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The local Solow growth model

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Abstract

This paper generalizes the empirical analysis of the Solow growth model to account for country-specific heterogeneity. This generalization relaxes the assumption made in bulk of empirical growth studies that all countries possess identical aggregate production functions. Our empirical results indicate that there is substantial country-specific heterogeneity in the Solow parameters-heterogeneity that is associated with differences in initial income. We therefore conclude that the explanatory value of the Solow growth model is substantially enhanced by allowing for country-specific, i.e. local, production functions. © 2001 Elsevier Science B.V. All rights reserved.

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1. Introduction

This paper is designed to contribute to our understanding of the capacity of the Solow growth model to explain cross-country growth patterns. In a seminal paper, Mankiw et al. (1992) demonstrated that the Solow model has impressive empirical explanatory power. We mean this in two respects. First, the empirical version of the model produces parameter estimates whose signs and

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statistical significance are predicted by the associated theory. Second, by conventional goodness-of-fit measures, the Solow model 'explains' over 40% of the cross-country variation in growth rates. For these reasons, the Solow growth model has become the baseline from which a very large part of the new empirical growth literature has developed. Typically, the evaluation of a new causal determinant of growth consists of adding an empirical proxy of the determinant to the basic Solow regression.

As a careful reading of Solow (1956, 1970) makes clear, the stylized facts for which this model was developed were not interpreted as universal properties for every country in the world. In contrast, the current literature imposes very strong homogeneity assumptions on the cross-country growth process as each country is assumed to have an identical (and Cobb–Douglas) aggregate production function. This is surprising, as modern growth theory, suggests that different countries should be described by distinct aggregate production functions, in the sense that the new causal theories of growth will presumably affect the aggregate production function of countries rather than constitute additive components of the growth process. To us, this suggests that for a given parsimonious growth regression, whether it is based on the Solow model or some other theory, one should explicitly account for parameter heterogeneity. In this paper, we provide some estimates of a local generalization of the Solow growth model. By local, we refer to the idea that a Solow model applies to each country, but the model's parameters vary across countries. In particular, we allow these parameters to vary according to a country's initial income. While this restricts the form of parameter heterogeneity, it is an appealing way to generalize current empirical practice, in that new growth theories such as Azariadis and Drazen (1990) suggest that initial conditions can index countries so as to produce behaviors that, near a steady state, are similar to that predicted by the Solow model. Our approach also provides a simple way of evaluating the local goodness-of-fit of the Solow model.

Our findings of parameter heterogeneity have several possible interpretations. First, our results may simply imply that the identical Cobb–Douglas technology assumption is unsatisfactory. Duffy and Papageorgiou (1999) find evidence in support of an alternative production function rather than the standard Cobb–Douglas specification; at least qualitatively we are consistent with this finding. Second, it may be the case that the parameter heterogeneity we find is induced by omitted growth determinants. Third, our results may indicate general nonlinearities in the growth process. Evidence of this has already been found by Durlauf and Johnson (1995), Desdoigts (1999), Kourtellos (2000) and Rappaport (2000) among others. This range of possible explanations does not mean, of course, that additional work cannot discriminate between them. This paper demonstrates the importance of explicitly accounting for parameter heterogeneity in evaluating how the Solow growth model approximates cross-country data.

2. A local generalization of the Solow growth model

Much of the new empirical growth literature is based on the regression

$$g_i = \gamma' \mathscr{X}_i + \varepsilon_i, \tag{1}$$

where g_i is real per capita growth in economy i over a given time period, $\mathscr{X}_i$ is a p-dimensional vector of country-specific controls which includes a constant and ε_i is an unexplained residual. When this regression represents the growth process implied by the standard Solow model, the controls consist of a constant, the log of $y_{i,0}$, the real per capita income of the country at the beginning of the period over which growth is measured, the log of $s_{k,i}$, the savings rate for physical capital accumulation out of real output, the log of $s_{h,i}$, the analogous savings rate for human capital, and the log of $(n_i + \rho + \delta)$, where n_i is the population growth rate of country i and ρ and δ represent common rates of technical change and depreciation of human and physical capital stocks. Following standard practice we assume that $(\rho + \delta)$ equals 0.05. The derivation of this regression (see Mankiw et al. (1992)) assumes that each country is associated with a common aggregate production function which (unless one wishes to claim that all countries are near their steady states) is Cobb–Douglas.

One way to think about a localized generalization of the Solow regression is to assume that each country obeys the Solow model, but that the aggregate production function which characterizes the country varies. Assuming that this variation can be indexed by a scalar index variable z_i, one can generalize the Solow regression to

$$g_i = \gamma(z_i)' \mathscr{X}_i + \varepsilon_i, \tag{2}$$

where $\gamma(z_i)' = (\gamma_1(z_i), \ldots, \gamma_p(z_i))$ is a function which maps the index into a set of country-specific Solow parameters and p is the number of Solow-type variables. Here, z_i is interpretable as some measure of development of the country. This type of dependence can be justified in several ways. For example, if one believes that there are threshold effects due to capital externalities of the type studied by Azariadis and Drazen (1990), then $\gamma(\cdot)$ will behave as a step function with respect to a capital stock. Alternatively, the index may proxy for omitted growth determinants. For example, if democracy causally affects growth (Barro, 1996), then a democracy index can be introduced in this way. Durlauf (2000) provides some additional discussion of this functional form. As stated earlier, this type of parameter heterogeneity is not completely general. On the other hand, this formulation provides a simple way of modelling cross-country differences in the way aggregate economic growth is influenced by physical capital accumulation, human capital accumulation and population growth.

3. Data

We employ the Heston–Summers data as used in Mankiw et al. (1992). The various savings and growth rates we use are computed for the period 1960–1985 for 98 countries, which are identified in Table 1 in the appendix. The five variables employed are (i) g, the change in the log of income per capita over the period 1960 to 1985; (ii) $\log(n + 0.05)$, average growth rate of the working age population (defined as population between the ages of 15 and 64); (iii) $\log(s_k)$, average proportion of real investments (including government) to real GDP; (iv) $\log(s_h)$, average percentage of working age population that is in secondary school; (v) $\log(y_0)$, initial per capita income. Following Durlauf and Johnson (1995), we use $\log(y_0)$ as our development index. We plan to explore other indices in subsequent work; estimates with initial literacy produced qualitatively similar results. In estimating the model, we also allow for a country-varying intercept term.

4. Estimation issues

The varying coefficient model we apply is based on the work of Hastie and Tibshirani (1993) and follows the conditional linear structure given by Eq. (2) with

$$\mathrm{E}(g_i \mid \mathscr{X}_i = X_i, z_i = z_i) = \gamma(z_i)' X_i, \tag{3}$$

$$\mathrm{Var}(g_i \mid \mathscr{X}_i = X_i, z_i = z_i) = \sigma^2_{g_i}(z_i). \tag{4}$$

The sampling model is assumed to be a random sample $\{z_i, X_i\}_{i=1}^{n}$ drawn from a distribution $F_{z,\mathscr{X}}$.

For each given point z_0, we approximate the functions $\gamma_j(z)$, $j = 1, \ldots, p$, locally as

$$\gamma_j(z) \approx a_j + b_j(z - z_0) \tag{5}$$

for sample points z in a neighborhood of z_0. This results in the following weighted least squares problem:

$$\min_{a_1, \ldots, a_p, b_1, \ldots, b_p} \sum_{i=1}^{n} \left[g_i - \sum_{j=1}^{p} (a_j + b_j(z_i - z_0)) x_{ij} \right]^2 K_h(z_i - z_0), \tag{6}$$

where $K_h(\cdot) = (1/h)K(\cdot/h)$ is some kernel. In this paper we use the Epanechnikov kernel $K(z) = \frac{3}{4}(1 - z^2)I(|z| \leq 1)$.

While this estimation is very simple, it implicitly assumes that the functional coefficients have the same degrees of smoothness and hence can be approximated equally well in the same interval. In practice, though, the functional coefficients may possess different degrees of smoothness, rendering estimators derived from the more conventional one-step weighted least squares estimation suboptimal. In order to avoid this problem we adopt a two-stage estimation method proposed by Fan and Zhang (1999) that ensures that the optimal rate of convergence for the asymptotic mean-squared error is achieved.

The two-step estimation procedure assumes that $\gamma_p(\cdot)$ is smoother (that is it possesses a bounded fourth derivative) than the other coefficient functions and hence a second step is needed to correct for bias of the first step estimation.[1] In particular, the first step produces an initial estimate of $\gamma_1(\cdot), \ldots, \gamma_{p-1}(\cdot)$ by solving (6) and obtaining the partial residuals r_{-p},

$$r_{-p} = g - \gamma_1(z)x_1 - \cdots - \gamma_{p-1}(z)x_{p-1}. \tag{7}$$

Fan and Zhang (1999) recommend choosing the initial smoothing parameter so that the estimate is undersmoothed, which ensures that the bias of the initial estimator is small. The two-step estimation procedure is not sensitive to the choices of the initial bandwidth. In the second step, one solves[2]

$$\min_{a_p, b_p, c_p, d_p} \sum_{i=1}^{n} [r_{i,-p} - (a_p + b_p(z_i - z_0) + c_p(z_i - z_0)^2 + d_p(z_i - z_0)^3)x_{ip}]^2 \; K_{h_2}(z_i - z_0), \tag{8}$$

where h_2 is the second step bandwidth. Following suggestions by Fan and Zhang (1999), for the first step we use 10% of the data range for all the coefficients and for the second step we use 25%, 25%, 30% and 30% of the data range for $\gamma_1, \ldots, \gamma_4$, respectively.

5. Results

Figs. 1a–d report[3] our point estimates and associated 95% confidence intervals for the varying coefficient functions for (2). Table 1 in the appendix presents the associated point estimates together with standard errors for these functions for the different countries in the sample. The superimposed horizontal line in the graphs refers to the least squares coefficients of the Solow model (see Table V, pp. 426, Mankiw et al. (1992)). A number of general conclusions may be drawn.

[1] In practice one does not know in advance which coefficient function is smoother so we apply the two-step for all the coefficients. Fan and Zhang (1999) show that the two-step procedure is always more reliable than the one-step approach.

[2] In theory a local cubic fit should be used in the second step. In our reported results, however, we use a local linear fit which performs equally well.

[3] Tanzania is omitted from the graphs as it acts as an outlier and would render the graphs unreadable given space constraints. Parameter estimates are given in Table 1; complete graphs are available upon request.

First, evidence of parameter heterogeneity is strongest for the poorer economies in the sample. For the varying coefficients associated with the intercept, population growth, and human capital variables, our estimates of the Solow parameters are relatively stable for economies with per capita GDP in 1960 above \$944, which corresponds to Kenya, the 24th poorest country in our sample.

Second, our estimates of the physical capital coefficient are highly unstable throughout the sample, and do not exhibit any sort of monotonicity. Interestingly, the highest values of the physical capital coefficient are associated with the higher per capita income economies. For the majority of economies with a per capita income higher than \$1794, which corresponds to Sri Lanka, the point estimate for the physical capital coefficient is higher than that produced by the Solow model.

Third, we note that the varying intercept term exhibits substantially lower values for the poorest economies than the rest of the sample. This suggests that there may be a latent determinant of low growth by poor countries that is omitted from the Solow model.

6. Local goodness-of-fit

Associated with our varying coefficient estimates are local measures of the goodness-of-fit of the Solow model. The local goodness-of-fit measure we employ is the correlation curve due to Bjerve and Doksum (1993) and Doksum et al. (1994). An important virtue of the correlation curve is that it represents a natural generalization of the standard statistic R^2.

The local goodness-of-fit measure we employ is based on the following idea. Consider the regression (2). If the parameters $\gamma(z_i)$ which hold for a given z_i were to apply to all countries in the sample, one could compute an implied R^2 for the associated growth regression which holds under the counterfactual of constant coefficients. Varying this R^2 across different z_i values produces the local correlation curve. Doksum (1993) and Doksum et al. (1994) describe a number of justifications for this goodness-of-fit measure, which can be written in the case of our varying coefficient model (2) as

$$\rho^2(z_i) = \frac{\gamma(z_i)'\Sigma_{X_i}\gamma(z_i)}{\gamma(z_i)'\Sigma_{X_i}\gamma(z_i) + \sigma^2_{g_i}(z_i)}, \tag{9}$$

where Σ_{X_i} is the covariance matrix of X and $\sigma^2_{g_i}(z_i)$ is the conditional variance of the varying coefficient model. The latter can be estimated as a normalized weighted residual sum of squares.

$$\hat{\sigma}^2_{g_i}(z_0) = \frac{\sum_{i=1}^{n}(g_i - \hat{g}_i)^2 K_h(z_i - z_0)}{\sum_{i=1}^{n} K_h(z_i - z_0)}, \tag{10}$$

where the $\hat{g}_i = \hat{\gamma}(z_i)'X_i$ are the fitted values of (2).

Fig. 1f reports our estimates of the local correlation curves associated with our local estimates of the Solow growth model. The overall goodness-of-fit for the constant coefficient version of the model is 0.42, which we include as a baseline. What this curve suggests is that there is a monotonic tendency for the Solow growth model to better capture growth variation for richer than poorer economies. When juxtaposed against Fig. 1e, which provides estimates of the conditional residual variance, as well as the earlier figures, one can see why. The relatively high goodness-of-fit for the richer countries is produced both by a lower residual variance, as well due to different magnitudes of the various coefficients.

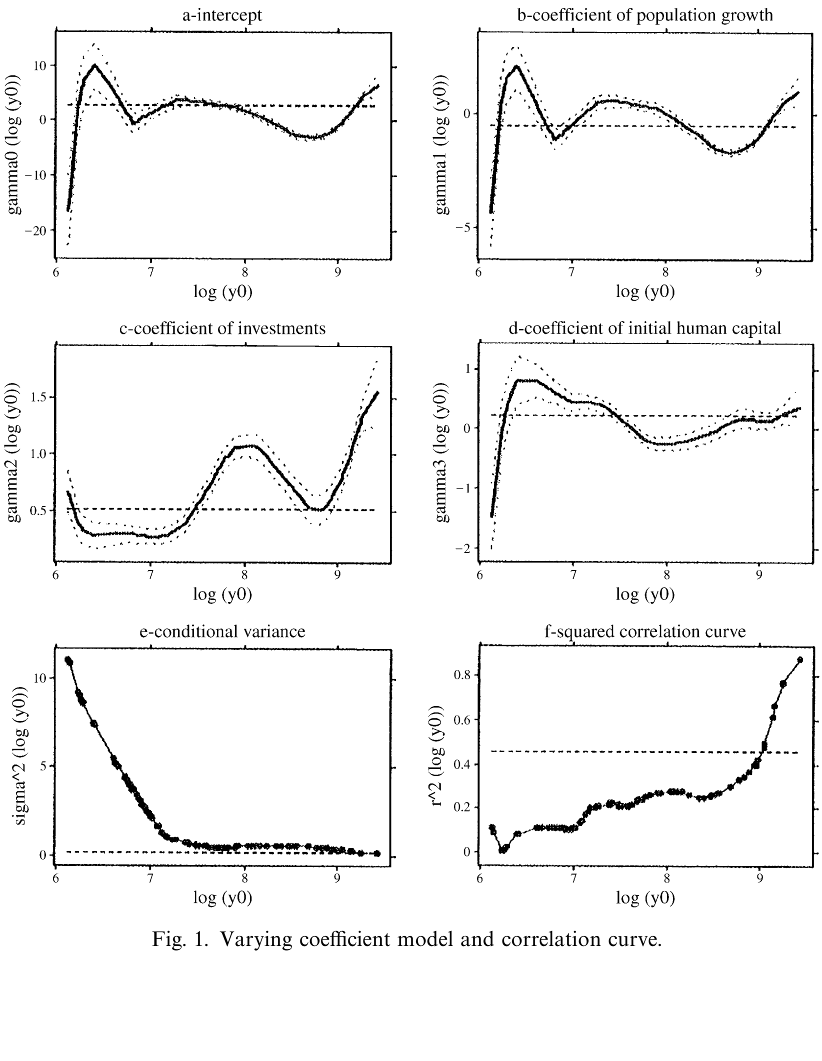

Fig. 1. Varying coefficient model and correlation curve.

7. Conclusions

This paper has argued that empirical versions of the Solow growth model should explicitly allow for cross-country parameter heterogeneity. In this respect, we find that a local Solow model better fits countries rather than the global one conventionally used. Our empirical work suggests that substantial heterogeneity exists and that the goodness-of-fit of the model differs across nations as well. Our results have two implications. First, empirical exercises which fail to incorporate parameter heterogeneity are likely to produce misleading results. Second, a full understanding of cross-country growth differences will need to explain why this parameter heterogeneity exists.

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Appendix

The varying coefficient model and correlation curve are shown in Fig. 1 and the variable coefficient estimates identified in Table 1.

Table 1
Variable coefficient estimates

Countries	GDP60 (y_0)	$\gamma_0(y_0)$	$\gamma_1(y_0)$	$\gamma_2(y_0)$	$\gamma_3(y_0)$
Tanzania	383	− 93.78	− 23.91	1.55	− 6.63
		9.38	2.12	0.28	0.75
Malawi	455	− 16.39	− 4.37	0.67	− 1.45
		3.26	0.75	0.09	0.28
Rwanda	460	− 13.83	− 3.71	0.63	− 1.26
		3.14	0.72	0.09	0.27
Sierra Leone	511	2.82	0.54	0.40	0.00
		2.53	0.58	0.07	0.23
Myanmar	517	3.94	0.81	0.38	0.10
		2.50	0.57	0.07	0.23
Burkina Faso	529	5.83	1.27	0.35	0.27
		2.43	0.56	0.06	0.23
Ethiopia	533	6.33	1.39	0.34	0.32
		2.41	0.56	0.06	0.23
Niger	539	7.04	1.56	0.33	0.40
		2.38	0.55	0.06	0.22

Table 1. (*continued.*)

Countries	GDP60 (y_0)	$\gamma_0(y_0)$	$\gamma_1(y_0)$	$\gamma_2(y_0)$	$\gamma_3(y_0)$
Zaire	594	9.82	2.08	0.28	0.79
		2.08	0.49	0.06	0.20
Uganda	601	9.79	2.05	0.28	0.82
		2.04	0.48	0.06	0.20
Mali	737	5.45	0.53	0.30	0.81
		1.33	0.33	0.05	0.14
Burundi	755	4.65	0.29	0.30	0.79
		1.26	0.31	0.05	0.13
Mauritania	777	3.68	0.01	0.30	0.76
		1.18	0.29	0.04	0.13
Togo	777	3.68	0.01	0.30	0.76
		1.18	0.29	0.04	0.13
Nepal	833	1.65	− 0.56	0.30	0.68
		1.01	0.26	0.04	0.11
Central Afr. Rep.	838	1.50	− 0.61	0.30	0.67
		1.00	0.25	0.04	0.11
Bangladesh	846	1.26	− 0.67	0.30	0.66
		0.98	0.25	0.04	0.11
Liberia	863	0.79	− 0.79	0.30	0.64
		0.94	0.24	0.04	0.10
Indonesia	879	0.37	− 0.90	0.30	0.63
		0.91	0.23	0.04	0.10
Cameroon	889	0.12	− 0.96	0.29	0.61
		0.89	0.23	0.04	0.10
Somalia	901	− 0.17	− 1.03	0.29	0.60
		0.87	0.23	0.04	0.10
Egypt	907	− 0.32	− 1.06	0.29	0.60
		0.86	0.22	0.04	0.10
Chad	908	− 0.35	− 1.07	0.29	0.59
		0.86	0.22	0.04	0.10
Kenya	944	− 0.09	− 0.98	0.29	0.56
		0.79	0.21	0.04	0.09
Botswana	959	0.09	− 0.92	0.29	0.54
		0.76	0.20	0.04	0.09
India	978	0.30	− 0.84	0.29	0.53
		0.72	0.19	0.03	0.09
Congo	1009	0.65	− 0.72	0.28	0.50
		0.67	0.18	0.03	0.08
Ghana	1009	0.65	− 0.72	0.28	0.50
		0.67	0.18	0.03	0.08
Morocco	1030	0.86	− 0.64	0.28	0.48
		0.64	0.18	0.03	0.08
Nigeria	1055	1.09	− 0.56	0.28	0.46
		0.61	0.17	0.03	0.08
Pakistan	1077	1.27	− 0.49	0.28	0.45
		0.58	0.17	0.03	0.08

Table 1. (*continued.*)

Countries	GDP60 (y_0)	$\gamma_0(y_0)$	$\gamma_1(y_0)$	$\gamma_2(y_0)$	$\gamma_3(y_0)$
Haiti	1096	1.43	− 0.43	0.27	0.45
		0.57	0.17	0.03	0.07
Benin	1116	1.61	− 0.35	0.27	0.45
		0.56	0.16	0.03	0.07
Zimbabwe	1187	2.12	− 0.15	0.27	0.45
		0.54	0.16	0.03	0.07
Madagascar	1194	2.16	− 0.13	0.27	0.45
		0.54	0.16	0.03	0.07
Sudan	1254	2.60	0.04	0.28	0.45
		0.54	0.16	0.03	0.06
South Korea	1285	2.85	0.15	0.29	0.45
		0.54	0.17	0.03	0.05
Thailand	1308	2.98	0.20	0.29	0.44
		0.53	0.17	0.03	0.05
Ivory Coast	1386	3.40	0.40	0.32	0.42
		0.51	0.16	0.04	0.05
Senegal	1392	3.44	0.42	0.32	0.42
		0.51	0.16	0.04	0.05
Zambia	1410	3.57	0.47	0.32	0.42
		0.51	0.16	0.04	0.05
Mozambique	1420	3.64	0.50	0.33	0.41
		0.50	0.16	0.04	0.05
Honduras	1430	3.69	0.52	0.33	0.41
		0.50	0.16	0.04	0.05
Angola	1588	3.69	0.57	0.41	0.34
		0.42	0.14	0.04	0.05
Bolivia	1618	3.69	0.58	0.43	0.32
		0.41	0.14	0.04	0.05
Tunisia	1623	3.68	0.58	0.43	0.31
		0.40	0.14	0.04	0.05
Philippines	1668	3.65	0.59	0.46	0.29
		0.38	0.13	0.04	0.05
Papua New Guinea	1781	3.54	0.57	0.54	0.20
		0.33	0.12	0.04	0.05
Sri Lanka	1794	3.52	0.57	0.55	0.19
		0.33	0.12	0.04	0.05
Brazil	1842	3.47	0.56	0.58	0.15
		0.31	0.12	0.04	0.05
Dominican Rep.	1939	3.36	0.53	0.65	0.08
		0.29	0.11	0.04	0.04
Paraguay	1951	3.34	0.52	0.66	0.07
		0.29	0.11	0.04	0.04
Mauritius	1973	3.31	0.51	0.68	0.06
		0.29	0.11	0.04	0.04
El Salvador	2042	3.21	0.48	0.72	0.01
		0.28	0.11	0.04	0.04

Table 1. (*continued.*)

Countries	GDP60 (y_0)	$\gamma_0(y_0)$	$\gamma_1(y_0)$	$\gamma_2(y_0)$	$\gamma_3(y_0)$
Malaysia	2154	3.05	0.44	0.80	− 0.06
		0.28	0.11	0.04	0.04
Jordan	2183	3.02	0.43	0.82	− 0.08
		0.28	0.11	0.04	0.05
Ecuador	2198	3.00	0.43	0.83	− 0.09
		0.28	0.11	0.04	0.05
Greece	2257	2.94	0.41	0.87	− 0.12
		0.28	0.11	0.05	0.05
Portugal	2272	2.92	0.40	0.88	− 0.13
		0.28	0.11	0.05	0.05
Turkey	2274	2.92	0.40	0.88	− 0.13
		0.28	0.11	0.05	0.05
Syrian Arab Rep.	2382	2.81	0.37	0.94	− 0.18
		0.29	0.11	0.05	0.05
Panama	2423	2.78	0.36	0.96	− 0.20
		0.29	0.11	0.05	0.05
Guatemala	2481	2.73	0.34	0.99	− 0.22
		0.30	0.11	0.05	0.05
Algeria	2485	2.73	0.34	0.99	− 0.22
		0.30	0.11	0.05	0.05
Colombia	2672	2.51	0.27	1.06	− 0.26
		0.31	0.12	0.05	0.06
Jamaica	2726	2.45	0.25	1.06	− 0.26
		0.32	0.12	0.05	0.06
Singapore	2793	2.33	0.20	1.06	− 0.25
		0.32	0.12	0.05	0.06
Hong Kong	3085	1.72	− 0.03	1.08	− 0.24
		0.32	0.12	0.05	0.06
Nicaragua	3195	1.48	− 0.12	1.08	− 0.24
		0.33	0.12	0.05	0.06
Peru	3310	1.21	− 0.22	1.07	− 0.23
		0.32	0.12	0.05	0.06
Costa Rica	3360	1.11	− 0.26	1.07	− 0.23
		0.32	0.12	0.05	0.06
Japan	3493	0.83	− 0.36	1.05	− 0.22
		0.32	0.12	0.05	0.06
Spain	3766	0.27	− 0.55	0.99	− 0.19
		0.32	0.11	0.05	0.06
Mexico	4229	− 0.79	− 0.91	0.87	− 0.14
		0.31	0.11	0.06	0.07
Ireland	4411	− 1.22	− 1.05	0.83	− 0.12
		0.29	0.10	0.06	0.07
South Africa	4768	− 2.03	− 1.32	0.75	− 0.07
		0.27	0.09	0.06	0.07
Israel	4802	− 2.10	− 1.35	0.74	− 0.06
		0.27	0.09	0.06	0.07

Table 1. (*continued.*)

Countries	GDP60 (y_0)	$\gamma_0(y_0)$	$\gamma_1(y_0)$	$\gamma_2(y_0)$	$\gamma_3(y_0)$
Argentina	4852	− 2.20	− 1.38	0.73	− 0.05
		0.27	0.09	0.06	0.07
Italy	4913	− 2.31	− 1.42	0.72	− 0.04
		0.26	0.09	0.06	0.07
Uruguay	5119	− 2.65	− 1.53	0.67	− 0.01
		0.26	0.09	0.06	0.07
Chile	5189	− 2.75	− 1.57	0.66	0.00
		0.26	0.09	0.06	0.07
Austria	5939	− 3.05	− 1.68	0.54	0.12
		0.23	0.08	0.06	0.08
Finland	6527	− 2.86	− 1.61	0.51	0.17
		0.23	0.07	0.06	0.08
Belgium	6789	− 2.67	− 1.55	0.52	0.18
		0.23	0.07	0.06	0.08
France	7215	− 2.24	− 1.40	0.57	0.17
		0.23	0.07	0.06	0.08
United Kingdom	7634	− 1.70	− 1.22	0.63	0.16
		0.24	0.07	0.06	0.08
Netherlands	7689	− 1.62	− 1.20	0.64	0.15
		0.24	0.07	0.06	0.08
West Germany	7695	− 1.61	− 1.20	0.65	0.15
		0.24	0.07	0.06	0.08
Sweden	7802	− 1.44	− 1.14	0.67	0.15
		0.24	0.08	0.06	0.08
Norway	7938	− 1.22	− 1.07	0.69	0.15
		0.25	0.08	0.06	0.08
Australia	8440	− 0.24	− 0.78	0.80	0.14
		0.26	0.08	0.06	0.07
Denmark	8551	0.00	− 0.71	0.83	0.14
		0.26	0.08	0.06	0.07
Trinidad & Tobago	9253	1.74	− 0.23	1.00	0.15
		0.30	0.10	0.05	0.07
New Zealand	9523	2.40	− 0.05	1.08	0.17
		0.31	0.10	0.05	0.07
Canada	10286	4.24	0.42	1.30	0.24
		0.36	0.12	0.06	0.07
Switzerland	10308	4.29	0.43	1.30	0.24
		0.36	0.12	0.06	0.07
Venezuela	10367	4.42	0.46	1.32	0.25
		0.37	0.12	0.06	0.07
United States	12362	6.51	1.06	1.56	0.37
		0.97	0.30	0.15	0.18

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