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Abstract

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1 Introduction

The central objective of the empirical growth literature is to understand what variables are *robustly* related to economic growth. Extensive attention has been dedicated to ensure that the conclusions are robust to parameter heterogeneity, outliers and model uncertainty (see for example, Durlauf, Johnson and Temple (2008) for a critical survey). Recently, a number of papers have emphasized considerable data uncertainty about the measurement income per capita and economic growth. This paper proposes a novel Measurement Error Model Averaging (MEMA) model that estimates growth determinants, taking into account model uncertainty, as well as data uncertainty, outliers and parameter heterogeneity.

The Penn World Tables (PWT), which is the basis for the analysis, publish Purchasing Power Parity (PPP) adjusted income levels for many countries (Kravis, Heston and Summers, 1978). There is a vast literature on the PWT measurement and the underlying International Comparison Program (ICP)[1]. However, the PWT is subject to substantial revisions where each revision is released as a separate *vintage*. Revisions to the PWT are caused by changes in the underlying income and price data, as well as changes in methodology (see for example, Deaton and Heston (2010) and Feenstra et al. (2009)). Recently, Johnson et al. (2013) and Ciccone and Jarociński (2010) have questioned the robustness of important results in the empirical growth literature when conditioning on particular vintages of the PWT and neglecting measurement error.

This paper proposes a novel *Measurement Error Model Averaging* (MEMA) approach that estimates GDP per capita across countries and over time and simultaneously investigates the robustness of determinants of long-run growth. Income is treated as a latent variable, which is observed with classical measurement error.

[1] See Johnson et al. (2013) for a background discussion and the ICP portal website: `http://icp.worldbank.org/icp/GlobalResult.aspx`

Using a Bayesian measurement error model, we use eight recent vintages of the PWT to identify the posterior distributions of income in 1960 and 1996. Vintage-specific fixed effects capture differences in baseline prices or other methodological differences of measuring income in the PWT. Combining the latent distributions of income per capita with a Bayesian model averaging approach allow us to assess the robustness of determinants of economic growth to measurement error and model uncertainty.

The main findings of the paper are as follows: First, we find evidence for systematic differences of measures of GDP per capita across different vintages of the PWT. Although there are exceptions, we generally find that newer vintages of the PWT are more precisely measured than older vintages. Second, countries differ in the quality of measured levels and growth of income per capita. Richer countries tend to be measured more accurately then poorer countries. However, we find the largest variability in income measurement for middle-to-low income countries, compared to the very poorest countries in the PWT sample. Third, we find that eighteen growth determinants appear robust to measurement error *and* model uncertainty in the PWT. These include variables measuring initial conditions, such as initial GDP per capita, regional factors controlling for regional differences in economic growth rates, variables measuring geographic and climatic conditions, and finally population characteristics and cultural variables. Finally, our results are robust to allowing for outliers and parameter heterogeneity by allowing for heteroscedastic model errors.

This paper is related to several strands in the literature.

First, there is an abundance of papers analysing growth determinants.[2] As shown in Kormendi and Meguire (1985), Grier and Tullock (1989), and Barro

[2]For a review of *theories* of economic growth, see for example the textbooks by Barro and Sala-i Martin (2004) or Acemoglu (2009).

(1991) the empirical growth literature have tested alternative models and particular combinations of variables explaining economic growth. The wide variation in results casts doubt on the robustness of growth determinants. Levine and Renelt (1992) use a version of an extreme bounds analysis for growth determinants in a cross-section of countries and found that few (if any) were robust. Sala-i Martin (1997) argues that the test was too extreme and one should rather look at the distribution of model estimates across models. Recent papers therefore address model uncertainty and investigate the robustness of growth determinants using model averaging. Fernandez, Ley and Steel (2001*b*) and Sala-i Martin, Doppelhofer and Miller (2004) came to more optimistic conclusions regarding the robustness of growth determinants and found a number of explanatory variables to be robust to model uncertainty. Durlauf, Johnson and Temple (2008) give a more recent survey the empirical growth literature.

Temple (2000) argue that growth regressions are hampered by outliers and potential parameter heterogeneity. A natural extension of linear growth regressions is therefore to accommodate that some observations might differ markedly from most of our data. To accomplish this we use a novel approach based on the Dirichlet distribution (Chigira and Shiba, 2015), as well as more established methods for outlier detection with either a binary outlier classification (Hoeting, Raftery and Madigan, 1996) or based on mixed-normal distributions (Geweke, 1993). Accounting for outliers is important for the robustness of some variables. For example, the importance of *Mining* as growth determinant is essentially driven by one country – Botswana. Furthermore, we find that a normal distribution is ill-suited to capture uncertainty of the growth process. The variance of the growth process is seven times higher in the most compared to the least noisy country. Following Geweke (1993), we find evidence for fat tailed errors of the growth process.

Deaton and Heston (2010) discuss revisions in the PWT, and explain how they are related to changes in factors such price benchmarks, methodology, extrapolation strategies and updates in the underlying data. Johnson et al. (2013) discuss the PWT-revision in general, and find no reason to believe that newer vintages of the PWT are better in terms of measuring growth. An important contribution to the empirical growth literature is Ciccone and Jarociński (2010) showing the sensitivity of results in Sala-i Martin, Doppelhofer and Miller (2004) to different PWT-vintage to measures economic growth. Jarociński (2010) uses Bayesian ridge regressions to estimate growth determinants for different PWT-vintages. This sensitivity of results highlights the need for directing attention to measurement error in growth regressions.

Hausman (2001) and Hyslop and Imbens (2001) discuss the consequences of measurement error in econometric analyses. Carroll et al. (2006, p 1) calls the consequences of measurement error a "triple whammy": Bias in parameter estimates, loss of power and masking of features of the data. Although there is a wide literature on how to model measurement error in a frequentist perspective[3] our approach is more similar to the classical measurement error discussed in Richardson and Gilks (1993).

There are some examples of analyses that combine the PWT-data with measurement error models. Rao, Rambaldi and Doran (2008) proposes a method to construct panels of incomes and prices using also data from national sources. Pinkovsky and Sala-i Martin (2016) highlight measurement error in GDP per capita based on either national accounts data and surveys, and argue that this has important consequences for comparing income levels and economic growth across countries. Finally, Cuaresma et al. (2015) use several PWT-vintages together with a latent variable model to construct consensus measures of income

[3]See e.g. Goldberger (1972), Leamer (1983), Aigner et al. (1984), Black and Smith (2006), Lubotsky and Wittenberg (2006) and Browning and Crossley (2009)

per country. Our paper differs from these papers by simultaneously modelling measurement error of income across countries and over time and simultaneously assessing the robustness of growth determinants.

The structure of the paper is as follows. Section 2 discuss the measurement error model, model averaging and discuss how we connect these two modules. We estimate the model, and present results in section 3. Section 4 concludes.

2 The model for measurement error and model uncertainty

This section describes the details of the MEMA-model. Section 2.1 starts with the measurement error model. Thereafter, section 2.2 discusses model averaging, as well as robust model averaging that allows for heteroscedastic model errors. Finally section 2.3 connects the measurement error and model averaging models.

2.1 Measurement Error

We propose the following model between observed measurements in the PWT and the true levels of income:

$$y^I_{v,i} = a_v + y^I_i + \sigma^I_{v,i}\varepsilon^I_{v,i} \quad (1)$$

$$y^E_{v,i} = a_v + y^E_i + \sigma^E_{v,i}\varepsilon^E_{v,i} \quad (2)$$

$y^I_{v,i}, y^E_{v,i}$ denote, respectively, the *observed* levels of income from the PWT for country i in vintages (v) for initial (I) and end (E) of period GDP; ${y_i}^I$ and ${y_i}^E$ denote the *true* (latent) values of income, and $\varepsilon^I_{v,i}, \varepsilon^E_{v,i}$ are measurement errors unique to each country-vintage. a_v is a vintage-specific level fixed effect, that allows for different PWT-vintages reported in different international US Dollars, but also other effects from the PPP methodology that shifts all measurements in a vintage.[4] To ensure identification, we fix one of the vintage specific fixed effects to zero, such that the level shifters are all defined relative to this fixed vintage. $\sigma^I_{v,i}$ and $\sigma^E_{v,i}$ are parameters that scale the variance of the measurement error for each country-vintage.

We give both the level shifters a_v and the true levels of income y^I_i, y^E_i a uniform prior over a large range. Furthermore, we assume that the measurement errors are independent, standard normal:[5]

$$\begin{aligned} \varepsilon^I_{v,i} &\sim N(0,1) \\ \varepsilon^E_{v,i} &\sim N(0,1) \end{aligned} \tag{3}$$

To close the measurement error model, we need to specify a prior structure for the scale terms $\sigma^I_{v,i}$ and $\sigma^E_{v,i}$ for the measurement errors across vintages and countries. A special feature of the data is that we have repeated measurements of both *countries* (i) and *vintages* (v). It could be the case that measurements in some vintages and some countries are inherently more noisy than others. To open for these possibilities, we separate the scale terms according to the following product:

$$\begin{aligned} {\sigma^I_{i,v}}^2 &= \omega^N_i \omega^V_v \ {\sigma^I}^2 \\ {\sigma^E_{i,v}}^2 &= \omega^N_i \omega^V_v \ {\sigma^E}^2 \end{aligned} \tag{4}$$

${\sigma^I_{i,v}}^2$ and ${\sigma^E_{i,v}}^2$ are now the variance of measurement error for country i in vintage v for initial and end period income, respectively. ${\sigma^I}^2$ and $Similarly, {\sigma^E}^2$ are *average*

[4]We would like to emphasize that even though this parameter is a "fixed effect" with the same value for all income measurements in a given vintage, we still treat the fixed effect as a parameter in a Bayesian sense - i.e. it has both a prior and posterior *distribution.*

[5]By independent, we mean that each error term is independent of all other error terms, i.e.

$$\begin{aligned} Cov(\varepsilon^I_{j,l}, \varepsilon^I_{h,m}) &= 0, \ \forall \ j,l \neq h,m \\ Cov(\varepsilon^E_{j,l}, \varepsilon^E_{h,m}) &= 0, \ \forall \ j,l \neq h,m \\ Cov(\varepsilon^I_{j,l}, \varepsilon^E_{h,m}) &= 0, \ \forall \ j,l \neq h,m \end{aligned}$$

variances of measurement errors for initial and end income across all countries and vintages, and ω_i^N and ω_v^V are the *relative* variance of measurement errors for countries and vintages. This setup implies that the average value of ω_v^V and ω_i^N must both be unity. A prior that satisfies this condition are scaled Dirichlet distributions:

$$\begin{aligned} \left(\omega_1^V, ...\omega_V^V\right)/V &\sim Dir\left(\Omega_1^V, ...\Omega_V^V\right) \\ \left(\omega_1^N, ...\omega_N^N\right)/N &\sim Dir\left(\Omega_1^N, ...\Omega_N^N\right) \end{aligned} \tag{5}$$

Where the parameters $\Omega_1^V, ...\Omega_V^V, \Omega_1^N, ..., \Omega_N^N$ are constants. First, we can note that by setting all constants $\Omega_1^V = ... = \Omega_V^V = \Omega_1^N ... = \Omega_N^N$ we are taking an *a priori* agnostic approach as to which countries and vintages are measured with error. Second, a higher value of these constants imply strengthening the prior. As an example, if we set all $\Omega_1^V, ...\Omega_V^V, \Omega_1^N, ..., \Omega_N^N$ to the same, high value, we impose a strong belief in that the variance of measurement error is the same in all countries and vintages. Hence, we will force the posterior to be close to the prior. Alternatively, by setting the constants $\Omega_1^V, ...\Omega_V^V, \Omega_1^N, ..., \Omega_N^N$ to the same low value, we let the data decide where variance of measurement error is higher. Third, we can essentially shut on or off one or both of the Dirichlet error components. For example, by setting $\Omega_1^V, ...\Omega_V^V$ to the same low value, and $\Omega_1^N, ..., \Omega_N^N$ to a high value, we let the data decide which *vintage* has higher variance of measurement error, but impose that all countries have the same variance of measurement error. Fourth, we do not have to place an equal value of $\Omega_1^V, ...\Omega_V^V$ or $\Omega_1^N, ..., \Omega_N^N$. If we have an *a priori* strong belief in that some vintages or countries have a better data quality than others we can impose this belief through the constants. Thus, we can note that the ME-model, in the limit where Ω_v approaches zero and the remaining Ω-parameters remain constant, nest approaches that condition on PWT-vintage v as the "truth".

Finally, we give an uniform prior for σ^I and σ^E over a large range.[6]

$$\sigma^I \sim U(0, 1000) \tag{6}$$

$$\sigma^E \sim U(0, 1000) \tag{7}$$

This completes the specification of the measurement error model.

2.2 Model Averaging

Consider the typical cross-country growth regression of the form:

$$\frac{y_i^E - y_i^I}{T_1 - T_0} = \alpha + \sum_{k=1}^{K} x_{k,i}\beta_k\gamma_k + \sigma_i\varepsilon_i \tag{8}$$

where the left hand side is average growth for country i, where latent initial y_i^I and end period y_i^E income are estimated using the measurement error model outlined in the previous section 2.1. β_k is the coefficient of variable k, σ_i is a scaling parameter and ε_i is an independent, standard normal error term. A particular model is described by the binary parameter parameter γ_k, indicating whether variable k is included in the regression or not. Note that an intercept is always included in the growth regression. The benchmark case usually assumes that the scaling parameters σ_i are identical, i.e. that the errors are *conditionally* homoscedastic. Equation (8) nests all possible linear combinations of growth determinants K. In our setting, this is a fairly large model space. To see this, note that we can use the binary conversion formula

$$M = \sum_{k=1}^{67} \gamma_k 2^{k-1} \tag{9}$$

Where now M is an integer, denoting one of 2^{67} unique models.

[6]See Gelman (2006) for a discussion of prior of variance parameters, as well as a brief discussion of the uniform prior on standard deviations.

Following the (Bayesian) model averaging literature, the following prior structure is assumed for parameters in each model (see for example Fernandez, Ley and Steel (2001*a*)). The prior slope coefficients β that are included in a given model are normally distributed with mean zero and variance $\sigma^2 \mathbf{V}_{0j}$:

$$\beta|\sigma^2, M \sim N(0, \sigma^2 \mathbf{V}_{0j}) \tag{10}$$

The prior variance matrix is assumed to be proportional to the sample covariance

$$\mathbf{V}_{0M} = (g_0 \mathbf{X}'_M \mathbf{X}_M)^{-1} \tag{11}$$

with factor of proportionality g_0, and $\mathbf{X}_M$ is the matrix of covariates that are included in model M. This *g-prior* was first suggested by Zellner (1986), and is a convenient way to specify the prior variance matrix, in particular in the presence of considerable model uncertainty. Different values of the g-prior parameter g_0 have been proposed in the literature (see Fernandez, Ley and Steel (2001*a*)).[7] To contrast the results in Sala-i Martin, Doppelhofer and Miller (2004), this paper follows their assumption that the prior distribution of the slope coefficient β is dominated by the sample information, implying a diffuse prior variance. We therefore set $g_0 = N^{-1}$ as a benchmark.[8]

In the benchmark case, we place a uniform prior on σ over a large, positive range:

$$\sigma \sim U(0, 1000) \tag{12}$$

[7] Zeugner and Feldkircher (2009) warn that an overly diffuse prior concentrates estimation on a few models, what they call the ‘supermodel effect’. This effect is contributing to the sensitivity of estimates across different samples of the Penn World Tables found by Ciccone and Jarociński (2010).

[8] Appendix C.1.1 allows for a hierarchical prior on the hyperparameter g_0.

2.2.1 Model Space Prior

Letting π_k be the independent prior inclusion probability of variable x_k in model M, the prior probability for model M is given by:

$$p(M) = \prod_{k=1}^{K} \pi_k^{\gamma_k}(1-\pi_k)^{1-\gamma_k} \tag{13}$$

Recall the binary indicator variable γ_k measures inclusion (exclusion) of variable x_k.[9] One approach is to assume a completely diffuse or uniform prior across all models, which corresponds to a prior inclusion probability equal to $\pi_k = 1/2$ for all variables. However, with a relatively large number of regressors, a uniform prior implies that the great majority of prior probability is allocated to models with a large number of variables. As an alternative, Sala-i Martin, Doppelhofer and Miller (2004) advocate in their Bayesian Averaging of Classical Estimates (BACE) approach a preference for more parsimonious models with a smaller prior expected model size $\bar{k} = 7$, which seems reasonable given the relatively large number of growth determinants ($K = 67$).[10] We follow the BACE-prior, and place independent Bernoulli priors on the γ_k, with prior inclusion probability 7/67:[11]

$$\gamma_k \sim Bern\left(\frac{7}{67}\right) \tag{14}$$

2.2.2 Modelling Outliers

The empirical growth model can fit poorly for some observations compared to other. This could be caused by a growth process being more variable in some

[9]Mitchell and Beauchamp (1988) first suggested this prior with discrete probability mass or "spike" at zero, representing the prior uncertainty that a regressor should be included. George and McCulloch (1993) propose a Bayesian alternative of using a proper prior distributions with large variance.

[10]O'Hara and Sillanpää (2009) note in their very practical review that "*sparsity has to be forced onto a model; the data themselves may not demand it*" (p 112).

[11]Appendix C.1.1 allows for a hierarchical prior on the prior model size.

countries than others, or possibly a misspecification of the model where relevant higher order terms are omitted. If this is the case, we would want to avoid these outliers have an unduly influence on results. We use two general modelling strategies that both accounts for this idea. The first case classifies each observation as an outlier or not, and then use a common, variance term to evaluate the likelihood of all observations that are classified as outliers. The second case utilises the same approach we used to capture heteroscedastic variance of measurement errors. Specifically, we estimate average model variance as one single parameter, and use a Dirichlet-weighting to estimate how variable the error is for each observation relative to the average.

Case 1: Binary classification of outliers A maintained assumption in the benchmark case is that regression errors are homoscedastic. A useful point of departure is to assume that the errors in the growth process can be described by a combination of two normal distributions.

$$p\left(\sigma_i \epsilon_i | \varpi_i, \rho, \sigma\right) = (1 - \varpi_i) N\left(0, \sigma^2\right) + \varpi_i N\left(0, \rho\sigma^2\right) \tag{15}$$

where the mixture is governed by two parameters. The binary parameter ϖ_i identifies whether an observation is an outlier, and the parameter ρ controls the degree of variance-inflation for the outlying observations. (Hoeting, Raftery and Madigan, 1996) adopt this approach in a study which simultaneously selects regressors and identifies outliers. In the particular application of their paper, the prior probability of an observation being classified as an outlier and ρ are treated as fixed, with the proportion of outliers chosen based upon the size of the dataset. We use the following distributional assumptions:

$$\begin{aligned} \varpi_i &\sim Bernoulli(.1) \\ \rho - 1 &\sim Exp(.1) \end{aligned} \tag{16}$$

This places a 10% prior probability on a given observation being classified as an outlier. The fairly non-informative exponential prior on variance-inflation parameter implies outliers have a far greater variance than non-outliers, with a prior expected value of $E[\rho - 1] = 10$. The variance of an observation in the growth model is therefore

$$\sigma_i^2|\varpi_i, \sigma, \rho = (1 - \varpi_i)\sigma^2 + \varpi_i \rho \sigma^2 \tag{17}$$

Case 2: Dirichlet weighting of outliers First, define relative variance of measurement errors as a Dirichlet of size N:

$$(\omega_1, ..., \omega_N)/N \sim Dir(\Omega, ..., \Omega) \tag{18}$$

We interact this with the average variance σ^2, such that the variance for a given observation is

$$\sigma_i^2|\omega_i, \sigma = \omega_i \sigma^2 \tag{19}$$

This setup is very similar to Chigira and Shiba (2015). An alternative would be to specify the model using the more common Geweke (1993) robust error structure.[12]

2.3 Measurement Error Model Averaging

We can now combine the measurement error model from section 2.1 with the model averaging 2.2. First, note that the growth equation can be written as

$$y_i^E = \mu_i + \varepsilon_i(T_1 - T_0) \tag{20}$$

[12]See Sims (2010, p20-23) for a discussion of heteroskedasticity robust estimation in a Bayesian setting. Chigira and Shiba (2015) further argue that the Dirichlet-model of heteroskedasticity is superior to the established Geweke (1993) Student-t model of outliers with gamma priors, as it is less informative on the model of heteroskedasticity.

where $\mu_i \equiv \left(\alpha + \sum_{k=1}^{K} x_{k,i}\beta_k\gamma_k\right)(T_1 - T_0) + y_i^I$ is the sum of initial income and economic growth predicted by the regression model. We use equation (20) to substitute for final income in the measurement equation. Considering all V measurements of end-of-period for country i, we can stack these in the following vector:

$$\begin{bmatrix} y_{1,i}^E \\ \vdots \\ y_{V,i}^E \end{bmatrix} = \begin{bmatrix} a_1 + \mu_i + \sigma_i\varepsilon_i(T_1 - T_0) + \sigma_{1,i}^E\varepsilon_{1,i}^E \\ \vdots \\ a_v + \mu_i + \sigma_i\varepsilon_i(T_1 - T_0) + \sigma_{V,i}^E\varepsilon_{V,i}^E \end{bmatrix} \tag{21}$$

This implies that end-of-period measures of GDP per capita of one country have a multivariate normal distribution with a given structure of the covariance matrix:[13]

$$\begin{bmatrix} y_{1,i}^E \\ \vdots \\ y_{V,i}^E \end{bmatrix} \sim N\left(\begin{bmatrix} a_1 + \mu_i \\ \vdots \\ a_V + \mu_i \end{bmatrix}, \begin{bmatrix} \tilde{\sigma}_i^2 + \sigma_{1,i}^2 & \cdots & \tilde{\sigma}_i^2 \\ \vdots & \ddots & \vdots \\ \tilde{\sigma}_i^2 & \cdots & \tilde{\sigma}_i^2 + \sigma_{V,i}^2 \end{bmatrix}\right) \tag{22}$$

Together with the priors for the ME and MA models, as well as the distributional assumptions on initial income, we have now completed the specification of the MEMA-model. The following section report the results we obtain with it.

3 Estimating the MEMA-model

This section presents the results from estimating the MEMA model under three different assumptions. First, we condition on a particular vintage and estimate results by benchmark model averaging, which is a special case of the MEMA model. Second, we allow for measurement errors across countries and PWT vintages using the MEMA model. Third, we allow for outliers using robust model averaging and the MEMA model combined. The data used is briefly described in appendix A. A compact description of the MEMA-model can be found in appendix B.

[13]Define $\tilde{\sigma_i}^2 \equiv \sigma_i^2(T_1 - T_0)^2$

3.1 Benchmark model averaging and vintage-specific results

First, we show the benchmark model averaging case that conditions on one specific vintage of the PWT. We assume that each vintage represents the " true" measure of income and economic growth. Note that this is a special case of the MEMA-model, as we through the Ω^V-constants can impose the assumption that one vintage accurately represents true income.[14]

Table 1 shows the posterior inclusion probabilities (PIP) associated with the 67 variables collected by Sala-i Martin, Doppelhofer and Miller (2004), in alphabetical order. The PIPs represent a summary measure of importance of a variable. Compared to the prior inclusion probability of 7/67, a higher (lower) posterior inclusion probability implies that our confidence in the importance of a variables is increased (reduced). PIPs exceeding the prior are highlighted in green in Table 2.

The conclusions one can draw from table 1 are similar to those in Ciccone and Jarociński (2010), except that they are extended also to newer PWT vintages. Among the 18 variables labelled "robustly" related to economic growth by Sala-i Martin, Doppelhofer and Miller (2004), only four – the *East Asian dummy*, *log GDP per capita in 1960*, *Life expectancy in 1960* and the *Fraction Confucian* – have PIP exceeding the prior inclusion probability across all vintages of the PWT (all columns in Table 1).[15] The remaining 14 variables drop in PIP below the

[14] Although we estimate models using information from one vintage only, the special case of the MEMA-model is however slightly richer than this due to vintages missing some countries. Thus, even if we impose that a particular vintage is the "truth", countries only present in vintages other than the "true" one will still contribute to the identification of the model. In this section however, we only use data from one vintage.

[15] The reason for the small differences between the PIPs in Sala-i Martin, Doppelhofer and Miller (2004) and our results is that we use fully Bayesian model averaging, compared to the

prior inclusion probability in at least one vintage of the PWT. Finally, another three variables found "marginally related" to economic growth by Sala-i Martin, Doppelhofer and Miller (2004) also have PIP below and above the prior inclusion probability for different PWT vintages.

As example, consider *Malaria Prevalance*, which has a posterior inclusion probability (PIP) of 31% if we estimate the BMA model on vintage PWT 6.0 alone, whereas the PIP is less than the prior inclusion probability of 7/67 in five of the other vintages. Hence, the when comparing results conditional on specific vintages from the PWT it is difficult to disagree with the pessimistic conclusion by Ciccone and Jarociński (2010) regarding the robustness of growth determinants.

[**Insert table 1 about here**]

3.2 MEMA-model results

Measurements of income per capita and economic growth across different vintages of the PWT exhibit a large degree of uncertainty (see Johnson et al. (2013) or Deaton and Heston (2010)). These papers also warn that there may be systematic mismeasurement across countries, for example that income in poorer countries is likely to be less precisely measured compared to richer countries GDP. We are therefore proposing to address measurement error across PWT-vintages and countries simultaneously.

(Mis)Measurement of incomes

We start by estimating the the measurement error (ME) model discussed in section 2.1. We use a flat prior on the relative variances of countries and vintages, where $\Omega_1^V = ... = \Omega_V^V = \Omega_1^N = ... = \Omega_N^N = 1$. This is a fairly uninformative prior, such

BACE approximation proposed by Sala-i Martin, Doppelhofer and Miller (2004).

that the data can pull the relative variances away from the prior. We estimate the true values of initial and end-of-period income per country in 1960 and 1996, respectively.[16]

Figures 1 and 2 show the posterior densities of estimated true initial and end-of-period income. The blue dots indicate median log income, the thick line shows a 68% and the thin line a 95% credible interval, respectively. The figures also show all measurements in all PWT-vintages with black circles. A striking feature of both these figures if that the greatest variability is not for the lowest income countries, but rather for those at the middle-to-low range. Hence, measuring PPP-adjusted income in countries that are close to subsistence might be easier than in countries that have risen somewhat above this low level of income.

[**Insert figure 1 about here**]

[**Insert figure 2 about here**]

The measurement error model estimates the relative variances across PWT vintages and countries. This helps us to understand measurement error problems present in this dataset, and make statistical inference and economic implications robust to measurement error.

Figure 3 shows the posterior densities of relative variance of measurement error of income per capita for each PWT vintage. In particular, PWT vintage 6.0 has at the mean more than twice the variance compared to the average vintage, whereas recent vintages 8.0 and 8.1 have almost half the variance of the average vintage. Although there are exceptions, we generally find that newer vintages are less noisy than older ones, adressing the question posed by Johnson et al. (2013).

[**Insert figure 3 about here**]

[16] The initial value in 1960 and end period in 1996 were chosen for comparison with the literature (see Sala-i Martin, Doppelhofer and Miller (2004), Ciccone and Jarociński (2010)).

Figure 4 shows relative variances of the measurement error of income per capita per country. There is a vast difference in noisiness across countries. Incomes in El Salvador, Zimbabwe and Liberia are at the extremely noisy end of the scale. At the other end of the scale we find France, Belgium and Canada, where there is very little difference of income measurement across different PWT-vintages.

[**Insert figure 4 about here**]

Finally, Figure 9 shows the residuals from the measurement error, as defined in equation (3). Once we allow for both weighting of variance of measurement error across vintages and countries, the residuals are close to normally distributed. With the more restrictive version of the model where we assume average variance of measurement error is constant across countries or vintages gives residuals that look less normal.[17]

Growth determinants

We now show estimation results for the growth determinants using the full MEMA-model. The estimated coefficients take measurement error across PWT vintages and countries, as well as model uncertainty into account (see section 2.3).

Table 2 shows the posterior inclusion probabilities (PIPs), which represent a summary measure of the importance of a growth determinant. In particular, we can contrast the PIPs shown in the table with the prior inclusion probability, which equals 7/67. PIPs exceeding the prior inclusion probability are highlighted in green in Table 2).

The first column of Table 2 shows the simplest version of the model, where variances of the measurement error are restricted to be constant for all countries and vintages ($\omega_v^V = 1$ and $\omega_n^N = 1$).[18] The second column is the same as the first,

[17]Figure 9 shows a density plot over estimated residuals from the ME-model.

[18]Again, this is the limiting case where the constants $\Omega_1^V, ..., \Omega_V^V, \Omega_1^N, .., \Omega_N^N$ are very high.

except that we allow for differing weighting of measurement error variance across PWT vintages with a unit prior on $\Omega_1^V, ..., \Omega_V^V$, and fixed $\omega_1^N = ... = \omega_N^N = 1$. The third column allows differing weighting of measurement error variance across countries with a unit prior on $\Omega_1^N, ..., \Omega_N^N$ and fixed $\omega_1^V = ... = \omega_v^V$, and the fourth column allows both differing weighting of countries and vintages with a unit prior on both $\Omega_1^V, ..., \Omega_V^V$ and $\Omega_1^N, ..., \Omega_N^N$. The first four columns the residuals in the *growth model* are assumed to be homoscedastic, thereby ruling out outliers ($\sigma_i = \sigma$).

[**Insert table 2 about here**]

The results in Table 2 show that for thirteen explanatory variables the data are indicating that they are important determinants of economic growth. These variables include variables based on neoclassical (or endogenous) growth models, such as *Initial log GDP per capita*, controlling for initial conditions or determinants of the steady state, *Primary school enrolment in 1960*, controlling for human capital, the *Price of investment goods* or *Life expectancy in 1960.* A second group of variables included regional factors, such as the *East Asian Dummy* and a dummy for *Sub-Saharan Africa.* These variables control for regional differences in economic growth that are present even after controlling for many other plausible growth determinants. A third set of variables measure geographic or climatic conditions, such as the *Fraction of Tropical Area*, *Air Distance*, the overall *Population density in 1960*, as well as *Coastal population density in 1960.* A final group includes population characteristics or cultural variables, such as the population *Fraction Confucian* and *Fraction Muslim.*

The posterior inclusion probabilities in the first four columns shows that the results are quite similar regardless of the exact specification of the variance of the measurement error. As an example, we can note that *Malaria prevalence* is marginally important, and *Fraction Confucian* as an important variable.

A researcher may not only be interested in the inclusion probability, but also the size of the coefficient associated with different growth determinants. Table 3 shows the mean posterior coefficients conditional on being included in the model[19] for five different versions of the model presented in section 2.1. Table 3 shows the mean of the coefficients, conditional on being included. These first four column show that the exact specification of of the variance of measurement errors across countries and vintages does not alter posterior mean coefficients.

[Insert table 3 about here]

3.3 Outlier robust results

An important issue in the context of the empirical growth literature is the possibility of outliers and heteroscedasticity of the model errors. We therefore estimate the MEMA model allowing a more flexible model error structure. The results are shown in the last two columns in Tables 2 and 3. The fifth column is the same as the fourth column allowing for measurement error across PWT vintages and countries, except that we also allow for outliers, where we use a binary classification of whether each observation is an outlier. The sixth column uses instead a flexible Dirichlet-weighing of model error variance, with a flat unit priors on $\Omega_1, ..., \Omega_N$.

The results of the MEMA model with and without allowing for outliers adds some interesting features. First, we can note that two additional variables, namely a dummy for *Latin America* and the Malaria Prevalence in 1960, have PIP exceeding the prior inclusion probability in almost all columns in Table 2. Interestingly, the PIP associated with these variables *increases* in the last two columns once we allow for heteroscedastic model errors, indicating that outliers might be present in models including these two variables. A few more marginal variables, such as a

[19]The unconditional posterior mean can simply be calculated by multiplying the mean conditional on inclusion by the posterior inclusion probability.

dummy for *Landlocked countries*, *Openness in the 1960s*, and a *European dummy*, are helped by allowing for outliers. The reverse is true for other variables, the PIPs clearly fall once we allow for heteroscedastic model errors. This implies that variables such as the *Number of years a country is open*, *Political rights*, *Ethnoliguistic fractionalization*, and notably the *Mining share of GDP* are not robust to outliers, indicating that a few extreme observations may be driving these results.

The mean of the posterior density if the variance inflation is 21.49 - i.e. variance of the model error is vastly greater for for outliers relative to non-outliers. Table 4 shows the posterior probability of each country being classified as an outlier, where the Philippines, Botswana and South Africa rank the highest. Figure 5 shows the posterior densities of the relative variance of countries' mode error. Here, variance of the most noisy country is almost seven times the variance of the least noisy country. Hence, with the Dirichlet weighting the most noisy country - e.g. Botswana - contribute very little to the identification of parameters of in the MA-model. Hence, the posterior inclusion probability of mining, which has a high value in Botswana, drops to 2% in the Dirichlet robust model.

[**Insert table 4 about here**]

Figure 6 Shows model predicted growth from the full MEMA-model with Dirichlet weighing outliers, together with measurements of growth from all PWT-vintages. From this figure we can see e.g. Botswana and Philippines and South Africa as countries where the MA-model fits poorly. Botswana is a case special as growth is has been exceptionally high. South Africa and the Philippines are at the other extreme, where performance has been lower than what their initial conditions predict.

[**Insert figure 6 about here**]

Finally, figures 7 shows the posterior densities of the standard errors of the model error and measurement errors for initial and end-of period income. We might wonder how large measurement error is relative to the model error. Figure 8 scales the standard deviations such that they are comparable, where the ME standard deviation is the standard deviation of measurement error for growth - i.e. the left hand side in a growth regression. The MA standard deviation is the comparable model error. This figure shows that in a standard growth regression, measurement noise dominates model errors.[20]

[**Insert figure 7 about here**]

[**Insert figure 8 about here**]

Table 5 shows detailed results for our preferred specification, the full MEMA-model with Dirichlet robust model error. The table reports the mean of each coefficient, conditional on being included and the standard deviation of each coefficient. The table further reports the sign certainty, which is the posterior probability of the sign of the coefficient being equal to the sign of the conditional mean. Finally, the table repeats the posterior inclusion probability for each variable.

[**Insert table 5 about here**]

The results reported in Table 5 give a clear indication regarding the robustness of growth determinants allowing for measurement error and outliers. Eighteen variables have PIP larger than the prior inclusion probability. Posterior coefficients are relatively precisely estimated with sign certainty exceeding 0.975.[21] For the

[20]Here we are ignoring the fact the initial income might enter as a separate regressor, adding additional measurement error to the equation. Hence, measurement error is likely to have be even more dominant than model errors in growth equations.

[21]This implies that the sign certainty probability can be interpreted as a test statistic associated with a two-sided confidence interval for a coefficient estimate being zero. The European dummy has sign certainty 0.967 and PIP equal to 0.11 marginally exceeding the prior threshold.

remaining 49 variables the posterior inclusion probability is below the prior and we are also less sure about the sign of the associated coefficients.

We allow for the following alternative specification of the MEMA model in Appendix C. First, we introduce a hierarchical prior for g-prior and the model size treating them as random hyper-parameters. Second, we estimate the MEMA model on the three last sub-vintages of PWT vintages 6.3, 7.1 and 8.1. Finally, we allow for alternative model of outliers proposed by Geweke (1993). The results table C.1 show that the results for the growth determinants found robustly related to economic growth using the MEMA model are robust to these alternative specifications.

4 Conclusion

There is considerable uncertainty about the levels and growth rates of income per capita. The PWT construct measures of income across countries and over time, however there is considerable variation across different vintages of the PWT. The uncertainty about the measures of income spills over to increased uncertainty about the robustness of growth determinants.

This paper proposes a MEMA approach that models measurement uncertainty together with model uncertainty. Using eight vintages of the PWT to estimate the model, we have found 18 variables robustly related to economic growth from 1960 to 1996. The results are robust to allowing for outliers in the form of heteroscedastic model errors. Furthermore, we have in this paper *quantified* the noisiness of data across both PWT vintages and countries, which extends the qualitative measure of data quality contained in some vintages of the PWT.

We are in this paper trying to remain agnostic in our prior specifications. However, given that we are asking a lot from a very limited amount of data, it is necessary to impose parametric assumptions to ensure a well behaved posterior. The MEMA model can be extended by introducing additional information that can help to identify income and economic growth.

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Tables and figures

Table 1: Posterior inclusion probabilies in MA-models with differing data samples

	PWT 6.0	PWT 6.1	PWT 6.2	PWT 6.3	PWT 7.0	PWT 7.1	PWT 8.0	PWT 8.1
ABSLATIT	0.035	0.149	0.051	0.094	0.045	0.037	0.102	0.119
AIRDIST	0.029	0.019	0.038	0.027	0.021	0.024	0.036	0.03
AVELF	0.092	0.03	0.022	0.034	0.036	0.029	0.072	0.074
BRIT	0.029	0.028	0.018	0.021	0.017	0.02	0.018	0.018
BUDDHA	0.098	0.114	0.225	0.036	0.064	0.188	0.287	0.34
CATH00	0.026	0.022	0.027	0.019	0.019	0.024	0.03	0.03
CIV72	0.03	0.027	0.019	0.015	0.017	0.016	0.031	0.042
COLONY	0.029	0.033	0.076	0.093	0.055	0.052	0.071	0.086
CONFUC	0.184	0.331	0.481	0.301	0.242	0.446	0.313	0.391
DENS60	0.059	0.118	0.016	0.532	0.445	0.527	0.202	0.206
DENS65C	0.337	0.102	0.041	0.041	0.024	0.022	0.043	0.063
DENS65I	0.014	0.017	0.022	0.026	0.014	0.015	0.015	0.015
DPOP6090	0.019	0.025	0.035	0.019	0.022	0.024	0.022	0.022
EAST	0.854	0.795	0.669	0.716	0.876	0.684	0.744	0.672
ECORG	0.015	0.023	0.022	0.077	0.015	0.014	0.015	0.016
ENGFRAC	0.02	0.026	0.031	0.041	0.074	0.076	0.061	0.055
EUROPE	0.028	0.023	0.037	0.022	0.024	0.029	0.042	0.065
FERTLDC1	0.03	0.027	0.034	0.027	0.027	0.029	0.027	0.03
GDE1	0.021	0.061	0.024	0.022	0.033	0.023	0.019	0.019
GEEREC1	0.02	0.023	0.017	0.019	0.024	0.024	0.057	0.057
GGCFD3	0.036	0.041	0.019	0.052	0.03	0.02	0.019	0.02
GOVNOM1	0.031	0.016	0.073	0.016	0.018	0.016	0.02	0.021
GOVSH61	0.058	0.019	0.015	0.015	0.016	0.015	0.015	0.016
GVR61	0.104	0.033	0.015	0.018	0.017	0.018	0.015	0.016
H60	0.067	0.027	0.057	0.039	0.061	0.053	0.039	0.04
HERF00	0.017	0.019	0.023	0.026	0.028	0.028	0.065	0.058
HINDU00	0.038	0.033	0.052	0.027	0.02	0.021	0.02	0.021
InitLGDP	0.553	0.97	0.992	1	0.946	0.935	0.716	0.685
IPRICE1	0.662	0.768	0.018	0.333	0.23	0.26	0.023	0.022
LAAM	0.131	0.048	0.111	0.026	0.032	0.029	0.129	0.143
LANDAREA	0.015	0.018	0.017	0.082	0.023	0.032	0.017	0.018
LANDLOCK	0.018	0.024	0.027	0.04	0.057	0.064	0.033	0.031
LHCPC	0.021	0.017	0.021	0.019	0.023	0.022	0.018	0.019
LIFE060	0.207	0.802	0.758	0.893	0.922	0.905	0.605	0.475
LT100CR	0.019	0.019	0.016	0.03	0.019	0.024	0.019	0.018
MALFAL66	0.315	0.033	0.062	0.093	0.161	0.128	0.084	0.076
MINING	0.098	0.426	0.018	0.387	0.539	0.458	0.79	0.794
MUSLIM00	0.101	0.318	0.194	0.138	0.072	0.132	0.131	0.128
NEWSTATE	0.019	0.024	0.039	0.05	0.019	0.02	0.022	0.023
OIL	0.018	0.016	0.018	0.016	0.015	0.016	0.019	0.02
OPENDEC1	0.077	0.256	0.259	0.414	0.064	0.067	0.122	0.151
ORTH00	0.015	0.014	0.015	0.015	0.014	0.015	0.016	0.016
OTHFRAC	0.068	0.073	0.066	0.132	0.13	0.111	0.097	0.109
P60	0.714	0.429	0.576	0.326	0.075	0.077	0.276	0.319
PI6090	0.019	0.017	0.018	0.02	0.018	0.016	0.019	0.023
POP1560	0.043	0.052	0.029	0.028	0.032	0.038	0.038	0.059
POP60	0.023	0.032	0.037	0.03	0.038	0.048	0.024	0.023
POP6560	0.023	0.042	0.07	0.025	0.025	0.022	0.054	0.096
PRIEXP70	0.052	0.063	0.071	0.051	0.05	0.052	0.094	0.051
PRIGHTS	0.048	0.018	0.021	0.018	0.019	0.022	0.025	0.023
PROT00	0.043	0.05	0.075	0.047	0.077	0.107	0.095	0.07
RERD	0.081	0.033	0.022	0.042	0.054	0.07	0.086	0.104
REVCOUP	0.028	0.015	0.015	0.016	0.018	0.019	0.07	0.081
SAFRICA	0.121	0.078	0.262	0.064	0.048	0.047	0.281	0.285
SCOUT	0.027	0.024	0.022	0.024	0.019	0.019	0.015	0.015
SIZE60	0.021	0.228	0.35	0.434	0.057	0.063	0.037	0.048
SOCIALIST	0.018	0.027	0.016	0.017	0.014	0.014	0.016	0.016
SPAIN	0.13	0.043	0.048	0.022	0.028	0.026	0.062	0.062
SQPI6090	0.017	0.015	0.019	0.017	0.017	0.016	0.018	0.019
TOT1DEC1	0.021	0.018	0.019	0.019	0.022	0.019	0.029	0.032
TOTIND	0.016	0.019	0.016	0.017	0.017	0.018	0.023	0.029
TROPICAR	0.521	0.206	0.175	0.081	0.079	0.051	0.445	0.385
TROPPOP	0.057	0.157	0.158	0.402	0.693	0.67	0.125	0.152
WARTIME	0.015	0.014	0.014	0.013	0.016	0.014	0.027	0.025
WARTORN	0.015	0.018	0.017	0.014	0.014	0.016	0.015	0.015
YRSOPEN	0.115	0.077	0.09	0.146	0.407	0.488	0.064	0.088
ZTROPICS	0.017	0.018	0.017	0.016	0.015	0.016	0.019	0.02

Table 2: Posterior inclusion probabilities in measurement error models

ME-variance Outlier detection	Equal None	By Vintage None	By Country None	By country and vintage None	By country and vintage Binary	By country and vintage Dirichlet
InitLGDP	0.914	0.955	0.968	0.972	0.999	0.998
P60	0.831	0.869	0.882	0.892	0.839	0.917
EAST	0.765	0.759	0.801	0.808	0.979	0.884
TROPICAR	0.376	0.323	0.431	0.441	0.301	0.477
AIRDIST	0.172	0.122	0.260	0.288	0.362	0.411
SAFRICA	0.332	0.453	0.300	0.261	0.429	0.345
DENS60	0.647	0.653	0.740	0.765	0.174	0.336
IPRICE1	0.437	0.392	0.578	0.576	0.173	0.321
LIFE060	0.265	0.254	0.275	0.251	0.416	0.302
DENS65C	0.294	0.272	0.364	0.361	0.192	0.263
PRIEXP70	0.362	0.469	0.427	0.421	0.274	0.225
LAAM	0.115	0.126	0.103	0.091	0.307	0.218
MUSLIM00	0.226	0.225	0.239	0.234	0.217	0.199
MALFAL66	0.166	0.144	0.105	0.088	0.354	0.170
CONFUC	0.185	0.157	0.191	0.194	0.129	0.169
LANDLOCK	0.030	0.025	0.047	0.053	0.369	0.129
OPENDEC1	0.049	0.048	0.091	0.105	0.122	0.127
EUROPE	0.033	0.036	0.040	0.042	0.194	0.111
SCOUT	0.045	0.042	0.043	0.038	0.109	0.097
RERD	0.104	0.078	0.101	0.101	0.058	0.094
FERTLDC1	0.109	0.120	0.081	0.075	0.055	0.077
TROPPOP	0.094	0.096	0.172	0.196	0.060	0.077
OTHFRAC	0.063	0.059	0.071	0.068	0.125	0.069
BUDDHA	0.086	0.068	0.126	0.141	0.030	0.058
SPAIN	0.040	0.035	0.032	0.028	0.092	0.058
YRSOPEN	0.165	0.129	0.145	0.141	0.047	0.058
PRIGHTS	0.139	0.126	0.155	0.148	0.029	0.054
LHCPC	0.074	0.066	0.069	0.063	0.053	0.042
ABSLATIT	0.077	0.082	0.046	0.044	0.084	0.033
AVELF	0.111	0.082	0.108	0.109	0.026	0.032
REVCOUP	0.044	0.039	0.044	0.049	0.023	0.031
BRIT	0.032	0.030	0.026	0.027	0.024	0.026
MINING	0.229	0.233	0.237	0.238	0.027	0.026
SIZE60	0.019	0.018	0.019	0.019	0.036	0.026
DPOP6090	0.028	0.035	0.026	0.025	0.028	0.025
GOVSH61	0.040	0.056	0.041	0.033	0.035	0.024
PI6090	0.022	0.022	0.021	0.022	0.022	0.023
POP6560	0.034	0.034	0.032	0.037	0.046	0.023
COLONY	0.020	0.019	0.038	0.056	0.036	0.022
GOVNOM1	0.021	0.020	0.024	0.021	0.043	0.022
ZTROPICS	0.023	0.023	0.023	0.023	0.024	0.022
GVR61	0.049	0.058	0.046	0.037	0.028	0.021
SQPI6090	0.019	0.018	0.018	0.018	0.022	0.020
HINDU00	0.021	0.020	0.020	0.019	0.026	0.019
OIL	0.017	0.017	0.016	0.016	0.050	0.019
PROT00	0.025	0.022	0.024	0.026	0.035	0.019
NEWSTATE	0.021	0.021	0.021	0.024	0.027	0.018
GDE1	0.018	0.018	0.017	0.017	0.031	0.017
SOCIALIST	0.017	0.020	0.019	0.018	0.025	0.017
CATH00	0.023	0.024	0.021	0.021	0.044	0.016
POP1560	0.021	0.021	0.020	0.020	0.025	0.016
TOT1DEC1	0.028	0.024	0.021	0.019	0.024	0.016
WARTORN	0.055	0.073	0.029	0.027	0.021	0.016
ECORG	0.022	0.017	0.020	0.019	0.018	0.015
LANDAREA	0.019	0.019	0.019	0.020	0.025	0.015
LT100CR	0.021	0.020	0.026	0.029	0.022	0.015
TOTIND	0.023	0.020	0.022	0.025	0.025	0.015
CIV72	0.021	0.022	0.019	0.019	0.022	0.014
GGCFD3	0.018	0.018	0.026	0.027	0.018	0.014
HERF00	0.021	0.022	0.019	0.018	0.021	0.014
POP60	0.017	0.017	0.018	0.017	0.023	0.014
WARTIME	0.016	0.019	0.015	0.015	0.019	0.013
DENS65I	0.015	0.014	0.015	0.014	0.021	0.012
ENGFRAC	0.020	0.018	0.019	0.021	0.020	0.012
GEEREC1	0.028	0.025	0.023	0.024	0.019	0.012
H60	0.023	0.019	0.024	0.024	0.016	0.012
ORTH00	0.017	0.018	0.018	0.018	0.016	0.011

Note: The table shows the posterior inclusion probability of each covariate in the different model specifications. The numbers in the table are reported as percentages. Numbers are colored, such that values greater than 7/67 are green. Table is sorted by the rightmost column.

Table 3: Posterior mean of coefficients, conditional on being included

ME-variance	Equal	By Vintage	By Country	By country and vintage	By country and vintage	By country and vintage
Outlier detection	None	None	None	None	Binary	Dirichlet
InitLGDP	-1.220E-02	-1.304E-02	-1.177E-02	-1.140E-02	-1.118E-02	-1.131E-02
P60	3.289E-02	3.327E-02	3.282E-02	3.300E-02	3.211E-02	3.482E-02
EAST	2.029E-02	1.925E-02	1.837E-02	1.839E-02	2.199E-02	2.158E-02
TROPICAR	-1.377E-02	-1.322E-02	-1.339E-02	-1.340E-02	-1.048E-02	-1.278E-02
AIRDIST	-1.648E-06	-1.518E-06	-1.613E-06	-1.649E-06	-1.461E-06	-1.740E-06
SAFRICA	-1.547E-02	-1.599E-02	-1.388E-02	-1.341E-02	-1.393E-02	-1.520E-02
DENS60	2.343E-05	2.309E-05	2.280E-05	2.371E-05	1.588E-05	2.133E-05
IPRICE1	-7.143E-05	-6.855E-05	-7.038E-05	-7.007E-05	-7.334E-05	-7.642E-05
LIFE060	8.205E-04	8.039E-04	7.360E-04	7.141E-04	7.631E-04	6.915E-04
DENS65C	8.469E-06	8.109E-06	8.229E-06	8.148E-06	5.419E-06	6.420E-06
PRIEXP70	-1.996E-02	-2.101E-02	-1.934E-02	-1.929E-02	-1.245E-02	-1.481E-02
LAAM	-1.026E-02	-9.932E-03	-9.450E-03	-9.188E-03	-1.062E-02	-1.250E-02
MUSLIM00	1.435E-02	1.373E-02	1.343E-02	1.356E-02	1.149E-02	1.425E-02
MALFAL66	-1.387E-02	-1.323E-02	-1.180E-02	-1.124E-02	-1.280E-02	-1.369E-02
CONFUC	5.371E-02	5.083E-02	5.043E-02	5.136E-02	3.269E-02	4.950E-02
LANDLOCK	-4.416E-03	-3.804E-03	-5.177E-03	-5.383E-03	-7.665E-03	-7.379E-03
OPENDEC1	7.078E-03	6.817E-03	8.449E-03	8.877E-03	7.554E-03	8.720E-03
EUROPE	6.420E-03	6.690E-03	7.280E-03	7.979E-03	1.053E-02	1.133E-02
SCOUT	-4.136E-03	-4.001E-03	-3.492E-03	-3.351E-03	-4.112E-03	-4.316E-03
RERD	-8.286E-05	-7.468E-05	-7.309E-05	-7.285E-05	-4.431E-05	-6.122E-05
FERTLDC1	-1.739E-02	-1.699E-02	-1.428E-02	-1.405E-02	-9.432E-03	-1.451E-02
TROPPOP	-1.273E-02	-1.255E-02	-1.360E-02	-1.402E-02	-7.596E-03	-1.030E-02
OTHFRAC	6.430E-03	6.289E-03	5.902E-03	5.837E-03	5.411E-03	5.437E-03
BUDDHA	1.990E-02	1.825E-02	2.072E-02	2.145E-02	7.660E-03	1.602E-02
SPAIN	-6.495E-03	-5.611E-03	-5.027E-03	-4.316E-03	-7.210E-03	-7.863E-03
YRSOPEN	1.345E-02	1.245E-02	1.184E-02	1.192E-02	6.158E-03	8.841E-03
PRIGHTS	-2.395E-03	-2.382E-03	-2.158E-03	-2.107E-03	-4.020E-04	-1.562E-03
LHCPC	6.469E-04	6.047E-04	5.683E-04	5.521E-04	3.668E-04	4.016E-04
ABSLATIT	2.987E-04	3.074E-04	2.194E-04	2.198E-04	2.064E-04	1.271E-04
AVELF	-1.261E-02	-1.138E-02	-1.098E-02	-1.107E-02	-3.279E-03	-7.002E-03
REVCOUP	-9.074E-03	-8.421E-03	-8.171E-03	-8.298E-03	-3.488E-03	-6.275E-03
BRIT	4.075E-03	3.664E-03	2.940E-03	3.187E-03	1.059E-03	2.741E-03
MINING	5.324E-02	5.234E-02	5.209E-02	5.357E-02	-2.488E-03	1.780E-02
SIZE60	3.426E-04	4.726E-04	1.554E-04	3.240E-05	6.589E-04	7.486E-04
DPOP6090	-2.642E-01	-3.271E-01	-2.232E-01	-2.177E-01	-1.778E-01	-2.312E-01
GOVSH61	-3.109E-02	-3.483E-02	-2.807E-02	-2.476E-02	-1.806E-02	-1.899E-02
PI6090	-7.693E-05	-8.348E-05	-6.789E-05	-6.841E-05	-4.435E-05	-8.635E-05
POP6560	1.115E-01	1.104E-01	9.654E-02	1.103E-01	9.966E-02	8.544E-02
COLONY	-2.163E-03	-1.145E-03	-5.601E-03	-7.012E-03	-3.721E-03	-4.102E-03
GOVNOM1	-1.498E-02	-1.492E-02	-1.814E-02	-1.572E-02	-2.342E-02	-1.669E-02
ZTROPICS	3.833E-03	4.364E-03	4.349E-03	4.357E-03	2.845E-03	4.172E-03
GVR61	-3.537E-02	-3.658E-02	-3.051E-02	-2.728E-02	-1.241E-02	-1.600E-02
SQPI6090	-7.574E-07	-7.283E-07	-6.140E-07	-6.845E-07	-5.356E-07	-8.751E-07
HINDU00	4.874E-03	2.322E-03	3.381E-03	2.056E-03	2.013E-04	1.424E-03
OIL	2.353E-03	2.433E-03	6.479E-04	-3.108E-04	-6.185E-03	-3.857E-03
PROT00	-6.470E-03	-5.593E-03	-5.829E-03	-6.459E-03	-4.954E-03	-4.646E-03
NEWSTATE	1.114E-03	7.920E-04	-5.779E-04	-9.732E-04	-1.178E-03	-7.311E-04
GDE1	7.062E-03	-5.956E-03	-2.659E-03	-3.536E-03	-2.938E-02	-1.982E-02
SOCIALIST	3.402E-03	4.056E-03	3.228E-03	2.965E-03	3.156E-03	2.937E-03
CATH00	-2.103E-03	-2.469E-03	-1.573E-03	-1.645E-03	4.543E-03	2.080E-03
POP1560	-3.915E-04	-5.856E-03	-1.331E-03	-3.828E-04	1.074E-02	2.054E-03
TOT1DEC1	4.923E-02	3.996E-02	2.013E-02	5.209E-03	-1.644E-02	-1.564E-02
WARTORN	-4.919E-03	-5.489E-03	-3.115E-03	-2.961E-03	-1.188E-03	-1.731E-03
ECORG	-8.558E-04	-4.807E-04	-5.557E-04	-5.652E-04	-1.832E-04	-3.496E-04
LANDAREA	-5.000E-10	-4.000E-10	-4.000E-10	-5.000E-10	4.000E-10	1.000E-10
LT100CR	1.506E-03	1.121E-03	3.575E-03	4.208E-03	-7.623E-04	1.053E-03
TOTIND	7.902E-03	6.135E-03	7.157E-03	8.310E-03	5.207E-03	5.342E-03
CIV72	2.609E-03	4.008E-03	1.163E-03	1.381E-03	-2.615E-03	-1.476E-03
GGCFD3	-1.241E-02	-1.413E-02	-3.614E-02	-3.629E-02	-7.411E-03	-3.258E-03
HERF00	-4.810E-03	-6.031E-03	-3.295E-03	-2.060E-03	2.723E-03	6.473E-04
POP60	4.700E-09	-2.300E-09	2.400E-09	4.200E-09	-8.400E-09	-3.800E-09
WARTIME	-8.339E-04	6.253E-03	-1.243E-03	-1.974E-03	2.103E-03	7.019E-04
DENS65I	3.621E-07	-5.280E-07	-1.336E-06	-1.174E-06	-6.396E-06	-3.989E-06
ENGFRAC	-4.696E-03	-3.356E-03	-4.061E-03	-4.544E-03	-2.080E-03	-1.149E-03
GEEREC1	1.752E-01	1.612E-01	1.332E-01	1.419E-01	-7.494E-03	1.616E-04
H60	-3.606E-02	-2.759E-02	-3.403E-02	-3.291E-02	-1.564E-03	-1.670E-02
ORTH00	7.499E-03	8.201E-03	7.031E-03	8.212E-03	1.999E-03	3.439E-03

Note: The table shows the posterior mean of each covariate, conditional on being included, in the different model specifications. Table is sorted by the the posterior inclusion probability in the Dirichlet-robust model (see table 2).

Table 4: Posterior probability of a country being an outlier

Country	P(Outlier)	Country	P(Outlier)	Country	P(Outlier)
BWA	0.995	NZL	0.058	PRT	0.038
PHL	0.984	ZWE	0.057	CHL	0.037
ZAR	0.859	NER	0.056	MEX	0.037
LBR	0.800	HKG	0.055	PRY	0.037
GAB	0.618	NOR	0.055	SEN	0.037
JOR	0.464	HND	0.054	DZA	0.036
MRT	0.371	TUN	0.054	PER	0.036
CAF	0.248	VEN	0.054	TTO	0.036
MDG	0.168	LSO	0.053	TUR	0.036
EGY	0.149	AUS	0.052	TZA	0.036
JAM	0.149	GMB	0.051	MWI	0.035
COG	0.130	PAN	0.05	SWE	0.035
BRA	0.128	PNG	0.05	CMR	0.033
DOM	0.105	ISR	0.047	KEN	0.032
PAK	0.098	TWN	0.047	UGA	0.032
SLV	0.095	CAN	0.045	USA	0.032
GTM	0.085	IND	0.044	ECU	0.031
SGP	0.083	NPL	0.043	ITA	0.031
ZMB	0.080	THA	0.042	TGO	0.031
RWA	0.076	ETH	0.041	ESP	0.03
AUT	0.071	GHA	0.041	DEU	0.029
JPN	0.071	IRL	0.041	GBR	0.029
COL	0.066	MAR	0.041	NLD	0.029
ARG	0.065	ZAF	0.041	FRA	0.028
LKA	0.064	CRI	0.04	GRC	0.028
BEN	0.063	SYR	0.04	BEL	0.027
IDN	0.063	BDI	0.039	DNK	0.027
KOR	0.063	BOL	0.039	FIN	0.027
URY	0.063	MYS	0.038		
HTI	0.062	NGA	0.038		

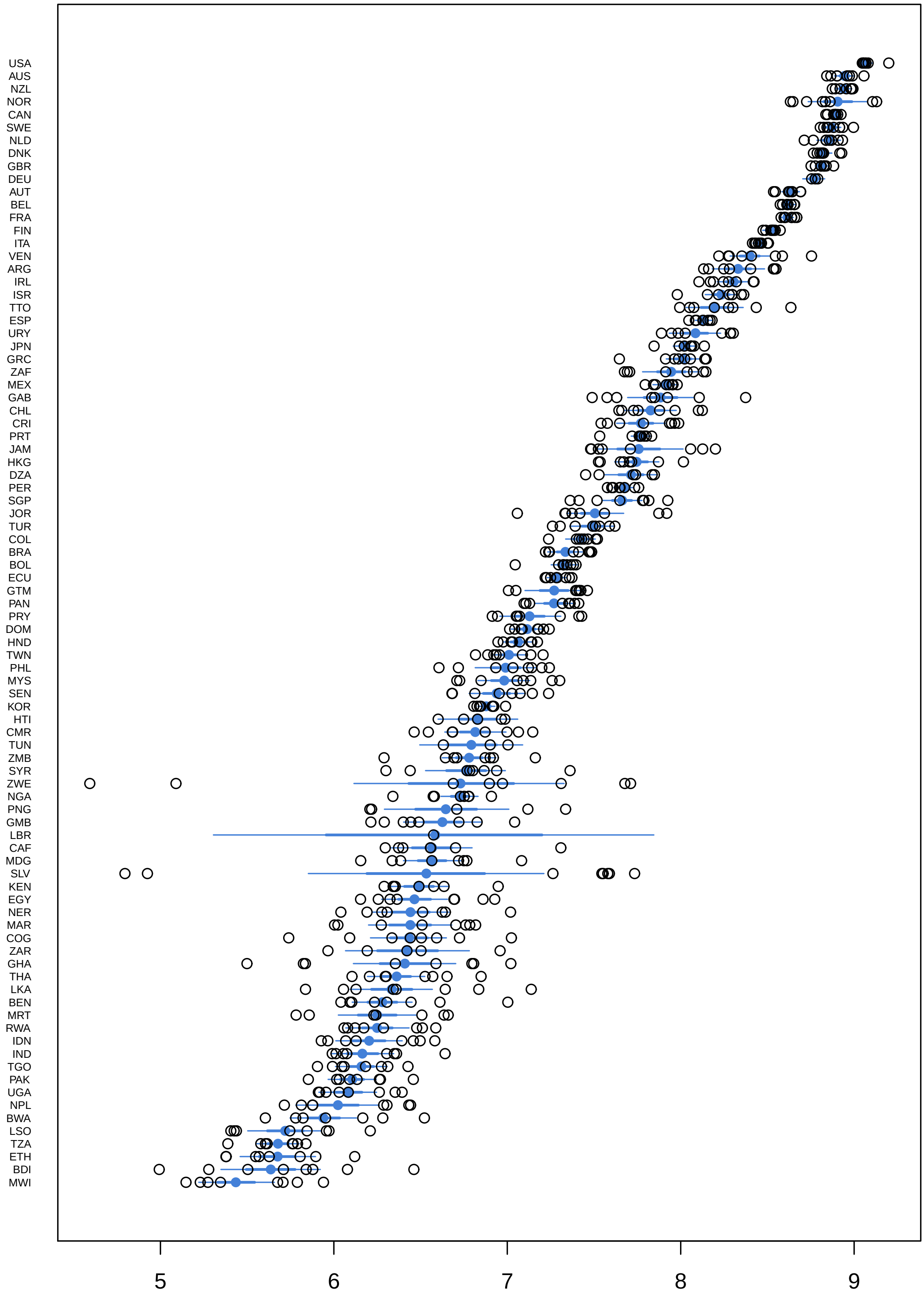
Note: The table shows the posterior probability of each country being an outlier. The results come from the MEMA-model with a binary outlier classification, and the prior probability of each observation being an outlier is 10%.

Table 5: Expanded results for the robust MEMA-model

	Cond. mean of coeff.	Std.d. of coeff.	Sign certainty	Posterior Inc. Prob
Init LGDP	-1.131E-02	2.720E-03	1.000	0.998
P60	3.482E-02	8.374E-03	1.000	0.917
EAST	2.158E-02	5.535E-03	1.000	0.884
TROPICAR	-1.278E-02	3.643E-03	0.997	0.477
AIRDIST	-1.740E-06	5.446E-07	0.996	0.411
SAFRICA	-1.520E-02	6.348E-03	0.995	0.345
DENS60	2.133E-05	7.303E-06	0.993	0.336
IPRICE1	-7.642E-05	2.706E-05	0.994	0.321
LIFE060	6.915E-04	2.935E-04	0.995	0.302
DENS65C	6.420E-06	2.288E-06	0.993	0.263
PRIEXP70	-1.481E-02	5.780E-03	0.991	0.225
LAAM	-1.250E-02	5.009E-03	0.977	0.218
MUSLIM00	1.425E-02	5.872E-03	0.990	0.199
MALFAL66	-1.369E-02	5.645E-03	0.981	0.170
CONFUC	4.950E-02	2.267E-02	0.987	0.169
LANDLOCK	-7.379E-03	3.372E-03	0.986	0.129
OPENDEC1	8.720E-03	4.252E-03	0.981	0.127
EUROPE	1.133E-02	5.551E-03	0.967	0.111
SCOUT	-4.316E-03	2.127E-03	0.979	0.097
RERD	-6.122E-05	3.000E-05	0.978	0.094
TROPPOP	-1.030E-02	5.687E-03	0.965	0.077
FERTLDC1	-1.451E-02	8.503E-03	0.957	0.077
OTHFRAC	5.437E-03	2.986E-03	0.971	0.069
YRSOPEN	8.841E-03	5.208E-03	0.957	0.058
BUDDHA	1.602E-02	1.026E-02	0.936	0.058
SPAIN	-7.863E-03	5.030E-03	0.927	0.058
PRIGHTS	-1.562E-03	1.074E-03	0.918	0.054
LHCPC	4.016E-04	2.618E-04	0.940	0.042
ABSLATIT	1.271E-04	2.010E-04	0.738	0.033
AVELF	-7.002E-03	5.687E-03	0.893	0.032
REVCOUP	-6.275E-03	4.761E-03	0.907	0.031
SIZE60	7.486E-04	1.480E-03	0.659	0.026
MINING	1.780E-02	2.400E-02	0.769	0.026
BRIT	2.741E-03	2.675E-03	0.849	0.026
DPOP6090	-2.312E-01	2.252E-01	0.859	0.025
GOVSH61	-1.899E-02	1.948E-02	0.844	0.024
PI6090	-8.635E-05	9.133E-05	0.830	0.023
POP6560	8.544E-02	8.964E-02	0.849	0.023
ZTROPICS	4.172E-03	5.831E-03	0.768	0.022
GOVNOM1	-1.669E-02	2.286E-02	0.772	0.022
COLONY	-4.102E-03	4.464E-03	0.825	0.022
GVR61	-1.600E-02	2.060E-02	0.794	0.021
SQPI6090	-8.751E-07	1.257E-06	0.783	0.020
OIL	-3.857E-03	4.532E-03	0.812	0.019
PROT00	-4.646E-03	4.368E-03	0.871	0.019
HINDU00	1.424E-03	1.230E-02	0.556	0.019
NEWSTATE	-7.311E-04	2.081E-03	0.626	0.018
SOCIALIST	2.937E-03	4.439E-03	0.747	0.017
GDE1	-1.982E-02	5.693E-02	0.645	0.017
CATH00	2.080E-03	4.137E-03	0.754	0.016
WARTORN	-1.731E-03	2.276E-03	0.777	0.016
POP1560	2.054E-03	3.782E-02	0.492	0.016
TOT1DEC1	-1.564E-02	3.312E-02	0.705	0.016
ECORG	-3.496E-04	8.995E-04	0.655	0.015
TOTIND	5.342E-03	6.699E-03	0.791	0.015
LT100CR	1.053E-03	4.065E-03	0.615	0.015
LANDAREA	1.000E-10	7.000E-10	0.567	0.015
CIV72	-1.476E-03	4.688E-03	0.618	0.014
GGCFD3	-3.258E-03	3.145E-02	0.549	0.014
POP60	-3.800E-09	2.300E-08	0.561	0.014
HERF00	6.473E-04	5.856E-03	0.532	0.014
WARTIME	7.019E-04	7.310E-03	0.547	0.013
H60	-1.670E-02	2.998E-02	0.708	0.012
DENS65I	-3.989E-06	1.157E-05	0.687	0.012
ENGFRAC	-1.149E-03	4.676E-03	0.587	0.012
GEEREC1	1.616E-04	1.177E-01	0.489	0.012
ORTH00	3.439E-03	1.052E-02	0.631	0.011

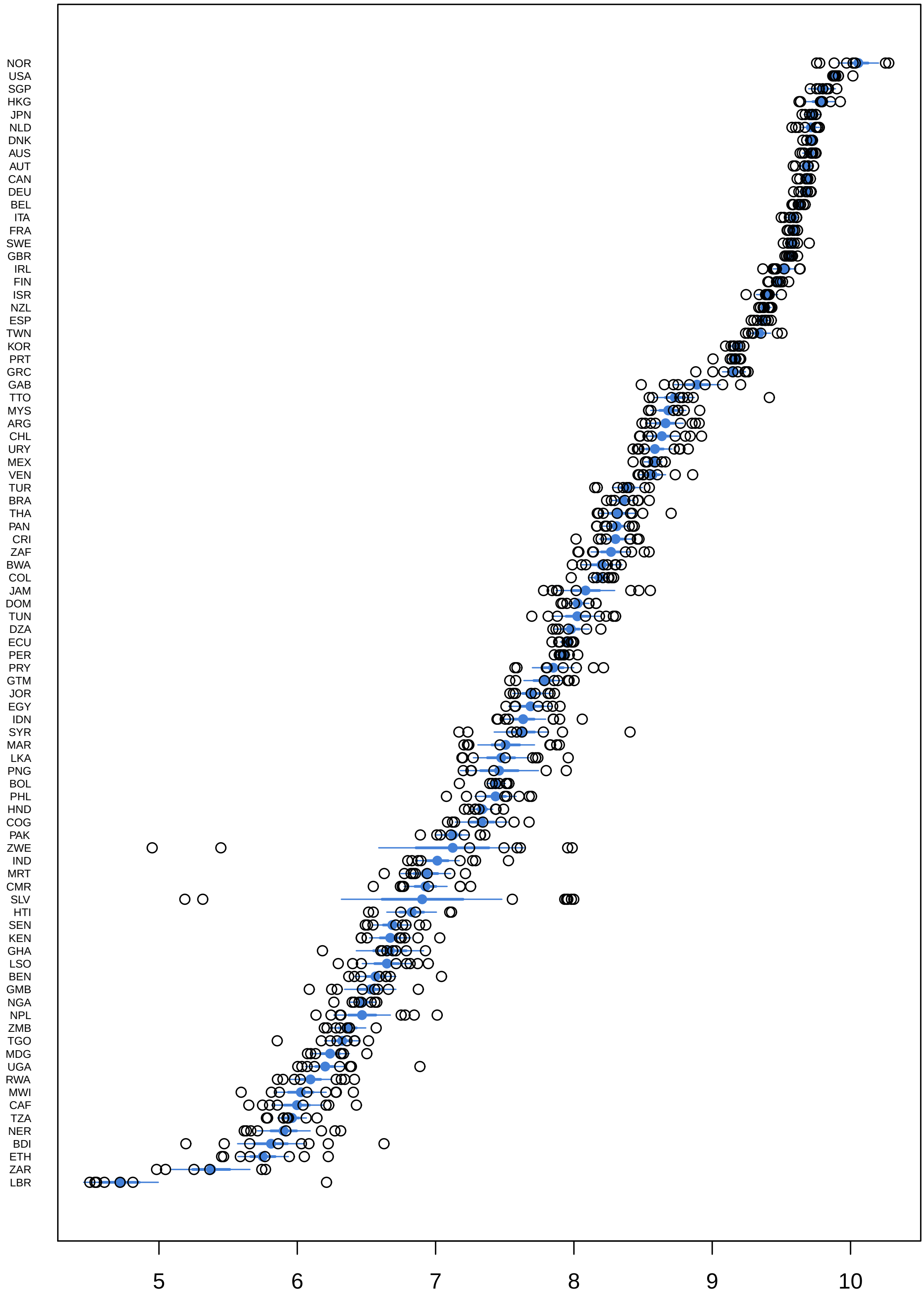
Note: The table shows detailed results for the Dirichlet robust MEMA-model. Table is sorted by PIP.

Figure 1: Income income 1960



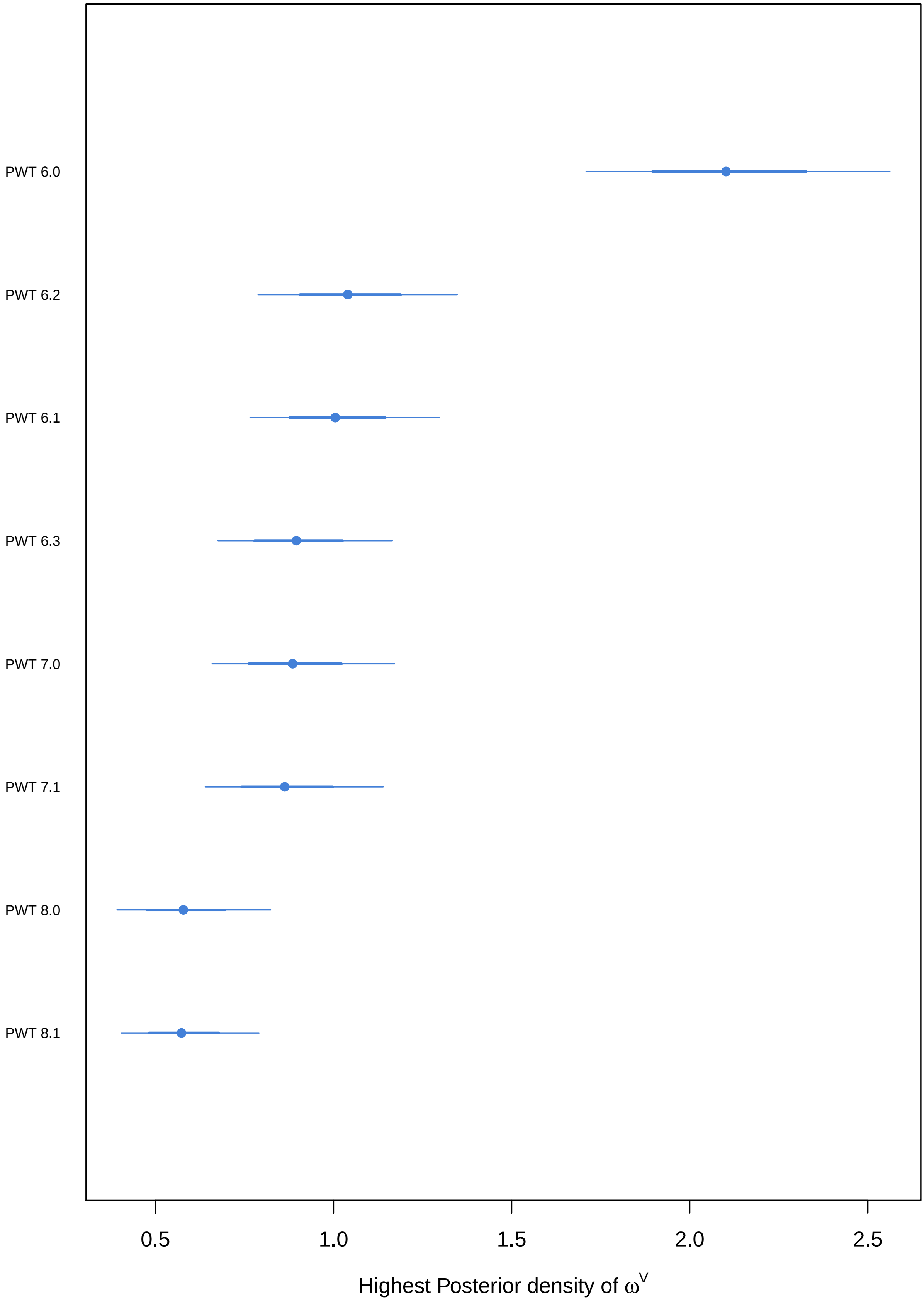
Note: The figure shows posterior density of PPP adjusted log GDP in 1960, estimated from all vintages 6.0 through 8.1 of the PWT. The circles indicate the level of log GDP the different Penn Vintages. Each vintage is scaled by the mean, estimated vintage level (α), such that all values are reported in "PWT 6.0"-level. The blue dot indicates the median of the estimated log income; the thick line shows a 68% credible interval and the thin line shows a 95% credible interval

Figure 2: Income income 1996



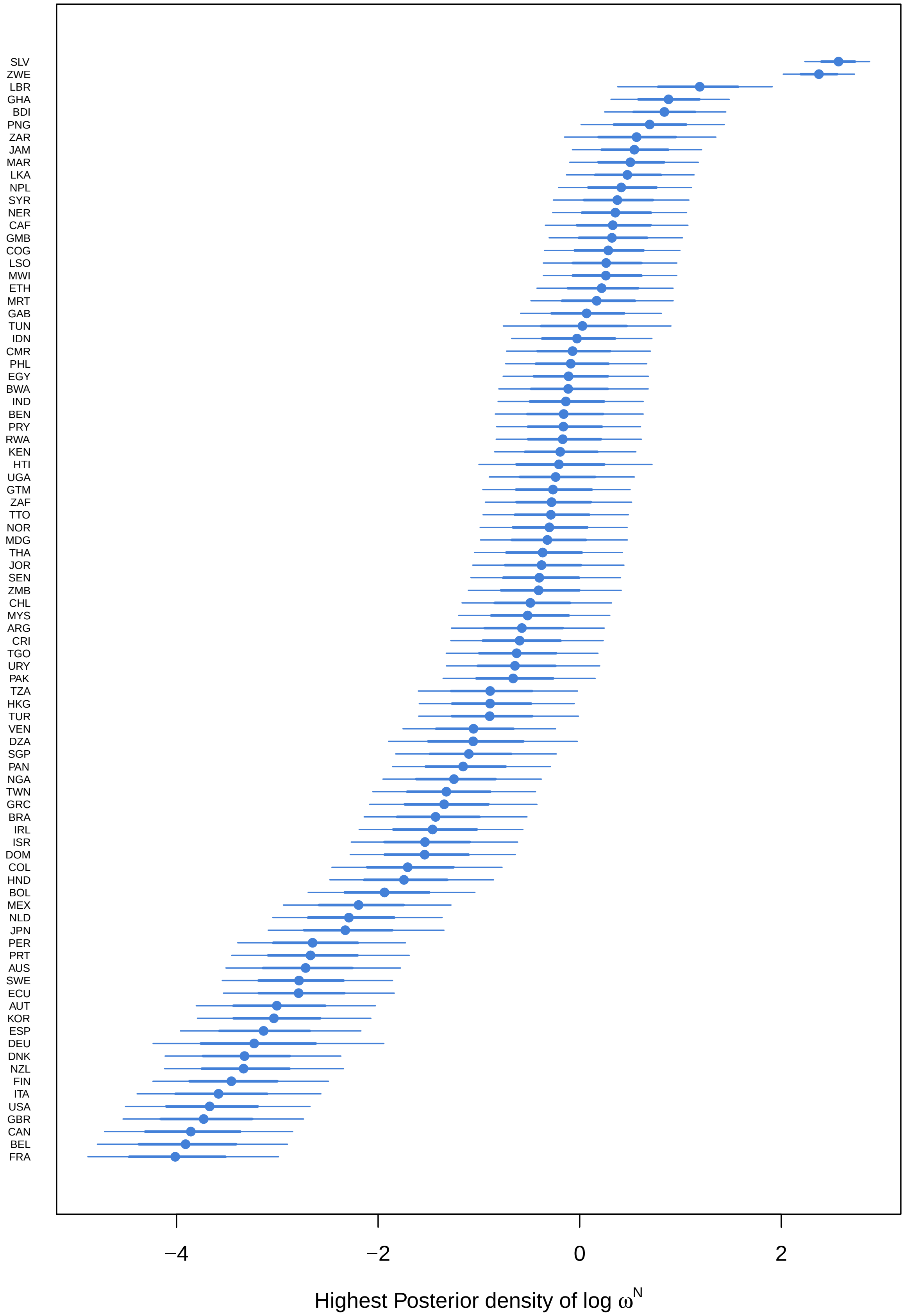
Note: The figure shows posterior density of PPP adjusted log GDP in 1960, estimated from all vintages 6.0 through 8.1 of the PWT. The circles indicate the level of log GDP the different Penn Vintages. Each vintage is scaled by the mean, estimated vintage level (α), such that all values are reported in "PWT 6.0"-level. The blue dot indicates the median of the estimated log income; the thick line shows a 68% credible interval and the thin line shows a 95% credible interval

Figure 3: Relative variance of measurement error in vintages



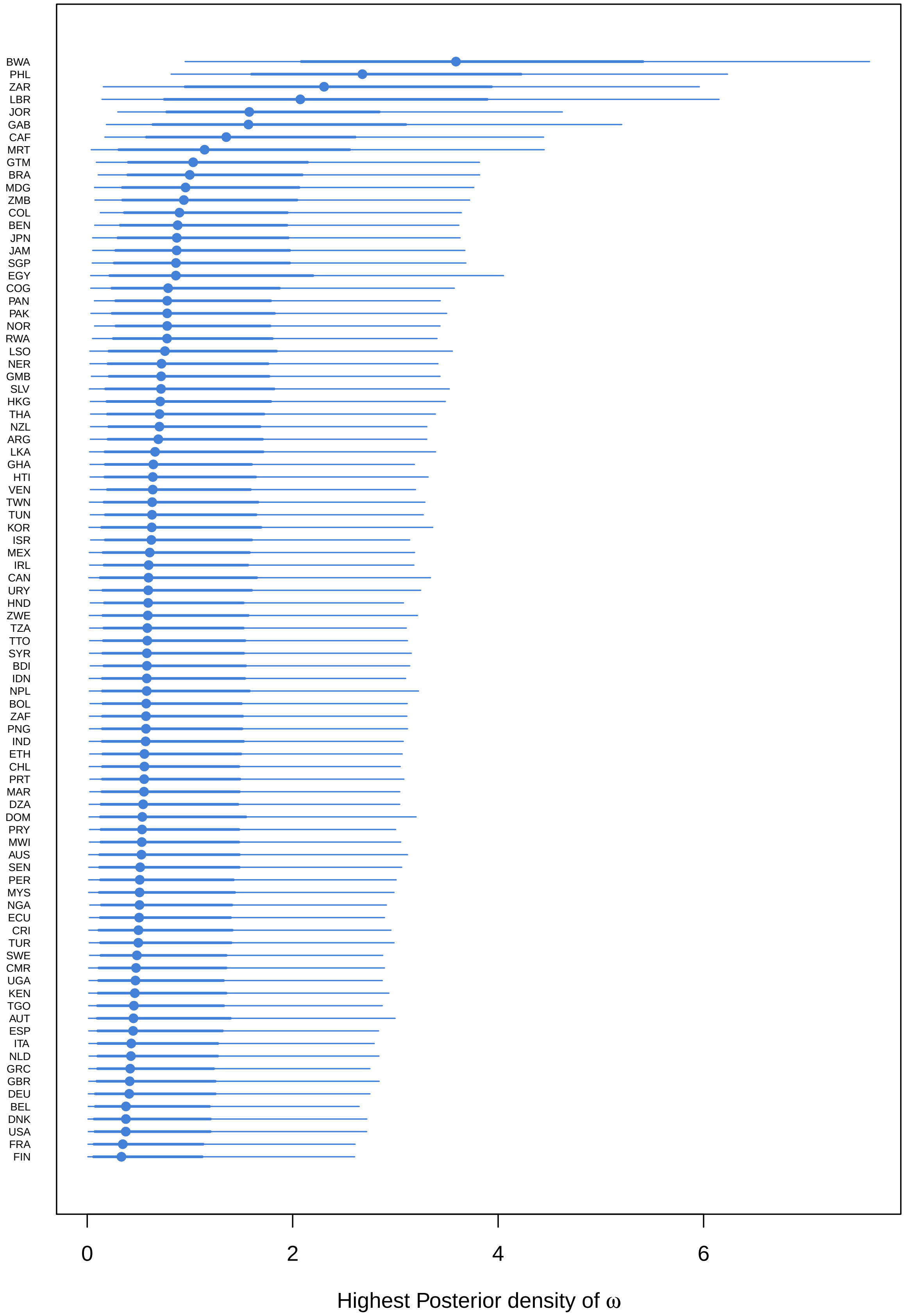
Note: The figure shows posterior of the relative variance of the different Penn Vintages. The dot indicates the median of the distributions; the thick line shows a 68% credible interval and the thin line shows a 95% credible interval

Figure 4: Relative variance of countries' measurement error



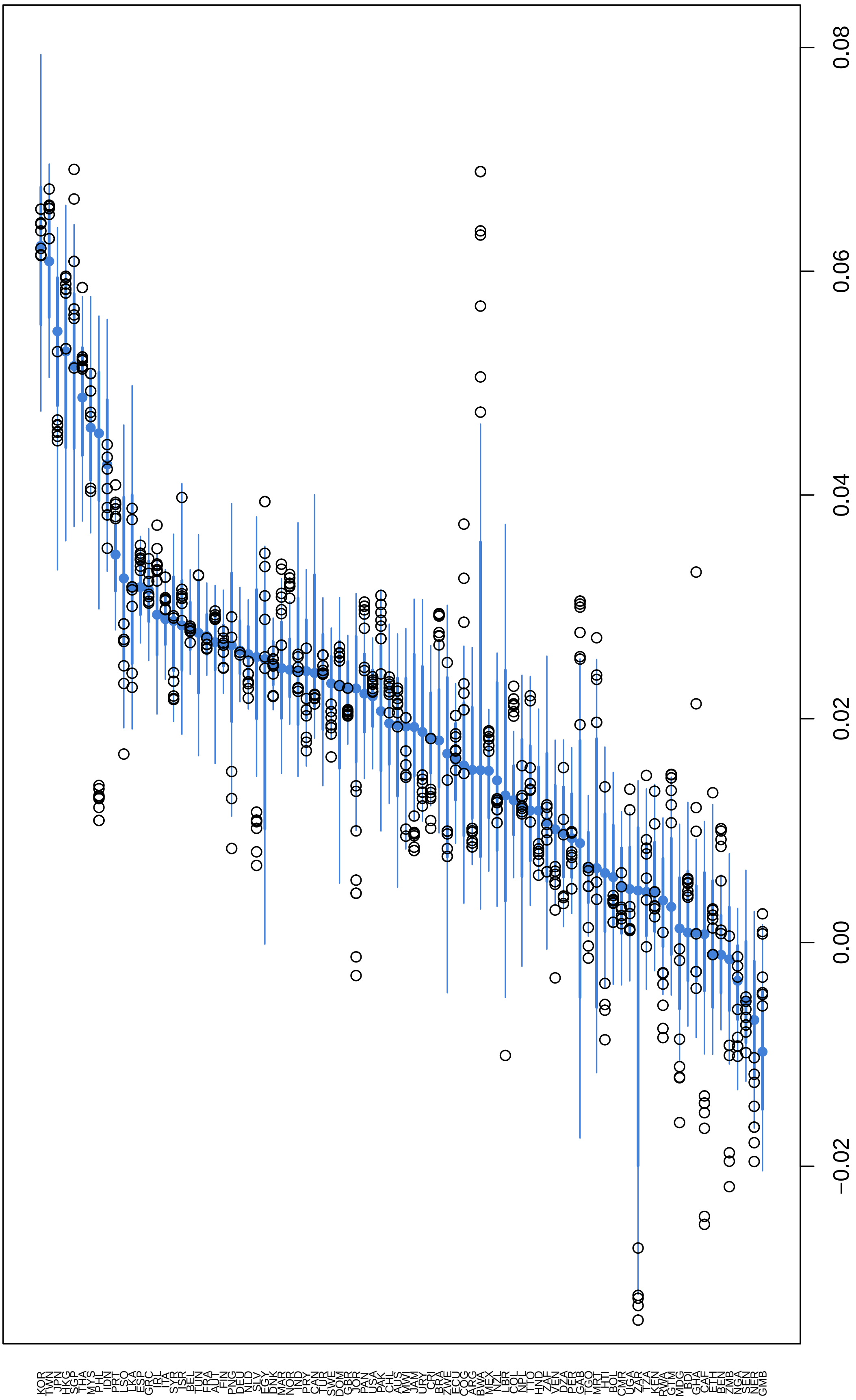
Note: The figure shows posterior variance of relative variance of per country measurement error on a log-scale. The dot indicates the median of the distributions; the thick line shows a 68% credible interval and the thin line shows a 95% credible interval

Figure 5: Relative variance of countries' model error



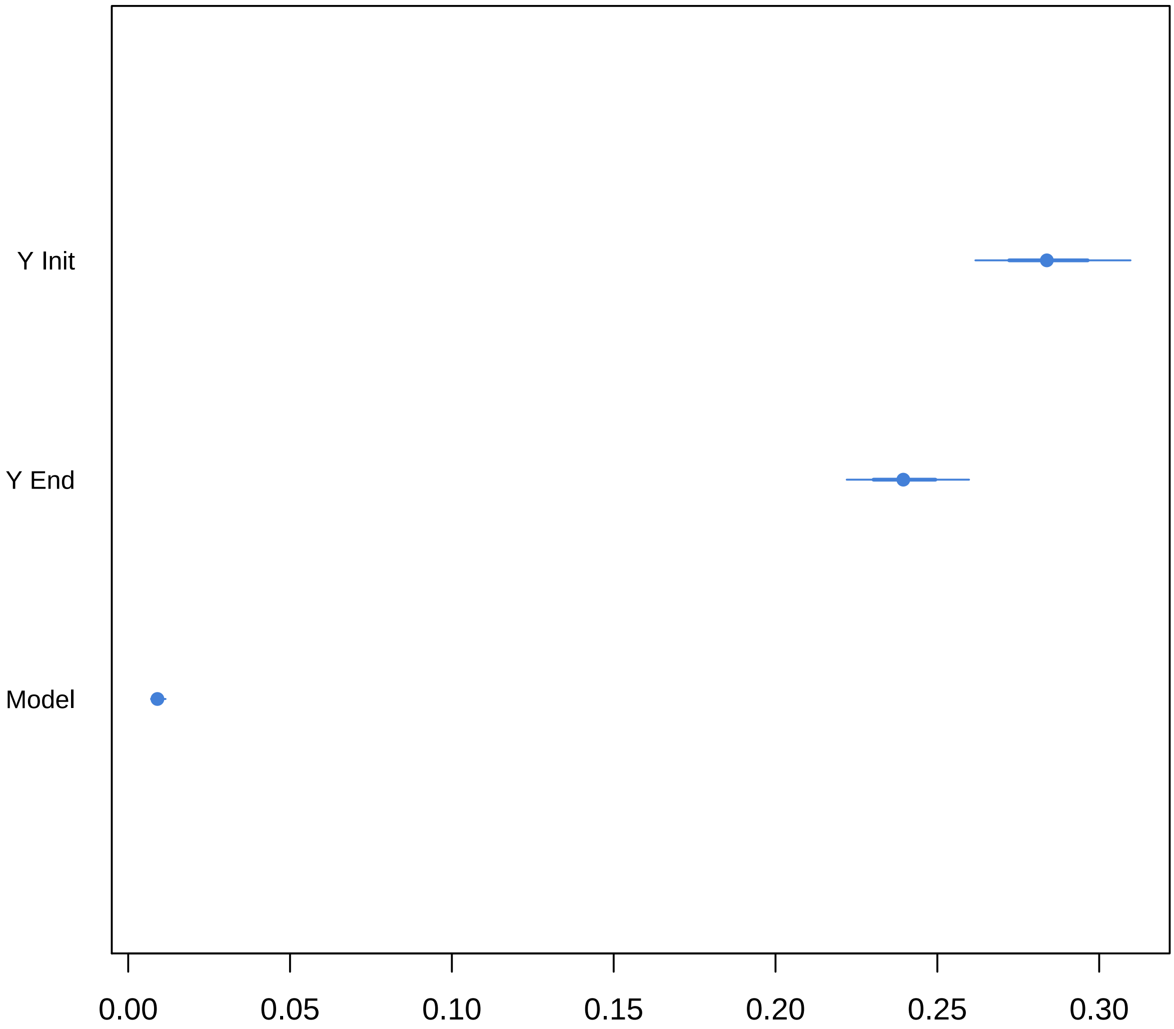
Note: The figure shows posterior variance of relative variance of per country model error. The dot indicates the median of the distributions; the thick line shows a 68% credible interval and the thin line shows a 95% credible interval

Figure 6: In-sample predicted, average annual growth rate and measures of realised growth rate



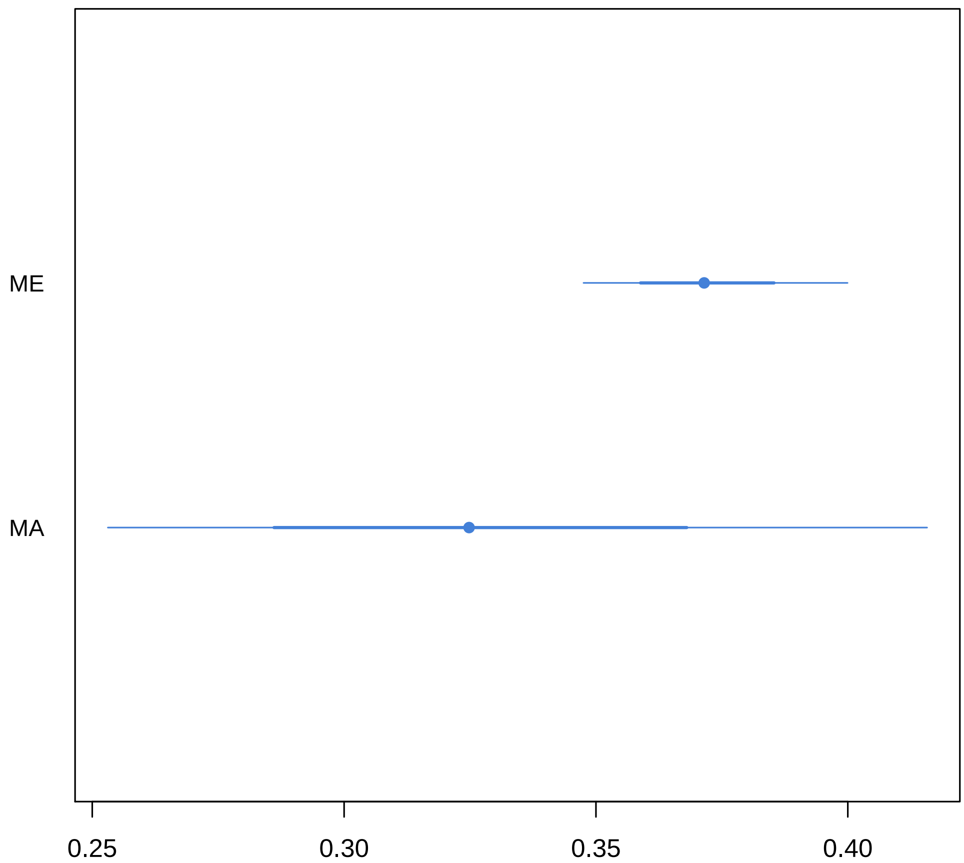
Note: The figure shows posterior predicted growth per country. The dot indicates the median of the distributions; the thick line shows a 68% credible interval and the thin line shows a 95% credible interval. Circles indicate growth as measured in each PWT vintage from 6.0 through 8.1.

Figure 7: Estimated standard deviations



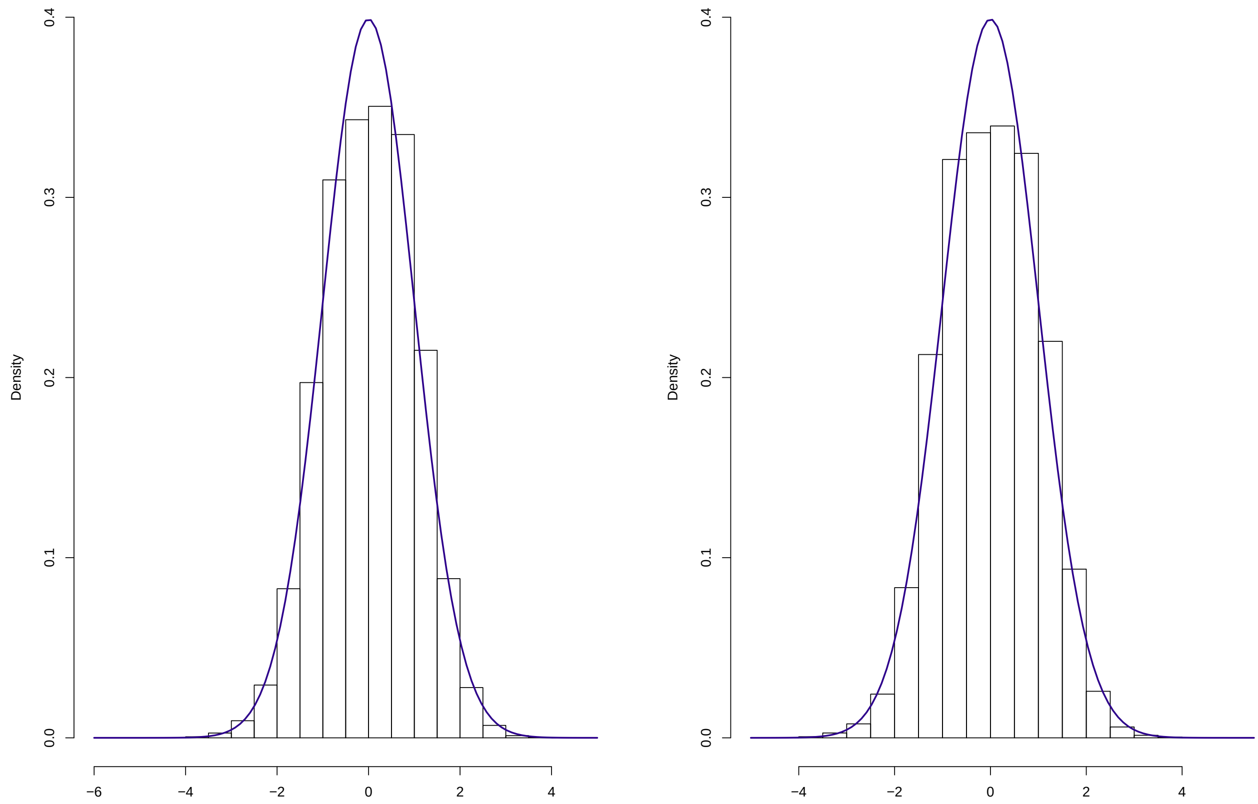
Note: Estimated standard errors for initial income σ^I, end income σ^E and model σ. The dot indicates the median of the distributions; the thick line shows a 68% credible interval and the thin line shows a 95% credible interval. The densities are from the full MEMA-model, with heteroscedastic model variances as well as heteriscedastic variance of measurement error across vintages and countries.

Figure 8: Comparison of measurement error model and model error



Note: Estimated standard errors for measurement error (ME) and model averaging (MA). The dot indicates the median of the distributions; the thick line shows a 68% credible interval and the thin line shows a 95% credible interval. The densities are from the full MEMA-model, with heteroscedastic model variances as well as heteroscedastic variance of measurement error across vintages and countries. The MA-bar shows the posterior distribution if the scaled deviation of model error, i.e. $(1996 - 1960)\sigma$. The ME-bar shows the posterior distribution of $\sqrt{{\sigma^{I}}^{2} + {\sigma^{E}}^{2}}$.

Figure 9: Residuals in measurement error model



Note: The figure shows histogram over residuals in the measurement error model, with dirichlet weighting of variances for both countries and vintages. Left panel shows residuals for initial income, and right panel for end of sample income. Blue curve shows the density of a standard normal distribution.

A Data

We use the covariates from `http://qed.econ.queensu.ca/jae/datasets/doppelhofer001/`. Table A.1 lists the short and full names of all variables. We also use data from the Penn World Tables, vintages 6.0, 6.1, 6.2, 6.3, 7.0, 7.1, 8.0 and 8.1. All vintages except 6.0 are available at the PWT-web site. Vintage 6.0 can be found in the online repository together with the covariates. We use all countries where we observe a full set of covariates. Tables A.2 and A.3 list all the income data we use in the analysis.

Table A.1: Variable shortnames

Short Name	Full Name	Short Name	Full Name
ABSLATIT	Absolute Latitude	LT100CR	Land Area Near Navigable Water
AIRDIST	Air Distance to Big Cities	MALFAL66	Malaria Prevalence
AVELF	Ethnolinguistic Fractionalization	MINING	Fraction GDP in Mining
BRIT	British Colony Dummy	MUSLIM00	Fraction Muslim
BUDDHA	Fraction Buddhist	NEWSTATE	Timing of Independence
CATH00	Fraction Catholic	OIL	Oil Producing Country Dummy
CIV72	Civil Liberties	OPENDEC1	Openness 1965-74
COLONY	Colony Dummy	ORTH00	Fraction Othodox
CONFUC	Fraction Confucian	OTHFRAC	Fraction Speaking Foreign Language
DENS60	Population Density	P60	Primary Schooling Enrollment
DENS65C	Population Coastal Density	PI6090	Average Inflation 1960-90
DENS65I	Interior Density	POP1560	Fraction Population Less than 15
DPOP6090	Population Growth Rate 1960-90	POP60	Population in 1960
EAST	East Asian Dummy	POP6560	Fraction Population Over 65
ECORG	Capitalism	PRIEXP70	Primary Exports
ENGFRAC	English Speahing Population	PRIGHTS	Political Rights
EUROPE	European Dummy	PROT00	Fraction Protestant
FERTLDC1	Fertility	RERD	Real Exchange Rate Distortions
GDE1	Defense Spending Share	REVCOUP	Revolutions and Coups
GEEREC1	Public Education Spending Share	SAFRICA	Sub-Saharan Africa Dummy
GGCFD3	Public Investment Share	SCOUT	Outward Orientation
GOVNOM1	Nominal Govertnment Share	SIZE60	Size of Economy
GOVSH61	Government Share of GDP	SOCIALIST	Socialist Dummy
GVR61	Government Consumption Share	SPAIN	Spanish Colony Dummy
H60	Higher Education Enrollment	SQPI6090	Square of Inflation 1960-90
HERF00	Religion Measure	TOT1DEC1	Terms of Trade Growth in 1960s
HINDU00	Fraction Hindu	TOTIND	Terms of Trade Ranking
IPRICE1	Investment Price	TROPICAR	Fraction of Tropical Area
LAAM	Latin American Dummy	TROPPOP	Fraction Population In Tropics
LANDAREA	Land Area	WARTIME	Fraction Spent in War 1960-90
LANDLOCK	Landlocked Country Dummy	WARTORN	War Particpation 1960-90
LHCPC	Hydrocarbon Deposits	YRSOPEN	Years Open 1950-94
LIFE060	Life Expectancy	ZTROPICS	Tropical Climate Zone

Table A.2: Income in 1960 in the Penn World Tables

	PWT6.0	PWT6.1	PWT6.2	PWT6.3	PWT7.0	PWT7.1	PWT8.0	PWT8.1
ARG	8.40	8.91	8.97	9.09	8.74	8.71	8.79	8.85
AUS	8.96	9.27	9.29	9.39	9.48	9.63	9.53	9.55
AUT	8.55	8.90	9.05	9.19	9.27	9.26	9.19	9.19
BDI	6.46	6.25	6.50	6.39	5.57	5.85	6.05	6.28
BEL	8.61	8.96	8.99	9.17	9.24	9.23	9.18	9.19
BEN	7.00	6.98	6.86	6.79	6.68	6.61	6.64	6.88
BOL	7.05	7.75	7.79	7.95	7.90	7.87	7.89	7.90
BRA	7.49	7.78	7.89	8.03	7.96	7.81	7.76	7.82
BWA	6.28	6.89		6.72	6.36	6.52	6.15	6.40
CAF	6.56	7.68		7.25	6.98	6.87	6.92	7.13
CAN	8.89	9.25	9.27	9.39	9.47	9.47	9.47	9.48
CHL	7.97	8.25	8.52	8.68	8.24	8.22	8.27	8.33
CMR	6.46	7.43	7.57	7.55	7.12	7.26	7.23	7.45
COG	7.02	6.11	6.86	7.06	6.67	6.91	7.14	7.30
COL	7.43	7.83	7.94	8.06	7.82	7.99	7.94	8.02
CRI	7.65	8.15	8.41	8.52	8.53	8.51	8.12	8.11
DEU	8.79						9.32	9.33
DNK	8.82	9.30	9.34	9.32	9.40	9.36	9.36	9.38
DOM	7.09	7.45	7.66	7.76	7.76	7.75	7.59	7.59
DZA	7.45	7.90	8.27	8.39	8.31	8.31		
ECU	7.29	7.59	7.76	7.92	7.94	7.86	7.77	7.82
EGY	6.70	7.30	7.28	7.24	6.94	6.83	6.70	6.90
ESP	8.05	8.45	8.51	8.68	8.75	8.75	8.70	8.70
ETH	5.55	6.27	5.99	6.67	5.96	5.95	6.17	6.38
FIN	8.57	8.91	8.95	9.07	9.11	9.11	9.03	9.05
FRA	8.67	8.97	9.06	9.15	9.22	9.23	9.15	9.15
GAB	7.49	8.00	8.79	8.13	8.41	8.50	8.39	8.68
GBR	8.83	9.18	9.25	9.33	9.46	9.32	9.38	9.38
GHA	6.80	6.72	5.92	6.39	6.40	7.16	7.35	7.59
GMB	6.40	6.86	6.63	7.27	6.87	7.02	7.37	7.62
GRC	7.65	8.33	8.33	8.69	8.73	8.63	8.57	8.56
GTM	7.41	7.76	7.82	8.01	8.00	7.99	7.59	7.58
HKG	7.72	8.02	8.09	8.26	8.12	8.10	8.42	8.59
HND	6.95	7.44	7.45	7.73	7.72	7.71	7.57	7.55
HTI	6.83	6.97		7.54	7.55	7.32		
IDN	6.46	6.87	7.00	6.94	6.55	6.50	6.61	6.70
IND	6.64	6.73	6.77	6.86	6.57	6.58	6.60	6.65
IRL	8.11	8.56	8.59	8.80	8.86	8.89	8.96	9.00
ISR	8.15	8.59	8.78	8.85	8.88	8.85	8.52	8.92
ITA	8.43	8.83	8.87	9.02	9.09	9.07	8.98	8.99
JAM	7.48	7.89	8.13	8.68	8.64	8.77	8.09	8.06
JOR	7.06	7.74	8.34	8.42	7.91	7.91	7.96	8.13
JPN	7.99	8.45	8.44	8.61	8.72	8.63	8.39	8.64
KEN	6.49	6.66	7.06	7.50	6.92	6.93	6.89	7.15
KOR	6.81	7.36	7.34	7.46	7.50	7.42	7.38	7.40
LBR	6.58							
LKA	7.14	7.20	6.76	7.19	6.64	6.41	6.67	6.93
LSO	5.75	6.58	6.39	6.51	6.01	5.98	5.98	6.42
MAR	6.70	7.19	7.18	7.33	6.60	6.58	6.82	7.08
MDG	7.08	7.12	7.14	6.89	6.73	6.96	7.11	7.34
MEX	7.95	8.29	8.21	8.39	8.43	8.51	8.52	8.53
MRT	6.66	7.00		6.79	6.36	6.43	6.77	7.08
MWI	5.94	6.05	6.13	6.34	5.85	5.80	5.69	5.92

MYS	7.26	7.67	7.51	7.69	7.31	7.28	7.39	7.63
NER	6.28	7.39	7.06	7.18	6.62	6.76	6.85	7.09
NGA	6.34	6.94	7.00	7.33	7.33	7.35	7.27	7.48
NLD	8.71	9.13	9.26	9.39	9.49	9.51	9.41	9.43
NOR	8.63	9.02	9.15	9.37	9.41	9.43	9.65	9.70
NPL	6.44	6.68	6.71	6.98	6.46	6.29	6.36	6.45
NZL	8.98	9.35	9.40	9.42	9.54	9.57	9.46	9.46
PAK	6.46	6.46	6.69	6.81	6.60	6.43	6.58	6.71
PAN	7.36	7.76	7.83	7.68	7.69	7.67	7.90	7.89
PER	7.61	8.04	8.02	8.20	8.23	8.15	8.28	8.33
PHL	7.03	7.61	7.62	7.69	7.19	7.29	7.48	7.69
PNG	7.12	7.71		6.76	6.80	7.28		
PRT	7.53	8.14	8.21	8.31	8.30	8.34	8.38	8.37
PRY	7.07	7.80	7.83	7.86	7.52	7.49	7.60	7.63
RWA	6.29	6.85	6.93	7.14	6.75	6.63	6.67	6.65
SEN	6.95	7.51	7.49	7.79	7.26	7.25	7.36	7.60
SGP	7.41	7.73	8.35	8.33	8.37	8.39	8.06	8.22
SLV	7.26	8.10	8.00	8.14	8.13	8.12	5.47	5.37
SWE	8.93	9.22	9.30	9.39	9.50	9.57	9.37	9.38
SYR	7.36	7.24	6.72	6.99	7.38	7.34	7.33	7.51
TGO	5.91	6.80	6.73	6.73	6.64	6.56	6.59	6.85
THA	6.85	7.02	6.99	7.08	6.88	6.87	6.65	6.78
TTO	8.64	8.36	8.72	8.83	8.77	9.01	8.60	8.65
TUN	7.00						7.18	7.47
TUR	7.39	7.90	7.72	7.81	8.09	8.07	8.16	8.16
TWN	7.14	7.29	7.31	7.37	7.52	7.53	7.63	7.78
TZA	5.77	5.95	6.21	6.17	6.19	5.96	6.30	6.41
UGA	6.39	6.32	6.77	6.81	6.49	6.49	6.57	6.66
URY	8.29	8.67	8.71	8.79	8.47	8.52	8.53	8.60
USA	9.20	9.43	9.48	9.60	9.65	9.64	9.62	9.62
VEN	8.75	8.96	8.69	9.10	8.80	8.85	8.90	8.98
ZAF	7.69	8.50	8.49	8.59	8.26	8.28	8.46	8.72
ZAR	6.19	6.87		7.51	7.00	6.54		
ZMB	6.87	7.06	6.71	7.71	7.50	7.22	7.25	7.47
ZWE	6.90	7.06	7.73	7.52	5.17	5.66	8.25	8.25

Table A.3: Income in 1996 in the Penn World Tables

	PWT6.0	PWT6.1	PWT6.2	PWT6.3	PWT7.0	PWT7.1	PWT8.0	PWT8.1
ARG	8.77	9.28	9.3	9.41	9.1	9.06	9.1	9.16
AUS	9.74	10.04	10.05	10.2	10.3	10.32	10.27	10.29
AUT	9.59	9.97	10.09	10.25	10.31	10.31	10.23	10.24
BDI	6.63	6.45	6.64	6.58	5.77	6.04	6.2	6.43
BEL	9.58	9.96	10	10.18	10.24	10.24	10.18	10.19
BEN	7.04	7.01	7.06	7.14	6.99	6.94	7	7.24
BOL	7.17	7.88	7.94	8.08	8.04	8.01	7.95	7.96
BRA	8.55	8.84	8.85	9.01	8.95	8.81	8.81	8.87
BWA	7.99	8.71	8.72	8.77	8.64	8.81	8.63	8.88
CAF	5.65	6.8	6.65	6.76	6.38	6.32	6.4	6.61
CAN	9.69	10.05	10.03	10.18	10.26	10.26	10.25	10.26
CHL	8.81	9.1	9.26	9.47	9.06	9.05	9.08	9.13
CMR	6.55	7.55	7.67	7.73	7.35	7.32	7.3	7.52
COG	7.57	7.46	7.69	8.23	7.7	7.71	7.89	8.05
COL	8.25	8.62	8.71	8.82	8.56	8.71	8.71	8.78
CRI	8.01	8.55	8.89	9.01	8.99	8.98	8.78	8.77
DEU	9.72	9.96	10.05	10.19	10.26	10.26	10.25	10.26
DNK	9.68	10.09	10.13	10.21	10.3	10.3	10.27	10.29
DOM	8	8.28	8.58	8.71	8.69	8.68	8.49	8.49
DZA	7.85	8.46	8.61	8.51	8.45	8.46		
ECU	7.84	8.26	8.42	8.54	8.53	8.47	8.5	8.55
EGY	7.58	8.22	8.32	8.36	8.15	8.08	8.12	8.32
ESP	9.32	9.65	9.72	9.93	9.99	10	9.93	9.93
ETH	5.66	6.31	6.47	6.78	6.03	6.04	6.13	6.34
FIN	9.55	9.88	9.83	9.95	10.04	10.07	10.04	10.05
FRA	9.62	9.91	10	10.09	10.18	10.19	10.13	10.13
GAB	8.49	9.09	9.49	9.21	9.33	9.41	9.49	9.78
GBR	9.56	9.91	9.99	10.08	10.2	10.14	10.12	10.12
GHA	6.65	7.16	7.11	7.15	6.76	7.19	7.26	7.5
GMB	6.29	6.95	6.67	7.11	6.67	7.04	7.2	7.45
GRC	8.88	9.45	9.42	9.79	9.84	9.82	9.73	9.72
GTM	7.86	8.25	8.21	8.55	8.55	8.53	8.12	8.11
HKG	9.86	10.17	10.21	10.35	10.22	10.2	10.33	10.5
HND	7.21	7.66	7.73	8.04	8.01	8.01	7.83	7.81
HTI	6.52	7.47	7.54	7.41	7.33	7.12		
IDN	8.06	8.27	8.27	8.4	8.11	8.02	7.99	8.08
IND	7.53	7.66	7.69	7.73	7.38	7.4	7.42	7.47
IRL	9.45	9.83	9.79	10.02	10.02	10.09	10.18	10.21
ISR	9.24	9.71	9.92	9.96	9.98	9.97	9.96	9.96
ITA	9.5	9.93	9.94	10.12	10.19	10.18	10.15	10.16
JAM	7.89	8.24	8.44	9.02	8.99	9.13	8.39	8.35
JOR	7.56	8.23	8.23	8.38	8.27	8.11	8.12	8.29
JPN	9.67	10.09	10.07	10.25	10.33	10.3	10.29	10.3
KEN	6.87	7.15	7.17	7.58	7.04	7.03	7.05	7.31
KOR	9.1	9.57	9.55	9.78	9.73	9.73	9.74	9.76
LBR	6.21		5.23	5.1	5.12	5.18	5.04	5.29
LKA	7.96	8.07	8.16	8.27	7.77	7.77	7.82	8.08
LSO	6.71	7.19	7.37	7.34	6.98	6.87	7.01	7.44
MAR	7.83	8.24	8.25	8.45	7.82	7.78	7.77	8.04
MDG	6.5	6.68	6.74	6.87	6.68	6.65	6.68	6.91
MEX	8.58	8.9	8.85	9.07	9.1	9.16	9.2	9.21
MRT	6.85	7.14	7.24	7.65	7.21	7.41	7.48	7.79
MWI	6.28	6.58	6.7	6.96	6.39	6.17	6.41	6.64

MYS	8.72	9.12	9.22	9.46	9.14	9.11	9.08	9.32
NER	5.63	6.68	6.69	6.73	6.2	6.24	6.26	6.49
NGA	6.26	6.83	6.95	7.11	7.03	6.99	6.94	7.15
NLD	9.58	9.97	10.04	10.22	10.35	10.32	10.32	10.33
NOR	9.78	10.12	10.3	10.52	10.6	10.61	10.8	10.85
NPL	7.01	7.15	7.17	7.4	6.9	6.71	6.79	6.88
NZL	9.37	9.78	9.85	9.89	9.99	9.99	9.92	9.92
PAK	7.32	7.58	7.78	7.88	7.61	7.46	7.55	7.68
PAN	8.24	8.64	8.84	8.78	8.74	8.74	8.98	8.97
PER	7.97	8.4	8.31	8.47	8.48	8.43	8.45	8.5
PHL	7.5	8.05	8.11	8.16	7.66	7.8	7.87	8.09
PNG	7.42	8.17	8.36	7.81	7.78	7.83		
PRT	9.01	9.51	9.63	9.72	9.71	9.73	9.74	9.74
PRY	8.02	8.58	8.56	8.47	8.17	8.15	8.34	8.38
RWA	6.32	6.71	6.83	6.83	6.48	6.43	6.57	6.55
SEN	6.71	7.3	7.21	7.43	7.09	7.06	7.09	7.33
SGP	9.9	10.12	10.19	10.35	10.41	10.4	10.25	10.41
SLV	7.55	8.35	8.42	8.51	8.53	8.51	5.86	5.76
SWE	9.7	9.95	9.99	10.06	10.2	10.17	10.11	10.12
SYR	8.41	8.29	7.59	7.78	8.17	8.12	8.17	8.35
TGO	5.85	6.79	6.78	6.96	6.82	6.75	6.83	7.09
THA	8.7	8.87	8.84	8.96	8.76	8.74	8.76	8.89
TTO	9.41	9.16	9.28	9.32	9.29	9.4	9.09	9.14
TUN	8.18	8.67	8.7	8.78	8.28	8.45	8.36	8.66
TUR	8.32	8.77	8.59	8.7	8.96	8.93	9.09	9.09
TWN	9.5	9.65	9.68	9.79	9.88	9.87	9.9	10.04
TZA	5.9	6.15	6.2	6.45	6.52	6.5	6.61	6.72
UGA	6.89	6.75	6.81	6.86	6.58	6.61	6.62	6.7
URY	8.73	9.14	9.25	9.31	9.01	9.03	9.01	9.08
USA	10.02	10.28	10.31	10.44	10.45	10.45	10.46	10.46
VEN	8.86	8.84	8.92	9.28	9.04	9.07	9.09	9.18
ZAF	8.13	8.91	8.93	8.97	8.61	8.61	8.69	8.95
ZAR	5.05	5.74	6.19	6.29	5.83	5.56		
ZMB	6.2	6.73	6.73	6.93	6.8	6.85	6.92	7.14
ZWE	7.25	7.96	8.03	8.05	5.53	6.02	8.53	8.53

B The full MEMA-model

We estimate the model using JAGS, which implies that we let JAGS decide on the exact choice of sampling strategy. To see how the model works, the following discussion highlights the dependencies of the parameters and the data.

First, the following are the priors for the parameter which do not depend on data or other parameters:

$$\begin{aligned}
\alpha &\sim U[-\infty,\infty] && \text{Intercept}\\
a_2,...,a_8 &\sim U[-\infty,\infty] && \text{Level shift of vintages. } a_1 \text{ fixed to zero.}\\
y_1^I,...y_N^I &\sim U[-\infty,\infty] && \text{True initial GDP pc}\\
\sigma &\sim U(0,1000) && \text{Model error}\\
\sigma^I &\sim U(0,1000) && \text{Std.d. initial GDP}\\
\sigma^E &\sim U(0,1000) && \text{Std.d. end GDP}\\
\left(\omega_1^V \cdots \omega_V^V\right)/V &\sim Dirichlet(\Omega_1^V,\cdots,\Omega_V^V) && \text{Relative variance of vintages}\\
\left(\omega_1^N \cdots \omega_N^N\right)/N &\sim Dirichlet(\Omega_N^N,\cdots,\Omega_N^N) && \text{Relative variance of countries}\\
\left(\omega_1 \cdots \omega_N\right)/N &\sim Dirichlet(\Omega_1,\cdots,\Omega_N) && \text{Relative variance of model error}\\
\gamma_1,...,\gamma_K &\sim Bern(7/67) && \text{Variable inclusion}
\end{aligned} \tag{23}$$

Note that we have only made a draw of initial income, and not end of period income. Conditional on a draw of all these parameters, we can take the draw of initial income, and add it to the set of potential explanatory variables $\mathbf{X}$. Let $M = \sum_{k=1}^{K} \gamma_k 2^{k-1}$ denote a unique model, and let $\mathbf{X_M}$ denote the subset of variables in X that are included in model M, and thereby have a corresponding $\gamma_k = 1$. We can then draw coefficients for included variables from the from the so-called Zellner g-prior:

$$\beta_\gamma|\sigma, M \sim N\left(0, \sigma^2\left(g_0 \mathbf{X_M}'\mathbf{X_M}\right)^{-1}\right) \tag{24}$$

With a draw of coefficients, we can find the model estimated growth rate per country. However, we scale up the annual growth rate by the time difference between the start and end of our sample, as well as adding initial income. This gives us model predicted level of income at the end of the sample:

$$\mu_i \equiv \left(\alpha + \sum_{k\in K} x_{k,i}\beta_k\gamma_k\right)(T_1 - T_0) + y_i^I \tag{25}$$

There are two distributions that link our priors to the data, namely, the *measurements* of initial and end of period income in all vintages. For initial income this is now a univariate normal.

$$y_{v,i}^I \sim N\left(\alpha_v + y_i^I, {\sigma_{v,i}^I}^2\right), \forall v, i \tag{26}$$

Next, we fit the model to end of period income. However, we must take into account the model error is common across all country observations. This implies that the vector of observed end of period income for a given country across vintages is a multivariate normal:

$$\begin{bmatrix} y^E_{1,i} \\ \vdots \\ y^E_{V,i} \end{bmatrix} \sim N\left(\begin{bmatrix} a_1 + \mu_i \\ \vdots \\ a_V + \mu_i \end{bmatrix}, \begin{bmatrix} \tilde{\sigma}_i^2 + \sigma^2_{1,i} & \cdots & \tilde{\sigma}_i^2 \\ \vdots & \ddots & \vdots \\ \tilde{\sigma}_i^2 & \cdots & \tilde{\sigma}_i^2 + \sigma^2_{V,i} \end{bmatrix} \right), \forall i \tag{27}$$

Where $\tilde{\sigma_i}^2 = (T_1 - T_0)^2 \sigma^2$. We run several MCMC-chains. All parameters are initialised with random draws from the priors, with the exception of the Dirichlets $\left(\omega_1^V \cdots \omega_V^V\right)/V$, $\left(\omega_1^N \cdots \omega_N^N\right)/N$ and $\left(\omega_1 \cdots \omega_N\right)/N$ and coefficients β. The relative variance parameters are all initialised to unity, as random draws reduce the numerical stability of the initial guess. The β coefficients are all initialised to zero. We use the point scale reduction factor, also called $\hat{R}$, to assess convergence. The chains have converged in the sense that all parameters have a $\hat{R}$ smaller than 1.1 (Gelman and Shirley, 2011).[22] Figure B.1 shows the MEMA-model graphically.

C Alternative specification of the MEMA-model

C.1 Specifications

C.1.1 Random g-prior and prior model size

In the baseline MEMA-model, we assume the prior inclusion probability is given by 7/67. Following Brown, Vannucci and Fearn (1998), we relax this assumption, by replacing the prior distribution of variable inclusion parameters to the following:

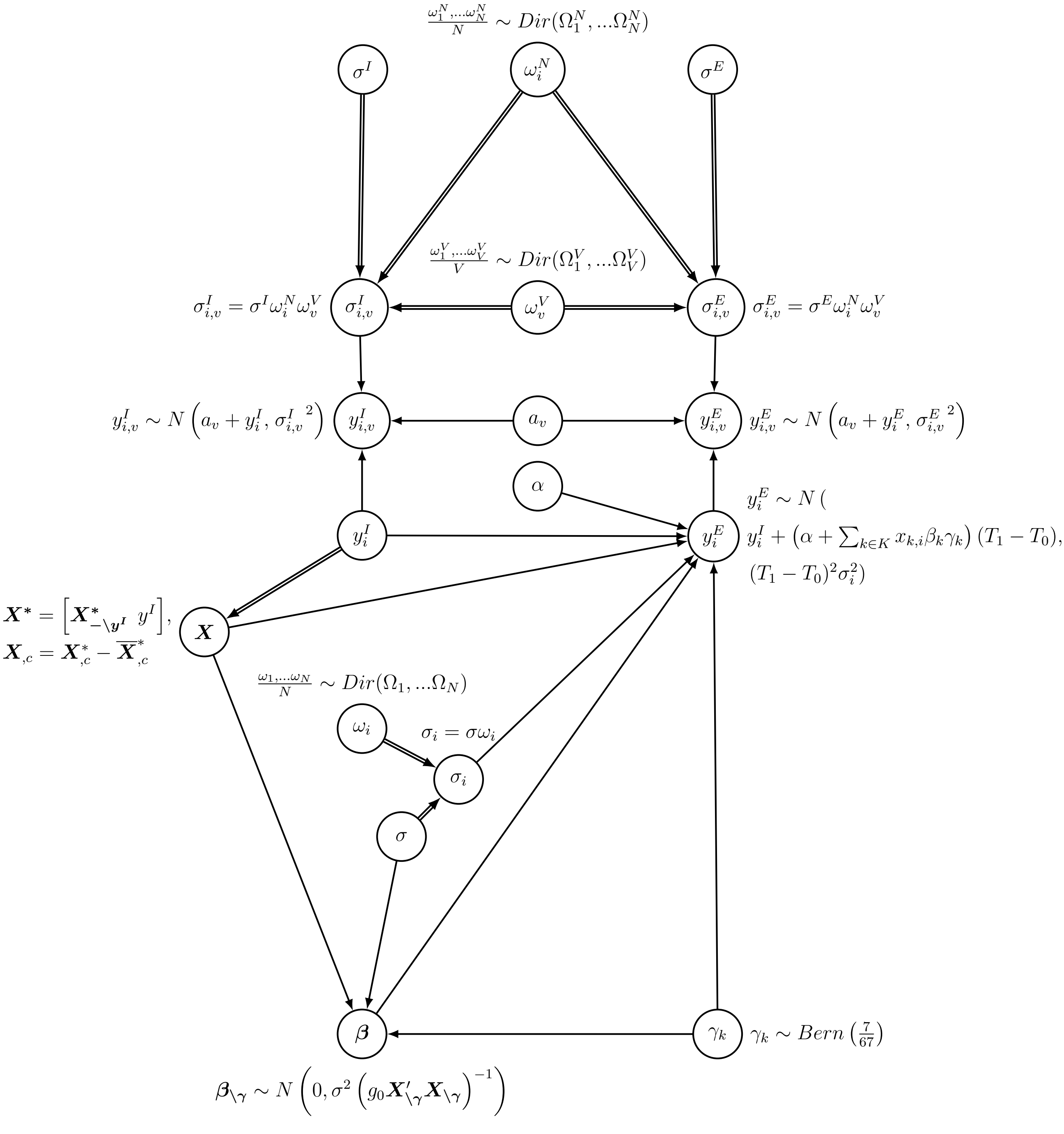
$$\begin{aligned} \theta &\sim Beta\left(1, \frac{60}{7}\right) \\ \gamma_k &\sim Bernoulli\left(\theta\right) \end{aligned} \tag{28}$$

This gives a prior expected model size equal to 7/67 as before, however, allows for another layer of uncertainty.[23]

[22]One iteration takes around 1.3 seconds on a regular laptop. We use several computers, and run chains in parallel on each computer to produce the results in this paper. It takes a bit less than a week of computing time to produce a usable MCMC-chain.

[23]See Ley and Steel (2009) for a discussion.

Figure B.1: Graphical representation of the MEMA-modell



Note: The figure shows a graphical representation of the MEMA-model. Straight arrorws indicate a stochastic dependence, hollow arrows denote a deterministic transformation. Uniform priors are not shown. The notation $\boldsymbol{X}^* = \left[\boldsymbol{X}^*_{-\backslash \boldsymbol{y^I}} \; y^I\right]$, $\boldsymbol{X}_{,c} = \boldsymbol{X}^*_{,c} - \overline{\boldsymbol{X}}^*_{,c}$ denotes that we add the column of "true" initial income to the matrix of covariates $\boldsymbol{X}^*$, and thereafter demean each column. Further $\boldsymbol{X}_{\backslash\gamma}$ indicates the subset of columns of $\boldsymbol{X}$ with a corresponding γ_k equal to one.

Another extension is to allow for more flexibility in the Zellner g-prior. In the benchmark MEMA model, we use $g_0 = N^{-1}$. However, following Liang et al. (1998)[24], this can be treated as a parameter as opposed to a constant with prior given by a Beta distribution

$$\frac{1}{1+g_0} \sim Beta\left(1, N^{-1}\right) \tag{29}$$

Which implies that $E\left[\frac{1}{1+g_0}\right] = \frac{1}{1+N^{-1}}$. This is within the range Liang et al. (1998) calls "reasonable", although it is close to being an improper prior.

C.1.2 Reduced data set

We also consider estimating the MEMA-model on a reduced data set. If there is correlation of measurement errors within main vintages, treating sub-vintages as independent will imply that we are understating the uncertainty of the latent measures of growth. We therefore estimate the model on one sub-vintage per main vintage only, where we use the latest subvintage within each main vintage. We are thus estimating the model on vintages PWT 6.3, 7.1 and 8.1. Note, however, that this implies that one country, Liberia, drops out as initial income is not observed in either of these vintages.

C.1.3 Geweke-robust model errors

Geweke (1993) propose a different parametric approach to the Dirichlet-weighting of country variances in the growth model. In particular, the Geweke-approach use the following setup:

$$\begin{aligned} \nu &\sim exp\left(25^{-1}\right) \\ \nu/\sigma_i &\sim \boldsymbol{\chi}\left(\nu\right) \end{aligned} \tag{30}$$

This is equivalent to interpreting the model errors as draw from a T-distribution with ν degrees of freedom.

C.2 Results

Table C.1 shows the results from these extensions, as well as repeating the results from the baseline MEMA-model in the leftmost column. The second column column shows PIPs from the extended MEMA-model with random prior model size

[24]Note that Liang et al. (1998) discuss the distribution of the *inverse* of g_0.

and Zellner factor g_0. First, we can note that the posterior mean of the hyper-incusion probability θ is .15, which gives a larger model size compared to baseline MEMA. Furthemore, the posterior mean of the Zellner factor g_0 is .04, slightly higher than the constant provided in baseline MEMA at $N^{-1} \approx .01$. It is therefore not surprising that this extension flags up more variables compared to baseline MEMA,where now additional six variable have a PIP over 7/67.

The third column shows results when estimating the model on a reduced data set. Here we can note that one marginal variable, Europe, has a PIP slightly below the prior. Furthermore, three additional variables have a PIP exceeding the prior.

The fourth column shows PIPs in with Geweke-robust errors. The posterior mean of ν is 2.64, which implies that the growth process has very fat tails. Apart from that, all variables from baseline MEMA still have a PIP over 7/67, in addition to two variables that now have a PIP marginally above the prior.

Table C.1: Posterior inclusion probabilies in measurement error models

	Benchmark MEMA	Random model size and g-shrinkage	Reduced data	Geweke-robust
InitLGDP	0.998	0.995	1.000	0.999
P60	0.917	0.950	0.909	0.889
EAST	0.884	0.905	0.921	0.944
TROPICAR	0.477	0.586	0.567	0.418
AIRDIST	0.411	0.537	0.537	0.432
SAFRICA	0.345	0.299	0.148	0.389
DENS60	0.336	0.557	0.595	0.229
IPRICE1	0.321	0.423	0.424	0.230
LIFE060	0.302	0.349	0.396	0.366
DENS65C	0.263	0.371	0.330	0.225
PRIEXP70	0.225	0.251	0.180	0.244
LAAM	0.218	0.171	0.084	0.246
MUSLIM00	0.199	0.239	0.182	0.218
MALFAL66	0.170	0.130	0.125	0.274
CONFUC	0.169	0.192	0.137	0.158
LANDLOCK	0.129	0.178	0.291	0.289
OPENDEC1	0.127	0.190	0.255	0.170
EUROPE	0.111	0.106	0.095	0.169
SCOUT	0.097	0.206	0.100	0.141
RERD	0.094	0.171	0.132	0.082
TROPPOP	0.077	0.119	0.169	0.074
FERTLDC1	0.077	0.109	0.089	0.071
OTHFRAC	0.069	0.110	0.080	0.105
YRSOPEN	0.058	0.098	0.120	0.065
SPAIN	0.058	0.062	0.033	0.075
BUDDHA	0.058	0.081	0.044	0.051
PRIGHTS	0.054	0.101	0.091	0.040
LHCPC	0.042	0.129	0.067	0.069
ABSLATIT	0.033	0.060	0.035	0.057
AVELF	0.032	0.064	0.037	0.037
REVCOUP	0.031	0.071	0.043	0.034

SIZE60	0.026	0.054	0.036	0.043
MINING	0.026	0.075	0.047	0.038
BRIT	0.026	0.070	0.027	0.030
DPOP6090	0.025	0.058	0.025	0.036
GOVSH61	0.024	0.054	0.026	0.037
POP6560	0.023	0.054	0.027	0.042
PI6090	0.023	0.048	0.026	0.031
ZTROPICS	0.022	0.055	0.029	0.031
GOVNOM1	0.022	0.062	0.031	0.042
COLONY	0.022	0.059	0.114	0.036
GVR61	0.021	0.049	0.022	0.031
SQPI6090	0.020	0.045	0.020	0.030
PROT00	0.019	0.043	0.017	0.033
OIL	0.019	0.044	0.020	0.047
HINDU00	0.019	0.046	0.017	0.031
NEWSTATE	0.018	0.046	0.033	0.031
SOCIALIST	0.017	0.042	0.018	0.027
GDE1	0.017	0.045	0.019	0.030
WARTORN	0.016	0.045	0.017	0.025
TOT1DEC1	0.016	0.044	0.025	0.031
POP1560	0.016	0.042	0.018	0.025
CATH00	0.016	0.041	0.018	0.031
TOTIND	0.015	0.044	0.017	0.025
LT100CR	0.015	0.044	0.022	0.025
LANDAREA	0.015	0.043	0.021	0.026
ECORG	0.015	0.039	0.015	0.021
POP60	0.014	0.037	0.016	0.024
HERF00	0.014	0.037	0.016	0.022
GGCFD3	0.014	0.039	0.017	0.022
CIV72	0.014	0.037	0.015	0.024
WARTIME	0.013	0.037	0.016	0.022
H60	0.012	0.040	0.015	0.019
GEEREC1	0.012	0.033	0.016	0.021
ENGFRAC	0.012	0.033	0.013	0.020
DENS65I	0.012	0.035	0.013	0.021
ORTH00	0.011	0.031	0.012	0.017

Note: Posterior inclusion probabilies in measurement error models. The first column repeats the PIP from the baseline MEMA-model estamated on all eight PWT-vintages. The second column shows PIPs from the extended MEMA-model with random prior model size and Zellner-factor g_0, as explained in section C.1.1. The third column shows PIPs from the MEMA-model with Geweke-robust growth model errors, as opposed to the Dirichlet-robust errors in baseline MEMA. This extension in explained in section C.1.3. Finally, the fourth column shows PIPs from the baseline MEMA-model estimated on only a subset of the data, namely PWT 6.3, 7.1 and 8.1. Cells with values greater than 7/67 are colored green. Table is sorter by leftmost column.