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The impact of data revisions on the robustness of growth determinants: A note on 'determinants of economic growth: will data tell?'

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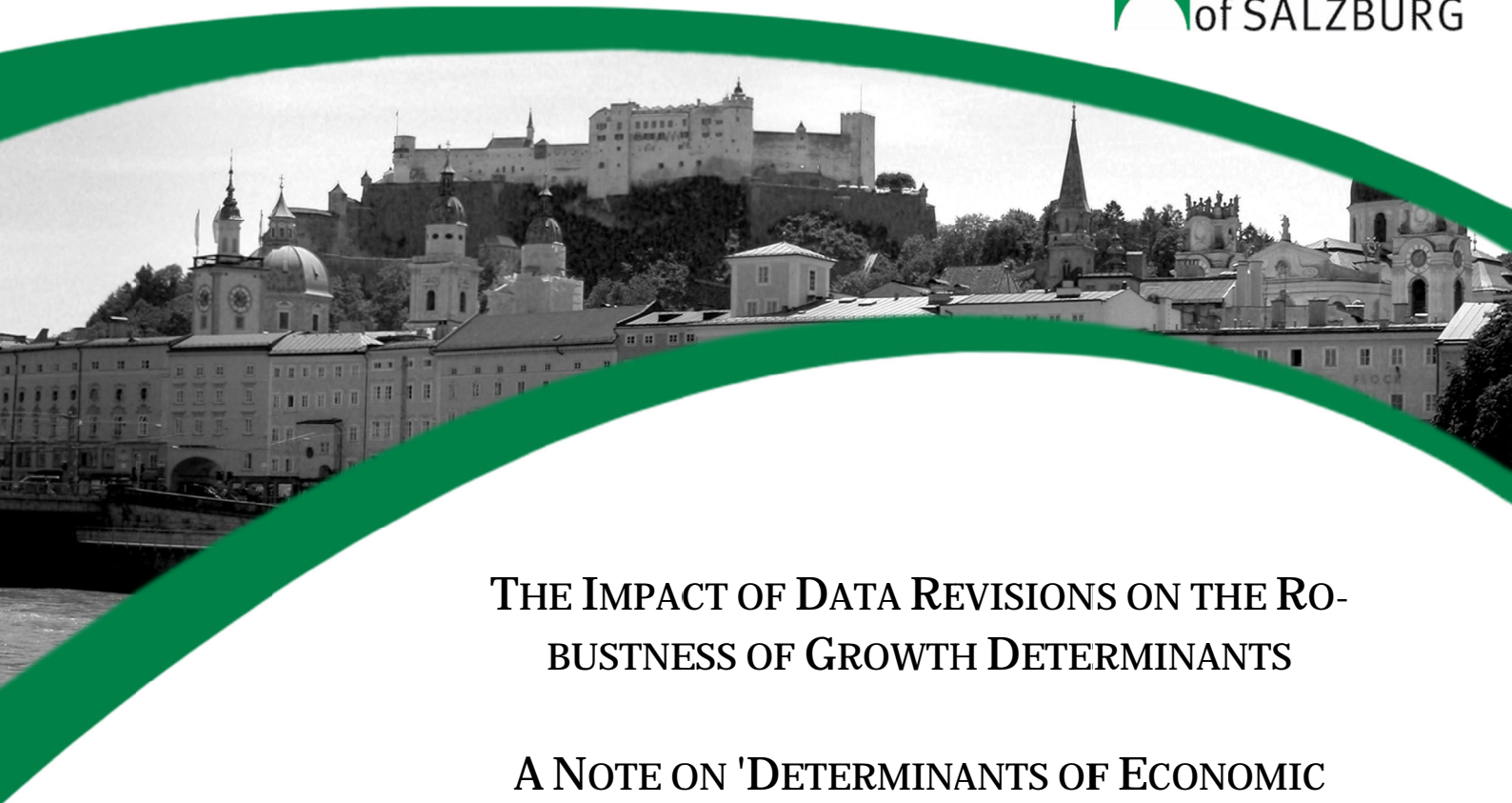
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THE IMPACT OF DATA REVISIONS ON THE ROBUSTNESS OF GROWTH DETERMINANTS

A NOTE ON 'DETERMINANTS OF ECONOMIC GROWTH. WILL DATA TELL'?

MARTIN FELDKIRCHER AND STEFAN ZEUGNER

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The Impact of Data Revisions on the Robustness of Growth Determinants - A Note on 'Determinants of Economic Growth. Will Data Tell?'

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Abstract

Ciccone and Jarociński (2010) show that inference in Bayesian model averaging (BMA) can be highly sensitive to small changes in the dependent variable. In particular they demonstrate that the importance of growth determinants in explaining growth varies tremendously over different revisions of Penn World Table (PWT) income data. They conclude that 'agnostic' priors appear too sensible for this strand of growth empirics. In response, we show that the instability found owes much to a specific BMA set-up: the variation in results can be considerably reduced by applying an evenly 'agnostic', but flexible prior.

Keywords: Bayesian model averaging, Growth determinants, Zellner's g prior, Model uncertainty.
JEL Classifications: C11, C15, E01, O47.

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1 Introduction

Ciccone and Jarociński (2010) present an intriguing paper that points to severe weaknesses of Bayesian Model Averaging (BMA). In particular, they criticize the appealing use of non-informative ('agnostic') priors as being plagued by robustness problems. Based on the ubiquitous growth dataset by Sala-i-Martin et al. (2004), the authors analyze the impact of adjusting the dependent variable to three different revisions of the Penn World Tables. Ciccone and Jarociński (2010) show that small perturbations of the dependent variable can lead to striking differences in posterior inclusion probabilities (PIP) - the importance of a covariate in explaining the data. The variable 'investment price', for instance, exhibits a PIP of 98% using PWT 6.1 data, but a mere 2% under PWT 6.2. The conclusions made in Ciccone and Jarociński (2010, p.2) are thus rather pessimistic in that *"margins of error in international income estimates are too large for agnostic growth empirics."*

In a replication exercise we confirm the view of Ciccone and Jarociński (2010) that results of 'agnostic' BMA have to be interpreted with caution. In the following note, however, we point to two caveats to the above findings: First, a considerable share of the PIP variation found by the authors is due to changing sample size and composition over PWT revisions. Secondly, the remaining variation can be attributed to the use of a 'default' prior framework that embodies overly confident prior beliefs – this second caveat constitutes the focus of this note. In response to Ciccone and Jarociński (2010), conditioning on the same country set through all revisions, we show that employing an alternative, flexible prior greatly reduces PIP instability.

2 Robustness under Revisions

Ciccone and Jarociński (2010) employ three different PWT revisions in order to represent income, and cross-check the results with World Bank data. Table 3 (left panel) replicates their results from the three PWT revisions: Indeed there are at least 8 covariates (in **boldface** in the table) that show a worrisome degree of variation in PIPs, consisting to a large part of regional dummies. Their varying impact suggests that country groups might play an important role in explaining the substantial changes between the revisions. Actually, Ciccone and Jarociński (2010) have used different sets of countries for the three data revisions with observations ranging from 88 (PWT 6.0) to 79 (PWT 6.2). Ciccone and Jarociński (2010, p.14) argue in favor of keeping sample sizes to their possible maximum, as it might be uncertain which countries may be included in future revisions. While this has its virtues from the perspective of a forward-looking policymaker, it could blur the conclusions on the robustness of the method (BMA). In order to disentangle this sampling effect from the impact of data revisions, we replicate¹ the estimations in Ciccone and Jarociński (2010) for the three data revisions but condition on the *same* set of countries². This renders the PIPs for the mentioned covariates (Table 3) far more similar over revisions. In particular, the investment price and population density variables as well as the tropical area dummy do not appear to matter for growth under either revision while the African dummy seems robust. This suggests that the additional countries from PWT 6.0 and PWT 6.1 can be interpreted as innovations (outliers) with the potential to change results.

3 A remark on the strength of default priors

Ciccone and Jarociński (2010) use two approaches that stem from the BMA literature: The 'BACE' methodology proposed by Sala-i-Martin et al. (2004) as well as the popular 'benchmark' type employed by Fernández et al. (2001). Since both yield similar results in the empirical application

(Ciccone and Jarociński, 2010) we follow the more Bayesian approach akin to Fernández et al. (2001).

3.1 The problem with 'default' priors

This framework calls for eliciting a key prior parameter: Zellner's g prior on the coefficient vector $\vec{\beta}_s | \sigma^2 \sim N(\vec{0}_s, \sigma^2 g [X'_s X_s]^{-1})$.³ The parameter g reflects the strength of the researcher's prior guess on slope coefficients. Small values correspond to stronger beliefs that the regression slopes are zero (ie the prior is tightened). By construction, the parameter g directly affects the posterior model probability (PMP) – the weight attributed to model M_s – and thus final inference:⁴

$$p(M_s | y, X) \propto (1 + g)^{-\frac{k_s}{2}} \left(1 - \frac{g}{1 + g} R_s^2\right)^{-\frac{N-1}{2}} \quad (1)$$

The choice of g can be crucial for the results: Consider a relatively large g (implying a large shrinkage factor $\frac{g}{1+g}$). As is evident from equation (1), this will not only favor parsimonious models but also amplify any differences in R_s^2 . The resulting distribution of posterior model probabilities will therefore be highly concentrated on the few models with the very highest R_s^2 .

Figure 1 (top panel) illustrates this by plotting the cumulated PMPs based on different settings for g . The chart demonstrates that for PWT data, larger g attributes more weight to the first-best model relative to the remaining ones. If the data is dominated by noise, this *supermodel effect* (Feldkircher and Zeugner, 2009) will skew posterior mass to concentrate on a few 'supermodels'. Consequently it may curve the distribution of PIPs and thus amplify variations that may be due to noise.

3.2 Addressing the supermodel effect

Several 'default' mechanisms have been proposed to elicit g , with the most prominent being the 'benchmark prior' by Fernández et al. (2001), who recommend $g = \max(N, K^2)$. Still, any of these fixed mechanisms risks to set g too small or too large with respect to the noise component in the data. In response, Feldkircher and Zeugner (2009) propose to forgo fixed g -priors outright and to place a prior distribution on the parameter instead – such as the *hyper-g* prior put forward by Liang et al. (2008).⁵

This approach is more flexible and less prior-sensitive as it allows for *model-specific* g_s values (and shrinkage factors) that adjust to data quality:⁶ If the data is characterized by minor noise, then posterior mass will concentrate on the true model(s) - even more than under fixed settings with large g . Conversely, if noise dominates the data, then posterior statistics will decrease g and PMPs under the hyper- g prior will be distributed more evenly. Even in such a case, BMA under a large fixed g will always come up with clear-cut results (a single model and a few covariates that obtain overwhelming support) not taking into account the small degree of data quality. The hyper- g framework, in contrast, will then point to inconclusiveness mirrored in evenly spread PMPs and PIPs.

3.3 The supermodel effect and PWT revisions

Turning to the application, Ciccone and Jarociński (2010) follow the 'benchmark' recommendation by Fernández et al. (2001) and set $g = \max(N, K^2) = 67^2$. Note that this renders the shrinkage

factor very close to unity ($g/(1+g) \approx 0.9998$). We can thus expect PMPs to become highly concentrated and small differences in R_s^2 to be translated into large differences in PMPs and PIPs. This large shrinkage factor treats the data as very informative with respect to the prior. In fact, however, the quality of the PWT data sets turns out to be rather poor. Using flexible g priors such as the hyper- g prior implies far smaller average shrinkage factors⁷ of around 0.95 (Table 1). This suggests that in order to avoid the supermodel effect, a fixed- g framework on PWT data should rather elicit $g \approx 20$. That said, any fixed g will always lack the flexibility of the hyper- g prior in adjusting to data quality.

	PWT 6.0	PWT 6.1	PWT 6.2
fixed $g = K^{2*}$	0.9998	0.9998	0.9998
fixed $g = N^*$	0.9875	0.9875	0.9875
hyper- g^*	0.9361	0.9476	0.9454

Table 1: Average shrinkage factors for three PWT revisions (each with 79 observations), under the benchmark case $g = 67^2$, $g = 79$ and the hyper- g prior (with prior expected shrinkage factor $\frac{g}{1+g} = 67^2/(1+67^2)$). All results are based on 80 million iterations after 20 million burn-ins.

For illustration, compare the results from the hyper- g setting (Table 3, right panel): In this case, the variation in PIPs over PWT revisions is far less than under the 'benchmark' framework. Note that PIPs are much larger on average – this results from the data inducing lower posterior shrinkage factors and therefore emphasizing larger models than under the 'benchmark' priors.⁸ As a consequence comparing *absolute* PIPs across revisions is prone to misleading conclusions since the levels of PIPs are by construction related to the respective posterior model size – which in turn strongly depends on the value of g . (For instance with $g \rightarrow \infty$ all PIPs will tend to zero, just like their absolute differences.)

Figure 1 (bottom panel) corroborates our findings by concentrating on relative terms: For each covariate and g -setting, it displays the ratio of maximum vs. minimum PIP over the three revisions compared to the fixed $g = K^{2*}$ setting. Values above (below) the zero line indicate more (less) variation of the posterior inclusion probabilities. The fixed $g = K^2$ setting based on changing observations reported in Ciccone and Jarociński (2010) displays by far the greatest PIP variation as compared to the estimation based on the same countries ($g = K^{2*}$). Demonstrating the supermodel effect present, a decrease in g (such as $g = N^*$) lowers PIP variation substantially. The most remarkable reduction, however, is achieved by the hyper- g prior, with minimum PIP variation for nearly all covariates. Table 2 summarizes this finding and shows that average PIP variation is considerably smaller when opting for the hyper- g framework.

	fixed $g = K^2$	fixed $g = K^{2*}$	hyper- g^*
Overall Max/Min Ratio	4.8580	2.4217	1.4013
PWT 6.0 vs. PWT 6.1	2.1179	1.9675	1.3260
PWT 6.0 vs. PWT 6.2	3.3578	1.9931	1.3003
PWT 6.1 vs. PWT 6.2	3.9466	1.5880	1.1451

Table 2: **Average PIP Max/Min ratios:** for each revision pair, the figures above display the mean of the ratio maximum vs. minimum PIP per variable.

There is one important caveat, though: the quite low shrinkage factor induced by hyper- g not only decreases PIP variation over data revisions, but also over covariates for a given revision. Consequently, this implies that there are less covariates that could be identified as 'important'. As

has been noted above, this is a direct result from posterior mass being spread out more evenly over models due to an important noise component in the data. Yet this trait may be desirable, as noisy data should not lead to the striking conclusions featured in the 'agnostic' approach criticized by Ciccone and Jarociński (2010).

4 Conclusion

This note addresses an important issue raised by Ciccone and Jarociński (2010): inference of (agnostic) BMA applied to growth empirics is not robust under small perturbations of the dependent variable. Our response demonstrates that such instability is partly due to the overconfident 'default' g -prior framework employed by the authors. Instead, we propose to rely on the hyper- g prior. While 'agnostic' in the sense of Ciccone and Jarociński (2010), it adjusts to data quality and induces smaller shrinkage factors according to the data's considerable noise component. This in turn renders BMA results considerably more stable over different revisions of PWT growth data. However, reflecting poor data quality, results under hyper- g discriminate far less among covariates. The empirical findings under a flexible prior may thus be characterized as 'robust ambiguity', limiting statements on the importance of growth determinants to a quite small subset of covariates.

Notes

¹All computations were done with the R package BMS, available at <http://cran.r-project.org/web/packages/BMS/index.html> and <http://bms.zeugner.eu>.

²Moreover the countries that change between revisions could be seen as outliers: Precisely, PWT 6.1 includes the countries of PWT 6.2 plus Botswana, Central African Republic, Mauritania, DR Congo (Zaire) and Papua New Guinea. PWT 6.0 includes the PWT 6.1 countries plus Liberia, Tunisia, West Germany and Haiti. Note that in terms of growth, these were either very successful or unsuccessful countries with respect to their regional peers. Furthermore it is a stylized fact in the empirical growth literature (e.g. Masanjala and Papageorgiou 2008, Crespo Cuaresma 2010) that growth determinants in Africa systematically differ in various instances. Thus it is difficult to consider this particular set of countries as a random draw from the data (or the samples are not representative).

³In what follows we denote by σ^2 the variance N the total number of observations and K the total number of explanatory variables at hand. Furthermore X_s denotes the design matrix, k_s the number of covariates and R_s^2 the OLS R-squared of model s .

⁴Note that there is a second key prior in this setting, namely prior model probability. We have omitted the model prior from the discussion since Ciccone and Jarociński (2010) assumed a uniform prior on the model space. Moreover, the impact of the model prior seems to be rather limited as compared to the importance of the g -prior (Ley and Steel, 2009).

⁵To be precise, this amounts to placing a beta distribution on the shrinkage factor $g/(1+g)$. Note that there are also other flexible ways such as the Empirical Bayes (EB) approach. For the sake of brevity, we have omitted the EB results in this note, since they are very similar to those under the hyper- g prior (Feldkircher and Zeugner, 2009, Appendix).

⁶In this note we refer to data quality by the degree of variation of the dependent variable explained by the data at hand.

⁷Note that this result even obtains if the prior expected shrinkage factor was set to 0.9998.

⁸The smaller model size penalty results into much larger posterior model size (≈ 25 vs. $7-9$ under the Benchmark case). Since the average PIP is posterior model size divided by K , the PIPs under hyper- g are substantially larger. Furthermore note that while the flexible prior greatly reduces PIP variation as compared to the other prior settings, there are still some variables left where results change considerably with PWT revisions.

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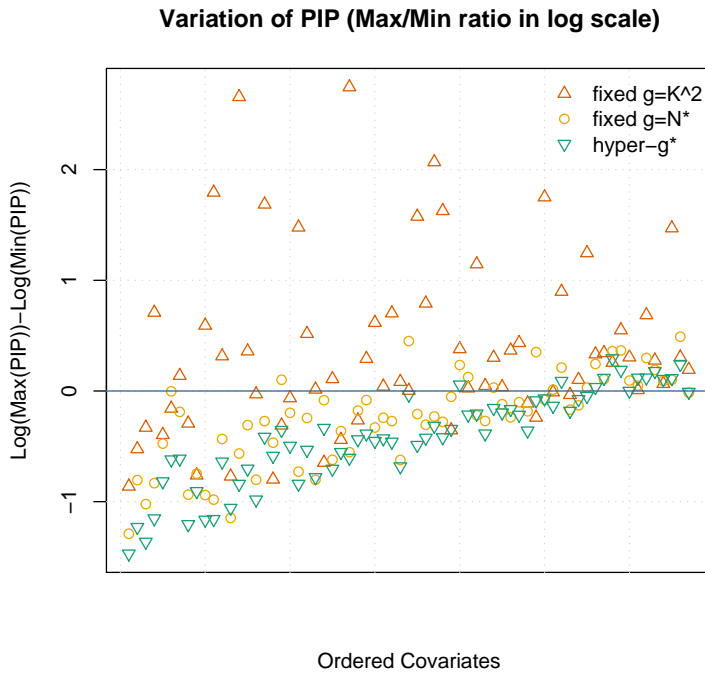
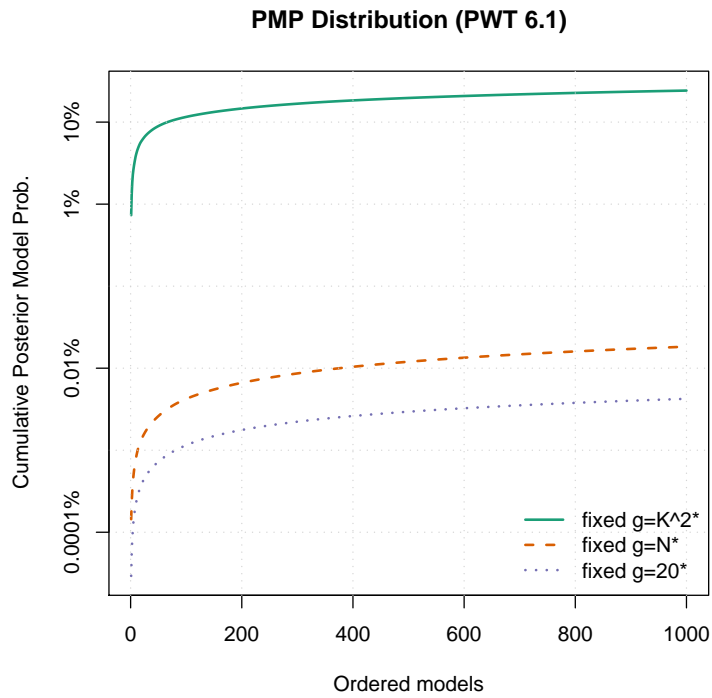


Figure 1: Top panel: Cumulative posterior model probability under different settings for g . Bottom panel: Log of the Max(PIP)/Min(PIP) ratio for each covariate over three PWT revisions. Values above (below) the zero line indicate more (less) variation than under the fixed $g = K^{2*}$ setting. The asterisk denotes the use of the common country set.

<i>PWT revisions</i>	6.0	6.1	6.2	6.0	6.1	6.2	6.0	6.1	6.2
GDP in 1960 (log)	0.73	1.00	1.00	0.81	1.00	1.00	0.87	1.00	1.00
Absolute Latitude	0.03	0.03	0.03	0.06	0.02	0.03	0.38	0.26	0.29
Air Distance to Big Cities	0.05	0.43	0.05	0.07	0.09	0.05	0.34	0.29	0.30
Ethnolinguistic Fractionalization	0.12	0.03	0.04	0.02	0.05	0.04	0.24	0.34	0.28
British Colony Dummy	0.03	0.03	0.02	0.02	0.02	0.02	0.25	0.26	0.23
Fraction Buddhist	0.13	0.13	0.30	0.12	0.17	0.30	0.39	0.59	0.48
Fraction Catholic	0.04	0.02	0.06	0.12	0.06	0.07	0.58	0.39	0.45
Civil Liberties	0.03	0.02	0.02	0.07	0.04	0.02	0.40	0.30	0.24
Colony Dummy	0.04	0.09	0.02	0.12	0.05	0.02	0.36	0.25	0.24
Fraction Confucius	0.24	0.18	0.84	0.55	0.61	0.84	0.77	0.93	0.96
Population Density 1960	0.11	0.70	0.02	0.02	0.04	0.02	0.29	0.25	0.24
Population Density Coastal in 1960s	0.44	0.76	0.11	0.42	0.37	0.11	0.34	0.31	0.38
Interior Density	0.02	0.02	0.03	0.03	0.06	0.03	0.28	0.37	0.26
Population Growth Rate 1960-90	0.02	0.03	0.03	0.03	0.03	0.03	0.30	0.23	0.28
East Asian Dummy	0.80	0.74	0.33	0.54	0.47	0.33	0.55	0.37	0.32
Capitalism	0.02	0.02	0.02	0.02	0.03	0.02	0.24	0.29	0.28
English Speaking Population	0.02	0.02	0.02	0.02	0.02	0.02	0.26	0.28	0.25
European Dummy	0.03	0.04	0.07	0.07	0.08	0.07	0.46	0.50	0.36
Fertility in 1960s	0.04	0.16	0.90	0.23	0.65	0.90	0.65	0.73	0.80
Defense Spending Share	0.02	0.02	0.04	0.03	0.02	0.04	0.31	0.30	0.30
Public Education Spending Share in GDP in 1960s	0.02	0.02	0.02	0.02	0.03	0.02	0.25	0.26	0.25
Public Investment Share	0.07	0.06	0.02	0.03	0.02	0.02	0.33	0.24	0.28
Nominal Government GDP Share 1960s	0.05	0.02	0.29	0.28	0.11	0.29	0.84	0.46	0.74
Government Share of GDP in 1960s	0.08	0.04	0.05	0.09	0.13	0.05	0.31	0.53	0.34
Gov. Consumption Share 1960s	0.12	0.06	0.03	0.05	0.06	0.03	0.29	0.37	0.29
Higher Education 1960	0.07	0.02	0.03	0.14	0.03	0.03	0.60	0.25	0.27
Religion Measure	0.02	0.03	0.02	0.02	0.02	0.02	0.30	0.27	0.24
Fraction Hindus	0.05	0.02	0.03	0.03	0.03	0.03	0.37	0.40	0.33
Investment Price	0.80	0.98	0.02	0.03	0.07	0.02	0.26	0.28	0.22
Latin American Dummy	0.17	0.08	0.34	0.34	0.28	0.34	0.39	0.33	0.34
Land Area	0.02	0.02	0.02	0.04	0.05	0.02	0.49	0.32	0.29
Landlocked Country Dummy	0.02	0.09	0.03	0.02	0.05	0.03	0.31	0.32	0.24
Hydrocarbon Deposits in 1993	0.03	0.13	0.11	0.03	0.22	0.11	0.35	0.73	0.65
Life Expectancy in 1960	0.23	0.26	0.03	0.03	0.03	0.03	0.25	0.23	0.28
Fraction of Land Area Near Navigable Water	0.02	0.05	0.02	0.03	0.04	0.02	0.28	0.26	0.24
Malaria Prevalence in 1960s	0.23	0.03	0.03	0.05	0.03	0.03	0.30	0.26	0.30
Fraction GDP in Mining	0.16	0.29	0.02	0.04	0.02	0.02	0.31	0.22	0.23
Fraction Muslim	0.13	0.23	0.42	0.06	0.49	0.43	0.50	0.88	0.84
Timing of Independence	0.02	0.09	0.14	0.03	0.09	0.13	0.30	0.70	0.85
Oil Producing Country Dummy	0.02	0.02	0.02	0.02	0.02	0.02	0.23	0.22	0.23
Openness measure 1965-74	0.08	0.07	0.16	0.13	0.31	0.16	0.66	0.68	0.62
Fraction Orthodox	0.02	0.02	0.03	0.02	0.03	0.03	0.28	0.35	0.37
Fraction Speaking Foreign Language	0.10	0.04	0.07	0.04	0.03	0.07	0.28	0.26	0.34
Primary Schooling in 1960	0.81	0.99	1.00	0.98	1.00	1.00	0.99	1.00	1.00
Average Inflation 1960-90	0.02	0.02	0.06	0.02	0.03	0.06	0.24	0.25	0.24
Square of Inflation 1960-90	0.02	0.02	0.04	0.02	0.02	0.04	0.24	0.23	0.23
Political Rights	0.07	0.24	0.02	0.05	0.04	0.02	0.43	0.44	0.42
Fraction Population Less than 15	0.04	0.03	0.04	0.03	0.04	0.04	0.42	0.33	0.32
Population in 1960	0.03	0.02	0.02	0.02	0.02	0.02	0.34	0.22	0.23
Fraction Population Over 65	0.03	0.06	0.05	0.05	0.07	0.05	0.48	0.41	0.39
Primary Exports 1970	0.06	0.23	0.28	0.14	0.49	0.28	0.44	0.84	0.76
Fraction Protestants	0.05	0.02	0.07	0.14	0.06	0.07	0.53	0.37	0.44
Real Exchange Rate Distortions	0.10	0.05	0.02	0.11	0.03	0.02	0.60	0.23	0.21
Revolutions and Coups	0.04	0.03	0.03	0.03	0.02	0.03	0.27	0.32	0.34
African Dummy	0.18	0.22	0.85	0.86	0.83	0.85	0.83	0.72	0.78
Outward Orientation	0.04	0.04	0.02	0.02	0.02	0.02	0.26	0.22	0.25
Size of Economy	0.02	0.03	0.04	0.02	0.07	0.04	0.31	0.28	0.28
Socialist Dummy	0.02	0.03	0.03	0.03	0.06	0.03	0.24	0.28	0.22
Spanish Colony	0.12	0.02	0.07	0.28	0.04	0.07	0.41	0.23	0.31
Terms of Trade Growth in 1960s	0.03	0.02	0.02	0.02	0.02	0.02	0.23	0.30	0.28
Terms of Trade Ranking	0.02	0.02	0.02	0.02	0.02	0.02	0.28	0.24	0.22
Fraction of Tropical Area	0.56	0.66	0.05	0.33	0.23	0.05	0.49	0.30	0.25
Fraction Population In Tropics	0.06	0.16	0.04	0.02	0.02	0.04	0.26	0.23	0.28
Fraction Spent in War 1960-90	0.02	0.02	0.02	0.02	0.02	0.02	0.25	0.22	0.26
War Participation 1960-90	0.02	0.02	0.03	0.02	0.02	0.03	0.25	0.22	0.26
Years Open 1950-94	0.12	0.06	0.09	0.12	0.08	0.09	0.31	0.24	0.25
Tropical Climate Zone	0.02	0.03	0.04	0.02	0.04	0.04	0.23	0.36	0.44
# Obs.	88	84	79	79	79	79	79	79	79

Table 3: Posterior Inclusion Probabilities. Left panel corresponds to data set with varying number of countries, center panel to data set with common countries over the three revisions. Right panel displays results of hyper-g BMA over common countries. Results are based on 80 million posterior draws after a burnin phase of 20 million draws.