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Research & development and growth: A Bayesian model averaging analysis

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ABSTRACT

We examine the effect of research and development (R&D) on long-term economic growth using the Bayesian model averaging (BMA) to deal rigorously with model uncertainty. Previous empirical studies, which applied BMA, investigated the effect of dozens of regressors on long-term growth, but they did not examine the effect of R&D due to data unavailability. We extend these studies by proposing to capture the investment in R&D by the number of Nobel prizes in science. Using our indicator, the estimates show that R&D exerts a positive effect on long-term growth. This result is robust to many different parameter and model prior structures as well as to alternative definitions of R&D indicator.

1. Introduction

The positive effect of R&D of long-term economic growth is well established in economic literature and numerous endogenous growth theory models put forward that R&D is a key for growth (Barro and Sala-i-Martin, 1995). However, the empirical evidence is more scant and available either for a single country or a limited group of developed countries (see Hasan and Tucci, 2010, or Lee and Kim, 2009). The underlying reason is that more comprehensive R&D data has become available for a wider set of countries only recently (for example, R&D expenditures from about mid-1990s) and at the same time, R&D is likely to influence the economic growth in the long-term. From empirical perspective, this poses challenges to identify the effect of R&D on long-term growth.

The current empirical literature on the cross-country determinants of long-term growth has emphasized the role of model uncertainty (e.g. the uncertainty about "correct" model specification). The number of potential determinants of long-term growth is plentiful and many earlier studies have chosen the set of regressors in growth regressions in an *ad hoc* way, to a large extent (see Durlauf et al., 2008). To deal with model uncertainty formally, Bayesian model averaging (BMA) techniques have recently gained popularity to study the determinants of long-term growth (Fernandez et al. (2001a), Durlauf et al. (2008), Ley and Steel (2009) or Eicher et al. (2011)). BMA has also been recently introduced to political science by Montgomery and Nyhan (2010) and is well established statistical technique in natural sciences, too.

It is noteworthy that BMA offers several advantages. First, the number of regressors is limited only by the number of countries included in the regression analysis and in consequence a large number of regressors can be examined jointly (for example, Fernandez et al. (2001a) and Eicher et al. (2011) examine 41 regressors). As a result, this decreases the potential omitted variable bias and many competing theories can be put in test concurrently. Second, the BMA introduces a rigorous way how to average across the models and thus, examine the robustness of results more systematically. Third, the BMA gives a so-called posterior inclusion probability, i.e. an estimate of probability that given regressor is contained in the "correct model".

As noted above, the set of regressors included in regression analysis in previous studies is large. Nevertheless, any of previous studies on long-term growth using BMA include the R&D indicators. To acknowledge the endogeneity in growth regressions in a full manner, previous studies explain the long-term growth (more specifically, typically growth from 1960s-1970s to present) using the regressors that are predetermined and mostly based on the data before 1960/1970 (or are exogenous by definition such as Asian dummy or the access to coast). In consequence, the data on R&D are omitted, as they are very scarce for the aforementioned period.

This article proposes to proxy the efforts various countries put in the R&D by the number of Nobel prizes received by the laureates. The Nobel prizes are the most reputable awards in science and it is very likely that the laureates will be affiliated with institutions in countries that devote more resources to R&D. First, we show that the number of Nobel prizes is correlated with the available data on R&D expenditures in the long-term. Second, we include our R&D indicator in the dataset employed first by Fernandez et al. (2001a) and subsequently

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by a number of other empirical growth studies, and examine its effect on economic growth.

Subject to various sensitivity tests, our results show that the R&D exhibits a positive effect on long-term economic growth. The posterior inclusion probability for our preferred prior structure is 0.25, which is not high, but comparable to variables such as exchange rate distortions, the share of primary exports or war dummy.

The paper is organized as follows. Section 2 briefly introduces the Bayesian model averaging. Section 3 presents the data. The results are available in section 4. Conclusions are provided in section 5. Appendix A contains the details about the dataset.

2. Bayesian model averaging

This section gives a brief introduction to the Bayesian model averaging. We heavily follow Eicher et al. (2011). Other excellent treatments of BMA are available in Koop (2003), Koop et al. (2007), Feldkircher and Zeugner (2009), Ley and Steel (2009) or Montgomery and Nyhan (2010) to name few. The BMA is typically applied to assess transparently and rigorously the robustness of results especially in the environment of many competing theories and many possible determinants. Similarly, BMA techniques are often applied for forecasting in a data rich environment.

Suppose we have a dependent variable Y (long-term GDP growth in our context) with a number of observations n (the number of countries) and k regressors $X_1.....X_k$. The standard procedure for researchers not applying model averaging techniques is to estimate one model $Y=\alpha_1X_1+..+\alpha_kX_k+e$, where $e\sim N(0, \sigma^2 I)$ (assume that X_1 is a constant) and assess the robustness of results by changing the set of control variables. However, in many applications there is a substantial uncertainty, which of possibly plentiful X's should be included. The choice of X's is often largely *ad hoc* in many empirical exercises. The BMA offers a viable alternative, as it considers all X's and averages the estimated parameters in a rigorous manner. In consequence, the application of BMA substantially reduces the possibility of omitted variable bias.

In principle, there are $l=2^k$ subsets of X's that can be considered and therefore $M_1....M_l$ models (regressions) to be examined. Let us denote the vector of parameter of i-th model as $\theta_i=(\alpha, \sigma)$. The likelihood function of i-th model, $pr(D|\theta_i, M_i)$ summarizes all the information about θ_i based on available data D. The marginal likelihood, the probability density of the data, D, conditional on M_i can be written as follows

$$pr(D|M_i) = \int pr(D|\theta_i, M_i) pr(\theta_i|M_i) d\theta_i, \quad (1)$$

e.g. the marginal likelihood is a product of the likelihood function and prior density $pr(\theta_i|M_i)$ integrated over parameter space. Using $pr(D|M_i)$ one can derive the prior probability that M_i is a correct model, this is denoted as $pr(M_i)$. Bayes's theorem gives the posterior model probability of M_i, $pr(M_i|D)$,

$$pr(M_i|D) = \frac{pr(D|\theta_i, M_i) pr(M_i)}{\sum_{l=1}^{i} pr(D|M_l) pr(M_l)} \quad (2)$$

the posterior inclusion probability of given regressor, $pr(\alpha_j\neq 0|D)$, is then received by taking a sum of posterior model probabilities across those models that include the regressor. The posterior inclusion probability is of primary importance here, since it indicates what is the probability that given regressor belongs into the “correct” model of long-term economic growth. This approach has been recently generalized to panel data setting to explicitly account for unobserved heterogeneity among countries (Moral-Benito, forthcoming).

It is computationally prohibitive to evaluate all the possible models (2^{42} in our case) and we use MC^3 to reduce the computational requirements (Madigan and York, 1995). MC^3 approximates the posterior distribution of model space by simulating a sample from it. We take 1,000,000 burn-ins and 3,000,000 draws, which leads to a sufficiently high correlation between exact and MC^3 posterior model probabilities (about 0.99).

2.1. Parameter priors

Parameter priors have to be specified in order to implement BMA. In general, the priors specify researcher's information or beliefs before seeing the actual data. Since the degree of belief is not particularly high in the context of growth regressions, uninformative priors are typically employed. The priors affect the marginal likelihood in (1) and there is a discussion in literature, which parameter priors (as well as model priors, more on this below) are preferable (Eicher et al. (2011), Feldkircher and Zeugner (2009) or Ley and Steel (2009)). This is examined by evaluating the predictive performance of model. For example, among 12 candidate parameter priors, Eicher et al. (2011) find that the Unit Information Prior (UIP) with uniform model prior tend to provide more accurate predictions than the other considered priors. On the other hand, Feldkircher and Zeugner (2009) prefer hyper g-priors. To deal with this issue, we carry out the estimations using several parameter priors (as well as model priors) to shed light on the robustness of results.

The first prior is defined as follows.

$$pr(D|M_i)\approx c-1/2BIC_i, \quad (3)$$

where

$$BIC_i = n\, log\left(1-R_i^2\right) + p_i\, log(n) \quad (4)$$

In Eqs. (3) and (4), c is a constant, R_i^2 stands the coefficient of determination and p_i for the number of regressors. This prior is typically labeled as UIP. This prior depends on data and it has been questioned, whether this commonly used prior is, in fact, valid for Bayesian analysis.

Next, we consider the following prior, so-called g-prior, proposed by Fernandez et al. (2001b):

$$pr(\alpha_1|M_i)\propto 1, \quad (5)$$

$$pr(\sigma|M_i)\propto 1, \quad (6)$$

$$pr\left(\alpha^{(k)}|\sigma, M_i\right)\sim N\left(0, \left(g_k Z^{(k)'} Z^{(k)}\right)^{-1}\right), \quad (7)$$

where $Z^{(k)}$ denote the matrix of size $n\times p_k$ with p_k demeaned regressors included in M_i. It is noteworthy that the values of g close to zero imply less informative prior and $g=1$ gives the same weight to the information contained in data and in prior. Two different values of g are examined. First, $g=1/max\ (N, k^2)$ is the one preferred by Fernandez et al. (2001b) called BRIC. Second, $g=1/(lnN)^3$ corresponds to Hannah-Quinn criterion. The third commonly employed g-prior set $g=1/k^2$ (Foster and George, 1984), but this is in our setting identical to $g=1/max\ (N, k^2)$.

Next, we also use parameter priors not employed previously in the growth literature (except Feldkircher and Zeugner, 2009), the so-called hyper-g prior (Liang et al, 2008):

$$\pi(g) = \frac{a}{a-2}(1+g)^{a/2}, \quad (8)$$

We use two different hyper-g priors. The first one sets the prior expected value of shrinkage factor to correspond to UIP, the second one sets it to conform to BRIC. All in all, this makes five different parameter priors that we employ for the empirical investigation of long-term economic growth.

2.2. Model priors

Two different model priors – uniform and random binomial – are investigated. We start with uniform model prior, which gives an equal prior probability to all models M_i. In consequence, $pr(M_i) = 1/L$ for each i. Next, more general model prior is employed.

$$pr(M_i) = \Pi_{j=1}^{p} \pi_j^{\delta_{kj}} \left(1 - \pi_j\right)^{1-\delta_{kj}}, \tag{9}$$

where $\delta_{kj} = 1$, if X_j is included in M_i, and 0 otherwise and π is treated as random variable drawn from $Beta(1, \frac{1-\pi}{\pi})$ distribution (Ley and Steel, 2009).

3. Data

To investigate the growth in a cross section of countries, we use the data from Fernandez et al. (2001a). The benefit of using this dataset is that it has been analyzed by a number of researchers afterwards (Koop (2003), Koop et al. (2007), Ley and Steel (2009) or Eicher et al. (2011)) and substantial sensitivity analysis is thus available. The original dataset contains 41 regressors from 72 countries leading to a total of 2^{41} models (almost 2.2 trillion).

The dataset is representative and covers both developed and developing countries. The regressors include various economic, political, geographical, demographic, religious, social or cultural variables considered to be important by previous literature. The list of countries and regressors is available in Appendix A. The dependent variable, economic growth, is defined as the change in the real GDP in 1960–1992.

Since ordinary least squares model enters into the BMA, it is important that the regressors are predetermined. Some regressors such as geographical variables are clearly exogenous to economic growth, while for others this is assured by using the data before 1960 or at worst from 1960s–1970s, where applicable. The comprehensive R&D data such as the ratio of expenditures on R&D to GDP is not available for this period and in fact these data are available for a sufficient number of countries only from mid-1990s onwards. Therefore, we propose to proxy the investment in R&D with the number of Nobel prizes in science by countries. We use the prizes in 1945–1975 to have a sufficient time coverage as well as country heterogeneity. We believe that our R&D indicator is predetermined to economic growth in 1960–1992, since the prizes are given with a substantial lag typically of more than two decades after the scientific discovery.

Our R&D indicator, RD, is calculated as follows:

$$RD_j = \sum_{i=1}^{4} \sum_{t=1945}^{1975} \left(\frac{1}{n}\right)_{i,t} \tag{10}$$

where i stands for the scientific field in which the laureate received the prize (physics, chemistry, medicine or economics) and t represents the year in which the laureate was honored. n stands for the number of laureates that received the prize in particular field and given year. For example, if three laureates share the prize in physics in year t, then $1/n = 1/3$. RD_j for country j is obtained by summing up $1/n$ over all the years and fields. It is noteworthy that the affiliation of laureate in the year the prize was given (and not citizenship or the place of birth) determines to which country the value of $1/n$ is assigned (the source of data is an official website of Nobel Foundation, www.nobelprize.org). This is so, as we believe that affiliation most closely captures which country invests more in the R&D. Alternatively, we calculated the R&D indicator not adjusting for the fact that prizes are often shared, but the regression results remained largely unchanged and are available upon request.

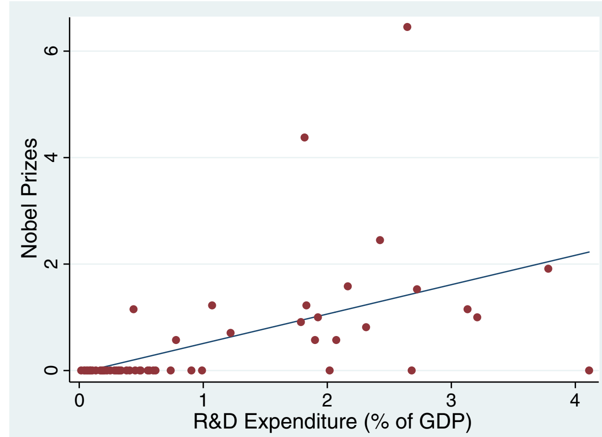


Fig. 1. R&D indicator based on Nobel prizes and the R&D expenditures to GDP.

To motivate the use of our R&D indicator based on Nobel prizes, Fig. 1 gives the scatter plot of R&D indicator ($\sqrt{RD_j}$) and the average share of R&D expenditures to GDP in 1996–2007. Visual inspection suggests that the link between these two variables is clearly positive. Two outliers are evidently present (US and UK) and we re-estimate our model without US and UK to shed light on the extent these outliers are eventually driving the results of the R&D on growth.

4. Results

This section presents the results of BMA analysis of long-term economic growth and in particular, discusses the effect of R&D indicator on growth. First, the baseline estimates are provided and substantial sensitivity analysis follows. The results are obtained in a chain of 2 million recorded draws (after 1 million burn-ins) and 1,576,409 models are visited (e.g. 3.6e−05% of model space). The posterior model size is 19.3 (i.e. the average number of included regressors). The UIP hyper g-prior and random binomial model prior is used as baseline with the results available in Table 1. The baseline choice is motivated by the simulations in Feldkircher and Zeugner (2009), who show that hyper g-prior is preferable in terms of the risk of mis-specification and predictive ability. Table 1 contains the posterior inclusion probability (PIP) as well as the posterior mean and standard deviation for each regressor.

The results suggest that the R&D indicator, although with rather lower posterior inclusion probability of 0.25, exerts a positive effect on long-term growth. We hypothesize that the lower PIP can be related to lower variability of our R&D indicator, as only 19 countries out of 72 received Nobel prizes, but comparing all regressors according to the coefficient of variation suggest that R&D indicator exhibits more variability than many regressors. More plausible explanation for somewhat lower PIP is related to the fact that Nobel prizes capture only the major scientific discoveries, which is clearly not a full picture of R&D in many countries. Additionally, many high growing East Asian countries intensified their investment in R&D only since 1970's. In consequence, the PIP for R&D coefficient is likely to be lower bound of the true effect of R&D on growth. Fig. 2 shows the posterior density of the coefficient on R&D indicator confirming the positive effect of R&D on growth.

Our results are largely in line with Fernandez et al. (2001a) both in terms of the ranking as well as the value of PIPs (with some exemption such as the variable no. of years open economy and Spanish colony dummy) as well as to other empirical growth studies using the BMA. Employing the Fernandez et al. (2001a) dataset, Ley and Steel (2009) and Eicher et al. (2011) report the PIPs of growth determinants using a large number of different prior structures. Comparing their results to ours, we can see that even the ranking of

Table 1
The determinants of growth.

Regressors	PIP	Post mean	Post SD
GDP level in 1960	1.00	−0.015881	0.003168
Fraction Confucian	0.99	0.059709	0.015711
Life expectancy	0.97	0.000843	0.000304
Equipment investment	0.91	0.127090	0.063307
Sub-Saharan dummy	0.88	−0.015376	0.008260
Fraction GDP in mining	0.79	0.030298	0.020778
Fraction Hindu	0.68	−0.044514	0.041067
Non-equipment investment	0.68	0.033619	0.029607
Rule of law	0.65	0.007596	0.007157
Degree of capitalism	0.62	0.001240	0.001259
Size labor force	0.61	1.47E−07	1.54E−07
Fraction Muslim	0.59	0.006995	0.007870
Fraction Protestants	0.58	−0.006025	0.006710
Black market premium	0.55	−0.003884	0.004449
Latin American dummy	0.54	−0.005473	0.006707
Higher school enrollment	0.54	−0.047661	0.055869
Ethnolinguistic fractionalization	0.53	0.005913	0.006913
Primary school enrollment	0.47	0.007941	0.010948
Civil liberties	0.42	−0.000885	0.001489
Fraction Buddhist	0.41	0.003931	0.006458
Spanish colony dummy	0.40	0.003369	0.005703
Number of years open economy	0.39	0.003012	0.006057
Fraction of pop. speaking English	0.37	−0.002601	0.004502
French colony dummy	0.37	0.002315	0.004191
Outward orientation	0.34	−0.001029	0.001942
Political rights	0.34	−0.000390	0.001078
Age	0.33	−1.28E−05	2.51E−05
War dummy	0.32	−0.000994	0.002056
British colony dummy	0.31	0.001060	0.003060
Fraction Catholic	0.30	−0.000398	0.003817
Public education share	0.28	0.038683	0.095647
Primary exports	0.26	−0.001514	0.004411
Exchange rate distortions	0.26	−7.60E−06	2.16E−05
Research and development	0.25	4.89E−05	0.000192
Fraction speaking foreign language	0.22	0.000225	0.001905
Absolute latitude	0.21	−3.26E−06	6.27E−05
Population growth	0.20	0.015666	0.102109
Area	0.20	−1.44E−08	3.13E−07
Ratio workers to population	0.20	−0.000509	0.003726
SD of black market premium	0.19	−7.72E−07	5.56E−06
Fraction Jewish	0.19	−0.000465	0.005237
Revolutions and coups	0.19	4.72E−05	0.002207

regressors according to PIP is largely similar. The results also broadly correspond – especially in terms of the sign of posterior means – to Eris (2010). Eris (2010) uses a similar dataset to Fernandez et al. (2001a) and examines the role of ethnic, linguistic and religious heterogeneity in a population for the long-term growth. Similarly to Durlauf et al. (2008), our results point to an importance of neoclassical factors such as initial income and investment as well as unobserved regional heterogeneity (such as sub-Saharan dummy and others). On the other hand, our results seem to give greater support for the role of institutions for growth, as compared to Durlauf et al. (2008).

There are several empirical studies investigating the effect of investment in R&D on growth employing a different econometric methods than BMA. All these studies document a positive impact of R&D on growth (see Guellec and Van Pottelsberghe De La Potterie, 2004; Falk, 2007, or Goel et al., 2008, among others). Using data from OECD countries, Falk (2007) puts forward that it is especially the R&D investment in high-tech sector that contributes to growth. Goel et al. (2008) investigate the impact of R&D on U.S. growth in 1953–2000 and argue that the structure of R&D spending is critical. Lee and Kim (2009) find that technology (as proxied by U.S. patent applications) promotes growth more in middle- and high-income countries more than in developing countries. In this regard, our results can be interpreted as s reassessment of the robustness of previous findings.

Next, we examine the sensitivity of the effect of R&D on growth to different parameters and models prior structures. Combining all prior structures gives ten different estimates of PIP and posterior mean. The results are given in Fig. 3. The results show that irrespective of prior structures the R&D indicator exerts a positive effect on long-term growth and the PIPs vary from 0.03 to 0.35. Clearly, as has been pointed out above, some prior structures are preferable to the others, so these results should not be overemphasized even though they suggest the positive effect of R&D in all cases. The positive link between the PIP and posterior mean should not come as a surprise. The posterior mean reports the coefficients averaged across all models, including the models wherein the variable was not contained (implying that the coefficient is zero in this case). In consequence, the more often the R&D was contained (i.e. higher posterior inclusion probability), the higher posterior mean is likely to be received, as more positive values for the R&D coefficient and less zeros are averaged together.

Further sensitivity analysis has been carried out by 1) excluding the US and UK, which can be classified as outliers according to Figs. 1, 2) including only 50 countries with the highest economic growth, 3) adjusting the formula in (10) for the calculation of the R&D indicator, as explained in the data section and 4) redefining RD_j as a dummy variable with four categories, with the following values: 0, for the countries without any Nobel prize (e.g. $RD_j = 0$), 1 for the countries with $RD_j < 1$, 2 for the countries with $RD_j > 1$, but except the US and UK, and 4 for the US and UK. The results indicate that the effect of R&D indicator is positive with the posterior inclusion probability

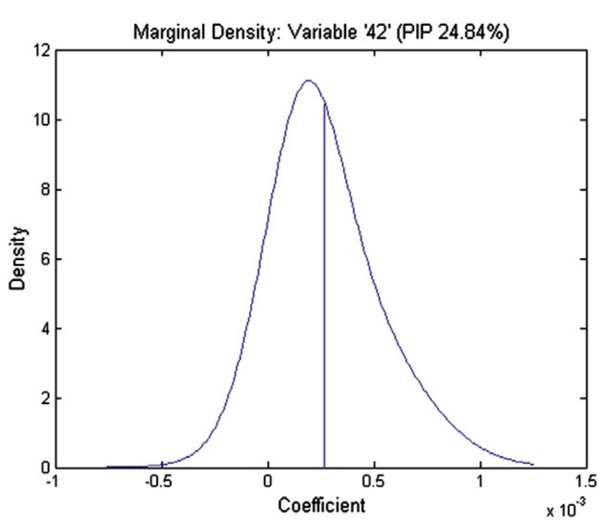
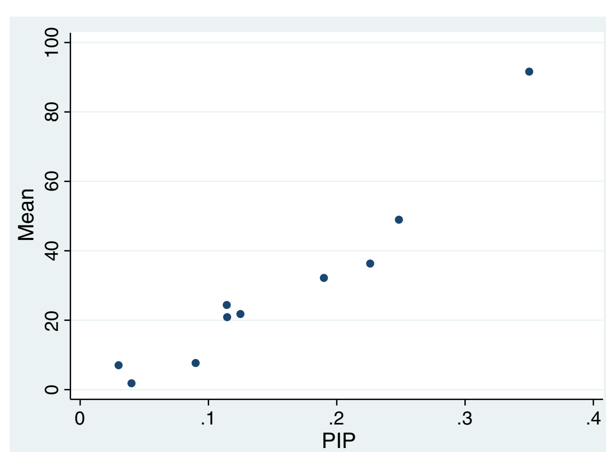


Fig. 2. Posterior density of R&D coefficient.



Note: *PIP* stands for posterior inclusion probability and *Mean* denotes posterior mean of the R&D indicator effect on economic growth. For convenience, the posterior mean multiplied by 10^6.

Fig. 3. The effect of R&D on growth: different parameter and model prior structures.

between 0.1 and 0.25 depending on the parameter and model prior structures, e.g. largely in line with the baseline results presented above. These results are available upon request.

5. Concluding remarks

We apply Bayesian model averaging to examine the effect of R&D on long-term economic growth. We use the dataset of Fernandez et al. (2001a) that has been commonly employed to investigate the cross-sectional determinants of long-term growth using Bayesian techniques, but additionally include the indicators assessing the investment in R&D.

Even though the previous studies using the Bayesian model averaging examined the effect of dozens of regressors on long-term economic growth, R&D remained untouched due to data unavailability. This is because the data on R&D with satisfactory time and country coverage became available mostly in the 1990s, which is rather insufficient for cross-country growth regressions. We propose to overcome this issue by constructing the R&D indicator based on the number of Nobel prizes in science. We show that our indicator is correlated with the recent data on R&D expenditures.

In terms of the results, it is noteworthy that we use several parameter prior and model prior structures to shed light on the robustness of results. Subject to extensive sensitivity analysis, our results show that R&D exerts a positive effect of long-term growth.

In terms of future research, we believe that it would be worthwhile to analyze the effect of R&D on growth within recently developed BMA framework using panel data (Moral-Benito, forthcoming). This would allow to account for the R&D in time. An additional extension could be to relax the linearity assumption and investigate the effect of R&D on growth non-parametrically within the BMA (Henderson et al., forthcoming).

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Appendix A

Fernandez et al. (2001a) dataset

The list of countries

Algeria, Argentina, Australia, Austria, Belgium, Bolivia, Botswana, Brazil, Cameroon, Canada, Chile, Colombia, Congo, Costa Rica, Cyprus, Denmark, Dominican Rep., Ecuador, El Salvador, Ethiopia, Finland, France, Germany West, Ghana, Greece, Guatemala, Haiti, Honduras, Hong Kong, India, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kenya, Korea, Madagascar, Malawi, Malaysia, Mexico, Morocco, Netherlands, Nicaragua, Nigeria, Norway, Pakistan, Panama, Paraguay, Peru, Philippines, Portugal, Senegal, Singapore, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Tanzania, Thailand, Tunisia, Turkey, Uganda, United Kingdom, United States, Uruguay, Venezuela, Zaire, Zambia, Zimbabwe.

The list of regressors

Economic factors: GDP level in 1960, Equipment investment, Fraction GDP in mining, Non-equipment investment, Outward orientation, Number of years open economy, Primary exports.

Political factors: Ethnolinguistic fractionalization, Civil liberties, Political rights, War dummy, Revolutions and coups.

Social factors: Size labor force, Higher school enrollment, Ethnolinguistic fractionalization, Primary school enrollment, Higher school enrollment, Public education share, Fraction of pop. speaking English, Ratio workers to population, Fraction speaking foreign language.

Health factors: Life Expectancy, Age, Population growth.

Institutional factors: Rule of law, Degree of capitalism, Black market premium, Spanish colony dummy, French colony dummy, Exchange rate distortions, SD of black market premium, British colony dummy.

Geographical factors: Sub-Saharan dummy, Latin American dummy, Absolute latitude, Area.

Religious factors: Fraction Confucian, Fraction Hindu, Fraction Muslim, Fraction Protestants, Fraction Buddhist, Fraction Catholic, Fraction Jewish.

Added in this paper: Research and development.

Note: For convenience, all regressors are divided into several broad categories. We are aware that some regressors could belong to more categories. The details about the dataset are available in Fernandez et al. (2001a).

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