) mismatch between educational qualifications and skills needed at the job and (iii) later entry into the labour market even in the absence of grade repetition. Although the 95% credible interval for population does contain the value 0, population has a substantial posterior probability of being positive (39.2%)[5].

Trade openness, government consumption expenditure and price level of investment have very high posterior probabilities of inclusion (96.7%, 96.4% and 90.7% respectively). Although the posterior probability of the trade openness being positive is very small (7.5%), the sign is not well determined because the corresponding 95% credible interval contains the value 0. However, as expected, the probabilities that government consumption and the price level of investment have a negative impact on grow are high (96.28% and 84.6%, respectively). Next, although the probabilities of inclusion of primary school enrolment rate and population density are relatively high (74.5% and 59.4% respectively), both of them have a substantial probability of being negative (51% and 39% respectively), which would go against our prior expectation.

Finally, the regressor "inflation above threshold level"(inf_high) has a 93.3% probability of having a non-zero impact on growth; the probability of having a negative impact is approximately 93%. This indicates 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) is very small (12%), 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 and labor force participation rate) 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.

Regarding the coefficient of the "initial level of GDP per capita", it has probability of inclusion equal to one only because we have imposed that as our prior assumption. However, the

[5]However, our sample includes China and India, and this might have a positive impact on the estimated coefficient.

probability of being positive is only 68.9%, so we cannot conclude whether the countries are conditionally converging or diverging.

In sum, the investment ratio of an economy is positively associated with its growth rate whereas the terms of trade, government consumption expenditure and the price level of investment are negatively correlated. The impacts of the investment ratio (see, Fernandez, Lee and Steel, 2001; Moral-Benito, 2010; Sala-i-Martin, 1997), the terms of trade (see, Samimi et al., 2011) the price level of investment (see, Moral-Benito, 2010; Agarwala 1983) and the government consumption expenditure (see, Barro, 1991; 1990; 1989) variables are in line with theoretical predictions and many of the empirical papers. Further, our empirical 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. The most recent empirical literature also gives evidence of a nonlinear relationship between the inflation rate and the economic growth rate (see, Bick, 2010; Bruno and Easterly, 1998; Fischer, 1993, Khan and Senhadji, 2001, Kremer, Bick, and Nautz, 2009; Vinayagathasan, 2013).

In addition, as a robustness check we carried out the BMA analysis by treating all regressors as potentially endogenous (see Table 5). The results reveal that only two variables, i.e. initial level of GDP per capita and government consumption expenditure, have a high posterior probability of inclusion (100% and 80.8% respectively). However, recall that we are forcing log_initial to be endogenous and to be included in the regression. Regarding the government consumption expenditure, the BMA method calculates that the probability of being an endogenous regressor is 0, and it negatively affects growth with probability 80.7%. Finally, the regressor "inflation above threshold level" (inf_high) has a probability around 40.6% of having a non-zero impact on growth; the probability of having a negative impact is approximately 40.2%. This indicates a substantial probability that the impact of inflation on growth is negative whenever inflation is beyond the threshold value of 5.43%.

The remaining regressors (investment ratio, inflation below threshold level, growth rate of population, trade openness, terms of trade, labor force participation rate, school enrolment rate in primary and secondary education, price level of investment, population and population density) have very small/close to 0 probabilities of inclusions, while some of these regressors (investment ratio, trade openness, terms of trade, school enrolment rate in primary and secondary education, price level of investment, population and population density) have high (close to 1) probabilities of being endogenous. Thus, when we allow for endogeneity we cannot find evidence that they explain the economic growth of Asian developing countries. However, even in this case the impact of these variables might be country specific.

In conclusion, both approaches (i.e. the all exogenous versus the all endogenous approach) find a negative impact of inflation over the threshold and a negative impact of government consumption. Treating all regressors as exogenous increases the identification power and so we also find other regressors to have an impact on growth.

4.1 Robustness Check

As a robustness check we estimated the model assuming equal prior probabilities for all models and fixing the value of the prior parameter g (see LM) equal to the sample size. Under the assumption of all regressors being exogenous (except log_initial), the results obtained vary in three different aspects (see Table 6). First, the regressors inflation above threshold level (inf_high), the primary school enrolment rate and the price level of investment become less important to growth with posterior probabilities of inclusion equal to 34.2%, 14.1% and 55.8%, respectively. Secondly, although government consumption expenditure is still negatively correlated to growth, the probability of having a negative impact has been reduced slightly from 96.3% to 79.6%. Finally, the regressors inflation below threshold, the growth rate of population, the labor force participation rate and the population density, which had low probabilities of inclusion, receive even lower probabilities of inclusion: 0.4%, 1.1%, 15.3% and 18.9%, respectively. With respect to the similarities, the investment ratio is positively correlated to growth (95.3%), whereas trade openness, terms of trade, secondary school enrolment rate and population are negatively correlated to growth (67%, 97.9%, 77.7%, and 58.7% respectively) with posterior inclusion probabilities close to 1. However, wherever there are differences in the results, we prefer the estimates obtained in Table 4 for the reasons outlined in Ley and Steel (2009, 2012).

Next, we examined the robustness of our results by treating all regressors as endogenous under a fixed value for g and equal prior probabilities for models. None of the variables receive a large probability of inclusion, indicating a lack of identification under this prior setup.

Finally we used 5 year average data as another robustness check (with random prior probabilities for models and a hyper-prior on *g*). When treating all regressors (except log_initial) as exogenous, the results obtained differ in the following aspects. The posterior inclusion probability of trade openness and the threshold variable (inflation above threshold level) decreased from (96.9%, 93.5%) to (59.5%, 65.4%), respectively. However, there is a substantial probability (58.3%) that inflation affects economic growth negatively whenever it exceeds the threshold level. Next, the probability that the coefficient of population is positive decreased from 39.2% to 26.5%, even though the probability of inclusion is still similar to our main results (i.e. close to 1). With respect to the similarities, the investment ratio is positively correlated (96.8%) to growth; whereas the terms of trade (97%), government consumption expenditure (99%), the price level of investment (79%) and the school enrolment rate in secondary education (78%) are all negatively correlated to growth with probabilities of inclusion close to 1. The remaining regressors (inflation below threshold level, growth rate of population, labor force participation rate, school enrolment rate in primary education, population density) seem less important due to the low posterior inclusion probabilities.

When we treat all regressors as endogenous with 5 year average data, BMA estimation does not find any regressor with a high posterior inclusion probability. Again this might be the result of lack of identification due to the smaller number of observations and the assumption that everything can be endogenous. Although we think that assuming that all regressors are exogenous except log_initial and taking two year averages are reasonable empirical strategies, some of our results still hold when we allow for all regressors to be endogenous, provided that we are taking two-year averages to increase the number of observations.

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 the purpose of comparison, 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[6]. The results obtained differ in three different aspects (see Table 7). First, the regressors population density and labor force participation rate, which showed a very small

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

probability of inclusion, become positively correlated to growth with a higher posterior inclusion probability (93.2% and 67.2%, respectively). Second, the probabilities of inclusion of regressors "inflation above the threshold level", "trade openness", "government consumption expenditure" and "price level of investment" decreased from nearly 1 to close to zero. Finally, posterior probabilities of inclusion of regressors "terms of trade" and "secondary school enrolment rate" decreased from nearly 100% to around 61% and 67% respectively. With respect to similarities, the investment ratio is positively correlated to growth, with a probability of inclusion close to 1 in both cases.

We also carry out a comparison with estimation methods that allow for endogeneity and/or fixed effects but do not allow for model uncertainty, such as the Generalized Method of Moments (GMM: Arellano and Bond, 1991), and the Fixed Effects (FE: Wooldridge, 2010, chapter 10) estimators. First, the results show that government consumption, which we found to be negatively correlated to growth with large probability of inclusion in our main BMA analysis, is statistically significant with FE but insignificant with GMM estimation. Second, the effect of the threshold variable (inflation above the threshold level) on growth is significant and negative in both cases (see Table 8). Third, 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 estimator does not find this. Fourth, the terms of trade is significant and negatively correlated to the growth rate according to these two estimators. Fifth, the school enrolment rate on secondary education, which had negative impact on growth with our main BMA technique, also affects growth negatively and significantly under the GMM approach but not under the FE estimator approach. Finally, the investment ratio, which was found important with our main BMA approach, is also found significant with these two approaches.

While the basic BMA analysis of Table 7 did not take into account endogeneity or fixed effects, the two approaches GMM and FE do not consider the problem of model uncertainty. However, our main BMA analysis considered the issues of model uncertainty, endogeneity, and fixed effects simultaneously.

6 Conclusions

The existing empirical studies have used various techniques to account for model uncertainty in growth regressions. Among these techniques, BMA analysis has been 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 a non-linear impact on economic growth and we focus on Asian countries.

Our empirical evidence on the determinants of growth has found four variables, namely, investment ratio, terms of trade, inflation above threshold level, and government consumption expenditure, to have a significant impact on growth. However, we were not able to determine whether countries are conditionally diverging or converging.

We also found evidence of a nonlinear relationship between inflation and economic growth, similar to that found in previous empirical studies. That is, inflation above the threshold level of 5.43% has a negative impact on growth with a 93.5% probability. We think this constitutes enough evidence to warn 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, Source(s) and Expected Results

Variables	*Definition*	*Source(s)*	*Expected Impact*
Y	GDP per capita growth rate in purchasing power parity (PPP) 2005 constant prices	PWT 7.0	Dependent Variable
log_initial	GDP per capita from previous period in PPP 2005 constant prices (in Log)	PWT 7.0	Negative
Inv	Annual percentage change of GDP per capita dedicated to investmentin PPP 2005 constant prices	PWT 7.0	Positive
inf[7]	Average percentage change of CPI for the year	EW	Nonlinear
gpop	Annual growth rate of population	WDI	Inconclusive
open	Share of export plus import in percentage of GDP 2005 constant prices	PWT 7.0	Positive
tot	Export value divided by import value (2000=100)	WDI	Positive
lfpr	Percentage of total population between ages 15 and 65	WDI	Positive
gce	Government consumption share of GDP per capita converted in PPP 2005 constant prices	PWT 7.0	Negative
prim	Gross enrollment rate in primary education (% of total enrollment regardless of age)	WDI[8]	Positive
Secnd	Gross enrollment rate in secondary education (% of total enrollment regardless of age)	WDI	Positive
Pi	Price level of investment in PPP 2005 constant prices	PWT 7.0	Negative
Pop	Total population in million	WDI	Positive

[7] 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).

[8] Since the school enrollment rate data for certain periods for some of the Asian countries are not available in the World Development Indicators database, 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*.

popdn	People per sq. km of land area	WDI	Inconclusive

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

Table 2

Summary Statistics of Full Sample

Variable	*Observation*	*Mean*	*Standard Deviation*	*Minimum*	*Maximum*
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: Authors' calculations based on data from Penn World Table (PWT 7.0), Economy Watch, and World Development Indicators. 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: Authors' 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 Estimates (following the Ley and Steel, 2009, 2012 approach) for two year averaged data by treating all regressors as exogenous except for the initial level of GDP per capita.

Variables	Probability	2.50%	97.50%	Mean	Positive	Pro.endo
			Exogenous Regressors			
inv	0.9999	0.0104	0.1753	0.0947	0.9851	0.0000
inf_low	0.1245	-0.4036	0.0527	-0.0218	0.0325	0.0000
inf_high	0.9357	-2.7190	0.0000	-1.5297	0.0022	0.0000
gpop	0.1275	-0.2095	0.0472	-0.0104	0.0375	0.0000
open	0.9698	-0.0448	0.0072	-0.0180	0.0756	0.0000
tot	1.0000	-0.0833	-0.0127	-0.0473	0.0043	0.0000
lfpr	0.3443	-0.0099	0.3181	0.0533	0.3173	0.0000
gce	0.9636	-0.5869	0.0000	-0.3460	0.0008	0.0000
prim	0.7457	-0.0674	0.0415	-0.0103	0.2358	0.0000
secnd	1.0000	-0.1366	0.0265	-0.0530	0.0939	0.0000
pi	0.9077	-0.0440	0.0051	-0.0172	0.0591	0.0000
pop	1.0000	-0.0261	0.0187	-0.0032	0.3923	0.0000
popdn	0.5938	-0.0019	0.0012	-0.0002	0.2020	0.0000
			Endogenous Regressor			
log_initial	1.0000	-12.986	22.863	4.4444	0.6894	1.0000
			Time Dummy Variables			
d1	0.1074	-1.2165	0.9015	-0.0154	0.0486	0.0000
d2	0.9823	-5.9538	-0.9485	-3.6878	0.0010	0.0000
d3	0.8184	-4.7819	0.0000	-2.3139	0.0032	0.0000
d4	0.4751	-3.8926	0.0000	-1.0387	0.0114	0.0000
d5	0.1103	-0.5423	1.1892	0.0354	0.0674	0.0000
d6	0.1498	-0.3288	1.7770	0.1086	0.1114	0.0000
d7	0.7468	0.0000	4.4124	1.9215	0.7438	0.0000
d8	0.1194	-0.5359	1.0523	0.0309	0.0723	0.0000
d9	0.1270	-0.8802	0.8489	-0.0010	0.0634	0.0000
d10	0.6694	-3.9395	0.0000	-1.5392	0.0043	0.0000
d11	0.1028	-0.9032	0.5153	-0.0195	0.0433	0.0000
d12	0.1117	-0.1058	1.4507	0.0761	0.0843	0.0000
d13	0.9375	0.0000	4.5864	2.5915	0.9348	0.0000
d14	0.9932	1.5571	5.6276	3.6489	0.9932	0.0000

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. The last column *pro.endo* gives the probability that the regressor is endogenous.

Table 5
BMA Estimates (following the Ley and Steel, 2009, 2012 approach) for two year averaged data by treating all regressors as potentially endogenous.

Variables	Probability	2.50%	97.50%	Mean	Positive	Pro.endo
log_initial	1.0000	-9.5738	6.6206	-1.4122	0.3677	1.0000
inv	0.0006	0.0000	0.0000	0.0000	0.0005	1.0000
inf_low	0.0044	0.0000	0.0000	-0.0005	0.0015	0.0000
inf_high	0.4057	-2.1002	0.0000	-0.5134	0.0042	0.0000
gpop	0.0006	0.0000	0.0000	0.0000	0.0004	0.0001
open	0.0005	0.0000	0.0000	0.0000	0.0001	1.0000
tot	0.0024	0.0000	0.0000	-0.0001	0.0001	1.0000
lfpr	0.0100	0.0000	0.0000	0.0014	0.0090	0.0018
gce	0.8089	-0.5406	0.0000	-0.2691	0.0011	0.0000
prim	0.0001	0.0000	0.0000	0.0000	0.0001	1.0000
secnd	0.0012	0.0000	0.0000	0.0000	0.0006	1.0000
pi	0.0002	0.0000	0.0000	0.0000	0.0000	0.9998
pop	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000
popdn	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000

Note: For the definition of columns, see Table 4. The BMA estimates of dummy variables are not reported in this table but are available upon request.

Table 6

BMA Estimates (using equal prior probability of models and fixed value equal to the sample size for the prior parameter *g*) for two year averaged data by treating all regressors as exogenous except for initial income.

Variables	Probability	2.50%	97.50%	Mean	Positive	Pro.endo
inv	0.996	-0.0154	0.1919	0.0925	0.9534	0.0000
inf_low	0.004	0.0000	0.0000	-0.0001	0.0018	0.0000
inf_high	0.342	-2.3826	0.0000	-0.5149	0.0031	0.0000
gpop	0.011	0.0000	0.0000	-0.0023	0.0013	0.0000
open	0.987	-0.0522	0.0231	-0.0137	0.2171	0.0000
tot	0.999	-0.0904	-0.0021	-0.0452	0.0203	0.0000
lfpr	0.153	0.0000	0.4188	0.0458	0.1511	0.0000
gce	0.796	-0.6584	0.0000	-0.3360	0.0003	0.0000
prim	0.141	-0.0340	0.0298	-0.0002	0.0662	0.0000
secnd	1.000	-0.1589	0.0631	-0.0412	0.2239	0.0000
pi	0.558	-0.0544	0.0000	-0.0149	0.0214	0.0000
pop	1.000	-0.0374	0.0267	-0.0038	0.4130	0.0000
popdn	0.189	0.0013	0.0011	-2.43E-05	0.0864	0.0000
log_initial	1.000	-15.943	35.841	8.1569	0.74224	1.0000

Note: For the definition of columns, see Table 4. The BMA estimates of dummy variables are not reported in this table but are available upon request.

Table 7

BMA estimation results of equation (1) by 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: Probability indicates the posterior inclusion probability of a variable entering the model as an exogenous regressor, *mean* denotes the posterior mean of the coefficient, and *SD* represents the standard deviation of parameters. The number of observations is 345.

Table 8
Arellano-Bond GMM and FE estimation results of equation (1)

	Arellano-Bond GMM Estimates			**Fixed Effect Estimates**		
Variables	**Coefficient**	**z-value**	**P-value**	**coefficient**	**t-value**	**p-value**
log_initial	0.026	0.020	0.981	-4.707	-1.600	0.110
inv	0.118**	5.300	0.000	0.121***	3.450	0.001
inf_low	-0.295	-1.200	0.229	-0.256	-0.930	0.351
inf_high	-1.312**	-2.580	0.010	-1.773***	-2.910	0.004
gpop	-0.172	-1.550	0.120	-0.011	-0.070	0.941
open	-0.011*	-1.950	0.051	-0.017	-1.480	0.141
tot	-0.032***	-3.080	0.002	-0.039***	-2.780	0.006
lfpr	0.059**	2.530	0.012	0.083	0.700	0.484
gce	0.051	1.150	0.248	-0.331***	-2.840	0.005
prim	0.029*	1.690	0.092	-0.032	-1.140	0.254
secnd	-0.040*	-1.870	0.062	-0.037	-1.250	0.213
pi	-0.005	-0.530	0.599	-0.011	-0.950	0.343
pop	0.000**	2.360	0.018	0.000	0.550	0.580
popdn	0.000***	3.980	0.000	0.000	-0.160	0.870
dum2	0.126	0.110	0.911	-3.919***	-3.180	0.002
dum3	-3.748***	-3.310	0.001	-2.779**	-2.210	0.028
dum4	-3.230***	-2.890	0.004	-1.737	-1.300	0.195
dum5	-2.028*	-1.790	0.074	0.571	0.440	0.662
dum6	0.092	0.080	0.933	0.769	0.590	0.557
dum7	-0.171	-0.160	0.874	3.095**	2.200	0.029
dum8	2.191**	1.990	0.047	0.946	0.640	0.521
dum9	0.458	0.430	0.669	0.884	0.550	0.580
dum10	0.125	0.120	0.908	-1.395	-0.870	0.384
dum11	-2.055*	-1.930	0.054	0.648	0.380	0.705
dum12	-0.062	-0.060	0.955	1.524	0.860	0.391
dum13	0.786	0.740	0.462	4.281**	2.320	0.021
dum14	3.338***	3.240	0.001	5.460***	2.810	0.005
dum15	3.895***	3.770	0.000	1.864	0.960	0.339
cons	-0.861	-0.230	0.820	25.583*	1.840	0.067

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