Human Development Research Paper 2010/24

Determinants of Human Development: Insights from State-Dependent Panel Models

Michael Binder
and Georgios Georgiadis

HDRP

United Nations Development Programme
Human Development Reports
Research Paper

September 2010

Human Development Research Paper 2010/24

Determinants of Human Development: Insights from State-Dependent Panel Models

Michael Binder
and Georgios Georgiadis

United Nations Development Programme
Human Development Reports
Research Paper 2010/24
September 2010

Determinants of Human Development: Insights from State-Dependent Panel Models

Michael Binder
and Georgios Georgiadis

Michael Binder is Professor of International Macroeconomics and Macroeconometrics at Goethe University Frankfurt and Director of the Policy Research Network of the Graduate School of Economics, Finance, and Management at Goethe University, Johannes Gutenberg University Mainz and Technical University Darmstadt and the Center for Financial Studies. E-mail: mbinder@wiwi.uni-frankfurt.de.

Georgios Georgiadis is a Ph.D. candiadate at the Graduate School of Economics, Finance, and Management at Goethe University, Johannes Gutenberg University Mainz and Technical University Darmstadt. E-mail: jorgo@georgiadis.de.

Comments should be addressed by email to the author(s).

Abstract

In this paper, we study economic development in a panel of 84 countries from 1970 to 2005. We focus on characterizing heterogeneities in the development effects of macroeconomic policies and on comparing the development process as measured by GDP to that measured by the Human Development Index (HDI). We do so within a novel dynamic panel modelling framework that can account for crucial aspects of both the cross-sectional and intertemporal features of the observed process of economic development, and that can capture the dependence of the development effects of macroeconomic policies on differences in countries' persistent characteristics, such as their social norms and institutions. Among our findings are that macroeconomic policies affect economic development with less delay than suggested by conventional econometric frameworks, yet impact HDI with longer delay and overall less strongly than GDP. Differences in countries' persistent characteristics may even affect the sign of the long-run development effects of a given macroeconomic policy: Fiscal stimuli in the form of government consumption positively affect GDP in countries with low institutional quality, but negatively affect long-run GDP in countries with high institutional quality.

Keywords: human development, institutions and social norms, dynamic panel modelling.

JEL classification: C23, O10

1 Introduction

Research aimed at understanding countries' long-run economic development has been a cornerstone of theoretical and empirical economic investigations for many decades. While substantial progress has been made during the last couple of decades, various issues remain controversially discussed or have received attention only recently. Among these issues are in particular (i) how correlates of economic growth can be distinguished from factors that are causal for economic growth, (ii) how the contributions of key development policies to advances in economic prosperity may depend on a country's institutions, social norms and other societal characteristics, as well as (iii) whether measures other than output/income should be considered when comparing economic development across countries. In this paper, we study economic development in a panel of 84 countries from 1970 to 2005. We investigate heterogeneities in the development effects of macroeconomic policies, and compare the development process as measured by GDP to that measured by the United Nations' Human Development Index (HDI). We do so within a novel dynamic panel modelling framework that can account for crucial aspects of both the cross-sectional and intertemporal features of the observed process of economic development. The framework we propose can also characterize a possible state dependence of the development effects of macroeconomic policies on differences in countries' persistent characteristics, such as their social norms and institutions as well as other key societal characteristics within which the development process takes place.

To motivate our panel modelling framework, it is useful to note that the predominant investigative tool used in the empirical output growth literature continues to be the "Barro regression", in which a country's rate of output growth during a certain time period is regressed on an initial condition for the level of output and a variety of other potential output growth determinants.[1] There are a number of problems with this Barro regression framework, however, which limit its usefulness for empirical analysis.[2] A first issue casting doubt on the appropriateness of the Barro regression framework is that - random effects apart - all cross-country heterogeneities of the output growth process are assumed to be fully captured by different realizations of the regression's explanatory variables. This is, however, extremely unlikely to be satisfied in practice, as due to finite sample issues only a limited number of explanatory variables - capturing only a portion of the overall cross-country heterogeneity - can be considered, and as many of the systematic differences prevailing across countries are difficult to observe or to measure. For this reason, Islam (1995) and Evans (1996) were among the first in the recent empirical output growth literature to move beyond the Barro regression framework, advocating to consider panel fixed-effects models, with the fixed effects accounting for time-invariant factors, such as a country's institutional and political environment, that exhibit systematic (as opposed to purely random) variation across countries. Pursuing this line of thought further, however, not only may countries' systematically differing societal characteristics imply different conditional means for the steady-state distribution of the relevant development measure, but countries may also feature different slopes of their steady-state growth paths, due to prolonged differences, say, in the rate of technological progress. As has been argued by Lee, Pesaran and Smith (1997) and Binder and Pesaran (1999), assuming that countries in the steady state grow at the same rate when steady-state growth rates in fact differ, leads to serious fallacies in empirical inference. More generally, a promising econometric framework for studying economic development beyond allowing for fixed effects must capture systematic heterogeneities in growth *dynamics* also. A second issue of concern

[1]This regression framework has become popular in empirical work following the seminal paper by Barro (1991).

[2]See also Hauk and Wacziarg (2009) for a recent discussion of some of these issues. In this paper we take a different perspective than Hauk and Wacziarg (2009), however, by arguing in favor of a dynamic panel model-based inference approach as being the appropriate means for the cross-country econometric analysis of economic development.

with default Barro regressions is that they are subject to endogeneity bias. Regressions of, say, output growth on a variable such as the rate of investment in physical capital that *a priori* postulate investment in physical capital to be exogenous may help one to understand the strength of the association of output growth with investment in physical capital, but cannot provide evidence as to whether investment in physical capital is in fact a determinant of a country's rate of output growth in the sense that a higher rate of investment in physical capital would precede accelerated output growth (as it may well be that a higher rate of investment in physical capital merely is a result of higher output levels and/or higher output growth rates). For purposes of policy analysis, it is clearly desirable, however, to work with an econometric framework that can distinguish between correlates and determinants of economic growth.[3] Third in terms of concerns with the Barro regression framework is that it does not feature a data-driven distinction between short- and long-run dynamics, and is not designed to deal with the possible presence of unit roots in the data and resulting issues of non-ergodicity (see Binder and Pesaran, 1999). Fourth and finally, there is mounting evidence that the process of economic development is subject to important nonlinearities, such as the dependence of the development effects of macroeconomic policies on country-specific conditions. Such nonlinearities are not captured by default Barro regressions. See, for example, Rodríguez (2007) and Binder, Georgiadis and Sharma (2010). Taking all four of these issues together, there appears to be a clear need for empirical work on economic development to move beyond econometric techniques as typically used in the empirical output growth literature.

Beyond giving careful consideration to econometric modelling issues, in this paper we also go beyond a strictly output-/income-based analysis of the development process. As prominently advocated by Sen (1999), the ultimate goal of economic development policies should be to enhance - in a rather broad sense - the set of people's opportunities.

[3]We should mention that there is important work tackling this endogeneity issue within the framework of Barro regressions. See, for example, Acemoglu, Johnson and Robinson (2001).

The empirical growth literature to date has, however, primarily focused on investigating the determinants of the level of output (income) per capita and its growth rate. While it is obviously true that a higher level of output/income can afford an expanded set of consumption goods, the focus of the empirical growth literature on output/income measures might cloud other key aspects of the complete set of opportunities available to individuals, as eminently described in the first Human Development Report in 1990:

> *First, national income figures, useful though they are for many purposes, do not reveal the composition of income or the real beneficiaries. Second, people often value achievements that do not show up at all, or not immediately, in higher measured income or growth figures: Better nutrition and health services, greater access to knowledge, more secure livelihoods, better working conditions, security against crime and physical violence, satisfying leisure hours, and a sense of participating in the economic, cultural and political activities of their communities. Of course, people also want higher incomes as one of their options. But income is not the sum total of human life.*

It therefore appears to be sensible to consider replacing/augmenting output as the sole measure of economic development by an alternative measure that shifts the focus of development economics from solely output-oriented to human-life-oriented policy design.[4]

Taking into account both these econometric and data-measurement considerations, in this paper, then, we move beyond a Barro regression based analysis of output growth. We take advantage of newly released United Nations HDI data, and examine some key aspects of these (as well as GDP) data within a novel dynamic panel modelling framework. In particular, we adapt a panel autoregressive distributed lag model with conditionally homogenous (state-dependent) long-run coefficients, as proposed by Binder and Offermanns

[4] We follow the lead of work in the United Nations Development Program, for example Gray Molina and Purser (2010), in moving beyond output-based development analysis.

(2007) as well as Binder, Georgiadis and Sharma (2010). The conditional pooled mean group (CPMG) state-dependent panel model introduced in these papers appears to be well-suited for the analysis of the determinants of HDI, as it can capture crucial aspects of both the cross-sectional as well as intertemporal features of the HDI development process, and can overcome the problems associated with the Barro regression approach detailed above. In particular, the CPMG state-dependent panel model (i) features a data-driven distinction between short- and long-run dynamics, (ii) allows for systematic cross-country heterogeneity in intercepts and dynamics while also identifying features of the development process that are common across countries, (iii) allows for the explanatory variables to be potentially endogenous, and (iv) remains applicable even when there are unit roots in the data. Perhaps most importantly, however, the CPMG state-dependent panel model allows us to investigate whether the development effects of changes in macroeconomic policies on HDI (GDP) vary across different types of societal environments within which the development process takes place. Modelling the development effects that macroeconomic policies have on HDI (GDP) as being dependent on slowly time-varying indices measuring countries' persistent characteristics appears to be a novel and promising way to reconcile a fixed effects empirical growth model with an analysis of social norms, institutions and other societal characteristics that are typically emphasized in empirical analyses using the (random effects based) Barro regression framework.[5] In this spirit, our approach to modelling state dependence of the development effects of macroeconomic policies involves modelling these effects as a function of indices involving grouped combinations of variables that in the recent empirical growth literature have been found to robustly affect output growth.

The plan for the remainder of this paper is as follows: In Section 2, we provide some stylized facts about the HDI development process, contrasting it to that for GDP. In Sec-

[5]It is important to recall that in a fixed effects panel data model one cannot identify the effects of strictly time-invariant regressors.

tion 3, we discuss our panel modelling framework, putting emphasis on how our model in a novel form captures both country fixed effects *and* the cross-country variation of the development effects of economic policies along countries' persistent characteristics such as its social norms and institutions. We also discuss our set of state variables measuring such persistent characteristics in Section 3. In Section 4, we present our main empirical results, contrasting these results to those we obtain for our data from conventional Barro regressions. We conclude in Section 5, also indicating some directions for future research. Several appendices provide details on data measurement and computational/econometric issues.

2 Some Stylized Facts About HDI Trends

While the (to date) official United Nations data for HDI are available only from 1980 onwards and for a total of 82 countries, the Gray Molina and Purser (2010) HDI data set that we can take advantage of in this paper significantly expands HDI data coverage both across years and countries: The Gray Molina and Purser (2010) data set spans 111 countries from 1970 to 2005.[6] We focus in this paper on those of these 111 countries

[6]It may be useful to briefly recall the measurement of HDI: HDI is constructed as an index aggregating information on the stage of human development as contained in GDP per capita, life expectancy, and education as measured by school enrolment and the adult literacy rate. Denoting by gdp^*_{it} the logarithm of GDP per capita, by $life^*_{it}$ life expectancy at birth, by $tger_{it}$ the tertiary gross enrolment rate, and by $liter_{it}$ the adult literacy rate, HDI by the United Nations is computed as follows:

$$hdi_{it} = \frac{1}{3} \cdot gdp_{it} + \frac{1}{3} \cdot life_{it} + \frac{1}{3} \cdot educ_{it}, \qquad (1)$$

where

$$educ_{it} = \frac{1}{3} \cdot tger_{it} + \frac{2}{3} \cdot liter_{it},$$

and with two of the components of HDI being re-scaled prior to entering on the right-hand side of Equation (1), so as to fall into the unit interval, $[0, 1]$:

$$life_{it} = \frac{life^*_{it} - 25}{85 - 25}, \qquad (2)$$

for which there is a sufficient number of time-series observations available for them to be included in the estimation of our state-dependent panel model, leaving us with a "world" sample of 84 countries.[7] Figure 1 provides the evolution of key first and second moments of the cross-sectional distributions of HDI for subsets of countries, and Figure 2 plots the evolutions of the cross-sectional distributions themselves. When interpreting the plots (of the moments of) these distributions, it should be kept in mind that HDI and GDP per capita may not be ergodic variables - that is, they may not converge to time-invariant steady-state distributions, and second moments may not be well defined (see Binder and Pesaran, 1999). With this caveat, Figures 1 and 2 indicate that, not too surprisingly, throughout the sample period the OECD countries have enjoyed the highest levels of human development followed by countries in Latin America and the Caribbean, by countries in Asia and finally by countries in Africa. Figures 1 and 2 also suggest that unconditional convergence of HDI with respect to initial values has taken place, in the sense that HDI has generally improved relatively more in less developed regions than in the OECD countries. The median of HDI in the OECD countries from 1970 to 2005 rose by 13%, whereas it rose by 22% in Latin America and the Caribbean, by 32% in Africa, and by 32% in Asia. The most rapid catch-up with the OECD countries' level of human development took place in Asia, for which mean (though not yet median) human development in 2005 surpassed that in Latin America and the Caribbean. Also, within each region except for Africa, the standard deviation of the cross-sectional distribution of HDI has decreased from 1970 to 2005: The standard deviation for the OECD countries from 1970 to 2005 fell by 66%, for the Latin American and Caribbean countries by 45%, and for the Asian countries by 23 %, whereas it rose for the African countries by 23%.

---

and

$$gdp_{it} = \frac{gdp^*_{it} - log(100)}{log(40,000) - log(100)}. \tag{3}$$

[7] See Section 3 for a detailed discussion of our data availability criteria. Table 1 provides a listing of all 84 countries that enter our "world" sample.

Analogously to Figures 1 and 2 for HDI, Figures 3 and 4 present the evolution of key first and second moments of the cross-sectional distributions of the logarithm of GDP per capita and the evolutions of the cross-sectional distributions themselves. Comparing Figures 3 and 4 for the logarithm of GDP per capita with Figures 1 and 2 for HDI, three observations stand out: First, while all regions have experienced notable improvements in HDI from 1970 to 2005, this is not the case for the logarithm of GDP per capita, as the mean and median of African countries' GDP per capita have not grown in comparable magnitude as those of the OECD, Asian as well as Latin American and Caribbean countries. Second, for the Latin American and Caribbean countries, the unconditional convergence to OECD development levels apparently present in the evolution of the mean and median of HDI does not appear to be present for the logarithm of GDP per capita. The median of the logarithm of GDP per capita in the OECD countries from 1970 to 2005 rose by 7%, whereas it rose by 6% in Latin America and the Caribbean, by 1% in Africa, and by 13% in Asia. Third, while except for Africa countries within a given region appear to unconditionally converge towards a common level of HDI, with the exception of Asia and of Latin America and the Caribbean there does not appear to be a general long-term decline of the within-region standard deviations for the logarithm of GDP per capita.[8]

Finally in terms of stylized facts for our data, Figure 5 provides scatter plots of the HDI levels in 2005 against the logarithm of GDP per capita in 2005, of the changes in HDI against GDP per capita growth rates between 1970 and 2005, and scatter plots of the change in (growth of) HDI (GDP per capita) between 1970 and 2005 against initial HDI (GDP per capita) in 1970. Still keeping in mind the caveat that HDI and GDP per capita may not be ergodic variables, there is a strong positive correlation (with a correlation coefficient of 0.96) between the levels of HDI and of the logarithm of GDP per capita in 2005. The relationship between the change of HDI between 1970 and 2005 and the

[8]For a more detailed investigation of (unconditional) convergence of HDI and its components, see Mayer-Foulkes (2010).

growth of GDP per capita during the same time period also is positive, though with a slope only about one third as large as for the corresponding levels relationship. While there appears to be a negative and statistically significant relationship between the initial level of HDI in 1970 and the change of HDI between 1970 and 2005, pointing to the presence of unconditional convergence for HDI, the same does not appear to be the case for GDP per capita. To move beyond such a simple graphical and regression analysis *inter alia* not involving any form of conditioning on country-specific characteristics and failing to account for the possible lack of ergodicity of the levels of HDI and GDP per capita, we move to our panel-econometric analysis.

3 Econometric Model

Let us consider a panel autoregressive distributed lag model, in which we allow the key coefficients to be state dependent, varying as a function of a (pre-determined) conditioning state variable, $z_{i,t-1}$:

$$\begin{aligned} y_{it} &= \mu_i + \varphi_i \cdot t + \sum_{k=1}^{p} \rho_{ik}(z_{i,t-1}) \cdot y_{i,t-k} \\ &\quad + \sum_{k=0}^{q} \varrho'_{ik}(z_{i,t-1}) \cdot \boldsymbol{x}_{i,t-k} + \epsilon_{it}, \qquad t = r, r+1, \ldots, T, \end{aligned} \tag{4}$$

where y_{it} denotes the dependent variable of country i at time t (hdi_{it} or gdp_{it}), μ_i and φ_i denote fixed-effects intercept and time-trend terms, $\boldsymbol{x}_{it}$ denotes an $m \times 1$ vector of explanatory variables, $\rho_{ik}(z_{i,t-1})$ and $\varrho'_{ik}(z_{i,t-1})$ denote state-dependent slope coefficients, $r = max(p, q)$, the disturbance term ϵ_{it} is distributed as $\epsilon_{it} \sim (0, \sigma_i^2)$, $i.i.d.$ across t, and with the disturbance terms in addition being independent across i.[9]

[9]For ease of exposition we assume in Equation (4) that all explanatory variables enter with the same lag order and that the time-series dimension is the same for all countries, involving observations for y_{it}, $\boldsymbol{x}_{it}$ and z_{it} for $t = 0, 1, \ldots, T$. In our empirical work, we certainly do allow for variable- and country-specific lag

The principal idea underlying our consideration of a model with state-dependent coefficients is as follows: In the Barro regression framework, the effects of time-invariant variables on the dependent variable are identified by restricting the country-specific effects to be random (rather than fixed) effects, imposing orthogonality between the country-specific effects and the model's other regressors, including those in $\boldsymbol{x}_{it}$. As discussed in the Introduction, such a random effects restriction for cross-country models is implausible in empirical practice, as many of the development factors forming the country-specific effects vary systematically (not randomly) across countries. It is thus imperative to allow for fixed-effects intercepts, the μ_i's in Equation (4). Of course, having introduced such fixed effects, it is no longer possible to identify the effects of any other regressors that are strictly time-invariant. Our conditioning states, the $z_{i,t-1}$'s, are indices involving variables that reflect similar aspects of a country's institutions, social norms or other key societal characteristics. Carefully combining such variables, we ensure that the $z_{i,t-1}$'s feature some time variation. Our model thus overcomes the implausible and costly random effects restriction of the Barro regression framework,[10] without having to pass on examining the quantitative importance of a country's institutions and aspects of its social norms for its development process.[11]

The error-correction representation of Equation (4), separating short- and long-run dynamics in a data-driven manner, is given by

$$\begin{aligned}\Delta y_{it} &= \mu_i + \varphi_i \cdot t + \alpha_i(z_{i,t-1}) \cdot y_{it-1} + \boldsymbol{\beta}_i'(z_{i,t-1}) \cdot \boldsymbol{x}_{i,t-1} + \boldsymbol{\psi}_i'(z_{i,t-1}) \cdot \boldsymbol{h}_{it} + \epsilon_{it} \\ &= \mu_i + \varphi_i \cdot t + \alpha_i(z_{i,t-1}) \cdot \left[y_{i,t-1} - \boldsymbol{\theta}_i'(z_{i,t-1}) \cdot \boldsymbol{x}_{i,t-1}\right] + \boldsymbol{\psi}_i'(z_{i,t-1}) \cdot \boldsymbol{h}_{it} + \epsilon_{it}, \qquad (5)\end{aligned}$$

orders p_i and q_{ik}, for $k = 1, 2, \dots, m$ and $i = 1, 2, \dots, N$, as well as for an unbalanced panel of observations.

[10]In separate simulation work in progress, we document the magnitude of the parameter estimate biases that may be incurred in the development context by erroneously modelling fixed effects as random effects.

[11]Due to reasons of model parsimony, we will not consider model specifications allowing for more than one conditioning state variable at a time, and will examine the influence of our set of conditioning state variables in sequential form, one state variable at a time. See Binder, Georgiadis and Sharma (2010) for a state-dependent dynamic panel data model with multivariate conditioning.

where

$$\alpha_i(z_{i,t-1}) = \sum\nolimits_{k=1}^{p} \rho_{ik}(z_{i,t-1}) - 1, \quad \boldsymbol{\beta}_i(z_{i,t-1}) = \sum\nolimits_{k=0}^{q} \boldsymbol{\varrho}_{ik}(z_{i,t-1}),$$

$$\boldsymbol{\psi}_i(z_{i,t-1}) = \Big[-\sum\nolimits_{k=2}^{p} \rho_{ik}(z_{i,t-1}), -\sum\nolimits_{k=3}^{p} \rho_{ik}(z_{i,t-1}), \ldots, -\rho_{ip}(z_{i,t-1}),$$

$$\boldsymbol{\varrho}'_{i0}(z_{i,t-1}), -\sum\nolimits_{k=2}^{q} \boldsymbol{\varrho}'_{ik}(z_{i,t-1}), -\sum\nolimits_{k=3}^{q} \boldsymbol{\varrho}'_{ik}(z_{i,t-1}), \ldots, -\boldsymbol{\varrho}'_{iq}(z_{i,t-1})\Big]',$$

$$\boldsymbol{h}_{it} = \left(\Delta y_{i,t-1}, \Delta y_{i,t-2}, \ldots, \Delta y_{i,t-p+1}, \Delta \boldsymbol{x}'_{it}, \Delta \boldsymbol{x}'_{i,t-1}, \ldots, \Delta \boldsymbol{x}'_{i,t-q+1}\right)',$$

and

$$\boldsymbol{\theta}_i(z_{i,t-1}) = -\boldsymbol{\beta}_i(z_{i,t-1})/\alpha_i(z_{i,t-1}).$$

Given the still relatively limited number of time-series observations typically available in cross-country development panel data sets such as the one we use for this paper, we need to restrict the degree of parameter variation allowed for by the model in Equation (5). To this end, we specify the speed of adjustment and the other model short-run dynamics as varying in unrestricted form across countries, but not varying with $z_{i,t-1}$. Also introducing the weak conditional/state-dependent pooling restriction that countries that share the same values of the conditioning state variables also share the same long-run multipliers, $\boldsymbol{\theta}_i(z_{i,t-1}) = \boldsymbol{\theta}(z_{i,t-1})$,[12] we then have the conditional pooled mean group (CPMG) panel data model

$$\begin{aligned} \Delta y_{it} &= \mu_i + \varphi_i \cdot t + \alpha_i \cdot y_{i,t-1} + \boldsymbol{\beta}'_i(z_{i,t-1}) \cdot \boldsymbol{x}_{i,t-1} + \boldsymbol{\psi}'_i \cdot \boldsymbol{h}_{it} + \epsilon_{it} \\ &= \mu_i + \varphi_i \cdot t + \alpha_i \cdot \left[y_{i,t-1} - \boldsymbol{\theta}'(z_{i,t-1}) \cdot \boldsymbol{x}_{i,t-1}\right] + \boldsymbol{\psi}'_i \cdot \boldsymbol{h}_{it} + \epsilon_{it}. \end{aligned} \tag{6}$$

[12]The restriction that $\boldsymbol{\theta}_i(z_{i,t-1}) = \boldsymbol{\theta}(z_{i,t-1})$, $i = 1, 2, \ldots, N$, is obviously much weaker than the unconditional generic slope coefficient pooling restriction of Barro regressions and fixed-effects panel data models, and also is significantly weaker still than the unconditional long-run pooling restriction of the pooled mean group model of Pesaran, Shin and Smith (1999), namely $\boldsymbol{\theta}_i(z_{i,t-1}) = \boldsymbol{\theta}$, $i = 1, 2, \ldots, N$. See Binder and Offermanns (2007) and Binder, Georgiadis and Sharma (2010) for previous empirical evidence in the context of exchange rate and output growth dynamics that the weak conditional/state-dependent long-run pooling restriction we consider here still sizeably increases the efficiency of parameter estimates compared to country-specific time-series analyses.

In this framework featuring *conditional* or *state-dependent* long-run homogeneity, all transitional dynamics are fully country-specific, and the long-run dynamics are homogeneous only for countries sharing the same conditioning environments. Note that this framework allows the long-run multipliers to differ across countries, but also over time for a given country, with variations in the conditioning state variable. Clearly, such a panel modelling framework cannot be a free lunch: For the model to be readily estimable for the type of panel data set we are working with in this paper, the number of variables in $\boldsymbol{x}_{it}$ has to be limited, and the time-series dimension of the data available for each country cannot be too small. Keeping these restrictions in mind, there are numerous advantages of the panel modelling framework of Equation (6) for the analysis of the development effects of economic policies, specifically also when compared to Barro regressions, with a typical such Barro regression given by

$$T^{-1} \cdot (y_{iT} - y_{i0}) = \beta_0 + \beta_1 \cdot y_{i0} + \boldsymbol{\gamma}' \cdot \boldsymbol{x}_i + \boldsymbol{\delta}' \cdot \mathbf{z}_i + v_{iT}. \tag{7}$$

The advantages of our state-dependent dynamic panel data model in Equation (6) compared to the Barro regression framework in Equation (7) stem from the facts that the model in Equation (6)

(i) is an explicitly dynamic model, with statistically optimal lag orders for all variables, unlike the limited dynamic structure in Equation (7), which is imposed on the data *a priori*;

(ii) allows for fixed-effects intercepts and time trends, μ_i and φ_i, whereas the model in Equation (7) only allows for random-effects intercepts as part of v_{iT};

(iii) allows for fixed-effects type (systematically varying) short-run slope coefficients, α_i and $\boldsymbol{\psi}_i$, and long-run coefficients $\boldsymbol{\theta}(z_{i,t-1})$ that are in general identical only for the same realizations of the state variables, $z_{i,t-1}$ – whereas the model in Equation (7) imposes full (cross-sectional and intertemporal) invariance of the slope coefficients in β_1, $\boldsymbol{\gamma}$ and $\boldsymbol{\delta}$;

(iv) allows for cross-sectionally heteroskedastic disturbance term variances, whereas the disturbance term variance is typically assumed to be cross-sectionally homoskedastic under the model in Equation (7);

(v) allows for non-linear terms in $z_{i,t-1}$ and $\boldsymbol{x}_{it-1}$, whereas the model in Equation (7) is fully linear.

In terms of substantive economic implications, these modelling features result in the following:

First, our model in Equation (6) lets the data determine as to what is labeled short- and what is labeled long-run dynamics.[13]

Second, our model in Equation (6) features a high degree of cross-country heterogeneity both concerning the short- and long-run parameters, while also capturing common long-run features prevailing under the same conditioning environments. When discussing our empirical results, we will highlight the substantive implications these two model features have: The development effects of changes in economic policies in our model set-up, unlike in the set-up of the Barro regression, can vary across countries that feature differing social norms, institutions, and other key societal characteristics. As we will document, the variations of the effects across countries can be sizeable, implying that policy recommendations based on Barro regressions for many countries will be subject to a "one size fits all" fallacy of sizeable proportions. As we will also document, the speed with which coun-

[13]Note that in order to use annual data series, we need to interpolate in particular the HDI series, as these are only available in quinquennial form. In separate simulation work, we document that our panel model's long-run coefficients (on which we focus in much of this paper) do reflect the variation actually available in the non-GDP components of HDI. Also, the long-run coefficients are not sensitive to plausible variations of the interpolation scheme we use for the HDI series.

tries' long-run development paths are reached after a development policy change exhibits significant cross-country variation. Barro regressions per construction cannot capture this data feature, leading to mis-assessments concerning the time horizon required for changes in economic policies to reach their long-run development effects.

Third, as noted by Pesaran and Shin (1999), an autoregressive distributed lag model of the form of Equation (6) can effectively deal with potential endogeneity of the explanatory variables in $\boldsymbol{x}_{it}$. To expand upon this point, consider for illustrative purposes a simplified special case of the model in Equation (4):

$$y_{it} = \mu_i + \varphi_i \cdot t + \rho_i(z_{i,t-1}) \cdot y_{i,t-1} + \varrho_i(z_{i,t-1}) \cdot x_{it} + \epsilon_{it}. \tag{8}$$

Suppose that x_{it} is correlated with ϵ_{it}:

$$x_{it} = \gamma_i + \delta_i \cdot t + \kappa_i \cdot x_{i,t-1} + u_{it}, \tag{9}$$

with $Cov(\epsilon_{it}, u_{it}) = \sigma_{\epsilon u,i} \neq 0$. The least squares estimator of the coefficients in Equation (8) clearly will be subject to an endogeneity bias. A great appeal of the autoregressive distributed lag model is that this endogeneity can be readily overcome without needing to resort to instrumental variables estimation. To see this, decompose ϵ_{it} using linear projection as

$$\epsilon_{it} = \frac{\sigma_{\epsilon u,i}}{\sigma^2_{u_i}} \cdot u_{it} + \xi_{it}, \tag{10}$$

where by construction $Cov(\xi_{it}, u_{it}) = 0$. Substituting from Equation (9) into Equation (10), we obtain

$$\epsilon_{it} = \frac{\sigma_{\epsilon u,i}}{\sigma^2_{u_i}} \cdot (x_{it} - \kappa_i \cdot x_{i,t-1} - \gamma_i - \delta_i \cdot t) + \xi_{it}. \tag{11}$$

Substituting from Equation (11) into Equation (8), we obtain an augmented autoregressive distributed lag model model involving the additional regressor $x_{i,t-1}$, but in which neither x_{it} nor $x_{i,t-1}$ causes an endogeneity bias, as $Cov(\xi_{it}, u_{it}) = Cov(\xi_{it}, u_{i,t-1}) = 0$. An autoregressive distributed lag model can therefore be estimated by standard least squares techniques, provided the model lag orders are not underspecified.

Fourth and finally, our model in Equation (6) allows us to investigate the dependence of the long-run development effects of economic policies on the state variables as varying according to non-linear, flexible-form functionals, for example Chebyshev polynomials. See Binder and Offermanns (2007) and Binder, Georgiadis and Sharma (2010) for a more detailed discussion of the rich set of nonlinearities this modelling approach can capture.

Before turning in the next section to the discussion of our empirical results, let us first outline our choices for the model variables, y, $\boldsymbol{x}$, and z. For y, we choose hdi or the logarithm of gdp; in $\boldsymbol{x}$, we include a set of variables that can be interpreted as capturing or reflecting different types of economic policies aimed at improving human development (output), namely the logarithm of per capita government consumption ($lgovpc$, reflecting aspects of fiscal policy), the logarithm of per capita investment (private plus public) in physical capital ($linvpc$, reflecting both aspects of fiscal policy and various policy incentives for private sector saving and investment), and the logarithm of per capita imports plus exports ($lopennpc$, reflecting various policy measures to stimulate international trade).[14] See Binder, Georgiadis and Sharma (2010) for a review of some of the theoretical growth literature discussing the mechanisms through which our three "$\boldsymbol{x}$" variables may affect long-run development, specifically GDP. Compared to much of the empirical output growth literature, our "$\boldsymbol{x}$" vector reflects a sizeably smaller set of regressors. We allow for additional regressors that have been considered in the Barro regression based empirical output growth literature to enter through two other aspects of our model: (i) the country-specific fixed-effects intercepts and time trends, and (ii) the set of conditioning variables z capturing the state dependence of the long-run development effects of changes

[14]An inflation-based measure of monetary policy turned out to be insignificant in all specifications, and we thus do not report on it further in this paper.

in government consumption, in investment in physical capital as well as in trade. As variables entering the set of conditioning state variables, we consider an index of institutional development (*instdev*), an index of gender inequality (*geninq*), and an index of the development conduciveness of the religious environment (*condrel*).[15] For us to incorporate a country in our sample, there must be 30 consecutive time-series observations available on the dependent, all explanatory and all conditioning state variables. Table 1 provides a list of the $N = 84$ countries among the 111 countries in the Gray Molina and Purser (2010) data set that we can thus include in our sample. See Appendix A for details concerning the measurement of our y and $\boldsymbol{x}$ variables.

Let us turn for the remainder of this section to a discussion of the measurement of our three state indices. For institutional development - see, for example, Acemoglu, Johnson and Robinson (2005) and Rodrik, Subramanian and Trebbi (2004) for contributions stressing the role of institutions for a country's economic development - we use the dynamic state-space model based index from Binder and Georgiadis (2010) with the component variables corruption, law and order, bureaucracy quality, investment profile and internal conflict, all drawn from the Political Risk Services Group's International Country Risk Guide, see Binder and Georgiadis (2010) for further details. As an illustration, Figure 6 provides the institutional development ranking sorted from highest (Finland) to lowest (Democratic Republic of Congo) levels of institutional development (the higher the index value, the higher the country's institutional quality). Motivating our second index, gender inequality, there is considerable concern expressed in the development economics literature about the role societal inequality may play as an obstacle to human development progressing to its potential; see, for example, the Human Development Report 1995. In this paper, we measure gender inequality on the basis of (i) the difference between the

[15]We abandoned attempts to also consider an index of income inequality, due to a lack of observations covering sufficiently long time intervals for a reasonably large number of countries in the United Nations' WIDER database.

ratio of a country's female to male gross enrolment in primary schooling and the grand cross-country average of this ratio and of (ii) the difference between the ratio of female to male life expectancy and the grand cross-country average of this ratio. Excluding females from access to education induces a gender bias due to the ensuing unequal distribution of human capital in the population; relative life expectancy of females compared to males is an indicator for gender bias as it is critically influenced by gender bias in health care and nutrition.[16] As an illustration, Figure 7 provides the gender inequality ranking for 2005, sorted from the lowest (Iran) to the highest (Niger) degree of observed such inequality (that is, the higher the index value for gender inequality, the more successful a country has been in moving towards gender equality). Our third index, development conduciveness of the religious environment, is motivated by the observation that the recent empirical growth literature (see, for example, Sala-i-Martin, Doppelhofer and Miller, 2004) has accumulated evidence that religious affinities are among the most robust output growth determinants, even though the mechanisms through which religious affiliation affects output growth are not clear. Our index of the development conduciveness of the religious environment is constructed by summing up the products of (i) a population's proportion being muslim, protestant etc. and of (ii) the coefficient estimate of the latter variable in the growth regressions of Sala-i-Martin, Doppelhofer and Miller (2004). As an illustration, Figure 8 provides the development conduciveness of the religious environment ranking for 2005, sorted from the highest (Japan) to the lowest (Iceland) degree of such development conduciveness. See Appendix B for further details concerning the measurement of our state indices. As the state dependence of economic policies that we model in Equation (6) concerns long-run dependence, for each of the conditioning state indices we extract the underlying long-run evolution using a recursive Hodrick-Prescott filter as detailed in Appendix B.4. For the conditioning functional, we work with first-

[16] See Sen (2001) for a more thorough discussion.

order Chebyshev polynomials, so that

$$\theta_\ell(z_{i,t-1}) = \theta_{\ell 0} + \theta_{\ell 1} \cdot z_{i,t-1}, \tag{12}$$

with $\ell = 1, 2, 3$.[17]

4 Empirical Findings

As motivated in detail in Section 3, we present estimation results and their substantive economic implications for two models: The set of Barro regression models[18]

$$\begin{aligned} T^{-1} \cdot (y_{iT} - y_{i0}) \quad &= \quad \beta_0 + \beta_1 \cdot y_{i0} + \gamma_1 \cdot govgdp_i + \gamma_2 \cdot invgdp_i + \gamma_3 \cdot openngdp_i \\ &\quad + \delta_1 \cdot instdev_i + \delta_2 \cdot geninq_i + \delta_3 \cdot condrel_i + v_{iT}, \end{aligned} \tag{13}$$

where y_{it} is hdi_{it} or gdp_i, $instdev_i$ reflects institutional development, $geninq_{it}$ gender inequality, and $condrel_{it}$ development conduciveness of the religious environment, and the set of state-dependent panel data models

$$\begin{aligned} \Delta y_{it} \quad &= \quad \mu_i + \varphi_i \cdot t + \alpha_i \cdot [y_{i,t-1} - \theta_1(z_{i,t-1}) \cdot lgovpc_{i,t-1} - \theta_2(z_{i,t-1}) \cdot linvpc_{i,t-1} \\ &\quad - \theta_3(z_{i,t-1}) \cdot lopennpc_{i,t-1}] + \boldsymbol{\psi}_i' \cdot \boldsymbol{h}_{it} + \epsilon_{it}, \end{aligned} \tag{14}$$

---

[17] While we also considered higher-order Chebyshev polynomials introducing yet richer forms of non-linearities, for reasons of parsimony we decided to restrict ourselves in this paper to first-order polynomial specifications.

[18] The regressors in Equation (13) except for y_{i0} are intertemporal averages over the sample period. Also, to stay as close as possible to the typical formulation of Barro regressions in the empirical growth literature, government consumption, investment in physical capital and imports plus exports enter Equation (13) as ratios relative to GDP, $govgdp_i$, $invgdp_i$ and $openngdp_i$, respectively.

where y_{it} is again hdi_{it} or gdp_{it}, and z_{it} is one of $instdev_{it}$, $geninq_{it}$, or $condrel_{it}$.[19] See Section 3 for a description of all the variables.

Tables 2 and 3 provide the coefficient estimates as well as implied speed of convergence coefficients for the Barro regression model.[20] There are two main dimensions of results for the Barro regression model: The speed of convergence to the steady state and the quantitative role of the various development determinants. With respect to the speed of convergence, the implied half-life for GDP for our sample is longer than reported in some of the previous literature (for example Barro and Sala-i-Martin, 2004), but shorter than implied by the results in Gray Molina and Purser (2010).[21] The half-lives tend to be significantly longer for HDI than for GDP, with the half-life of GDP in the model including the complete set of regressors being about 56% shorter than that for HDI. With respect to the development determinants, for the three regressors capturing or reflecting macroeconomic policies aimed at improving human development, except for trade openness these enter all Barro regressions with the same sign: a negative sign for government consumption (as also in Barro and Sala-i-Martin, 2004) and a positive sign for investment in physical capital. Trade openness has a negative sign in all regressions when HDI is chosen as the dependent variable, but a positive sign in one of the four regressions for the case of GDP being the left-hand side variable. Trade globalization has, however, in any case only insignificant effects on HDI and GDP. For the state variables reflecting social norms, institutions and other societal characteristics - institutional development, gender inequality,[22] and development conduciveness of the religious environment - these have significant effects both in the HDI and in the GDP model, with the sole exception being

[19] Note that for the CPMG panel data model in Equation (14), all regressors enter in their original time-varying format. See Section 3 for further discussion.

[20] See Appendix C for a derivation of the length of the half-lives implied by Equations (13) and (14).

[21] Some of the half-lives implied by the Gray Molina and Purser (2010) regressions are difficult to interpret, as they involve the initial level of GDP per capita even when the dependent variable is HDI.

[22] Recall that the higher the index value for gender inequality, the more successful a country has been in moving towards gender equality.

institutional development for HDI. Generally, according to the Barro regression model, investment in physical capital, reduction of gender inequality and a conducive religious environment appear to be the main determinants spurring long-run human development and output growth. Institutional quality appears to matter for long-run output development, but not for that of HDI. Fiscal (government consumption) stimuli, whether due to interest rate effects or due to accompanying distortionary tax schemes are harmful for long-run output development, and insignificant for HDI. Trade globalization, finally, according to the Barro regression model appears insignificant for both long-run GDP and HDI development.

Let us turn to the estimation results for our state-dependent panel model. As for the Barro regressions, we begin with commenting on the speeds of convergence to steady state/half-lives. In Tables 4 to 6 we provide the means and medians of the country-specific speed of adjustment parameter estimates for the various dependent and conditioning state variables. For example, when choosing institutional development as conditioning state variable and HDI as the dependent variable (Table 4), the average speed of adjustment of the 24 OECD economies in our sample is -0.1. The half-lives obtained from the state-dependent panel model are across the board much shorter than those obtained from the Barro regressions. To just give a couple of examples: For HDI, under the Barro regression the half-life, though depending on the details of the model specification, tends to be at least 78.1 years, but under the state-dependent panel model falls to somewhere between three to 17 years. For the logarithm of GDP, under the Barro regressions, the half-lives reduce up to 39 years, but are down to one year under the state-dependent panel model. As our dynamic panel framework is designed to filter out country-specific short-run dynamics, this result is not due to confusing short- with long-run dynamics, but rather a consequence of the fact that our panel model captures both short- and long-term cross-country heterogeneities, and can be successful in capturing the adjustment dynamics to the relevant conditional, country-specific long-run equilibrium. In general, across the three different index variables capturing state dependence - institutional development, gender inequality, and development conduciveness of the religious environment - we observe that conditioning on these for GDP has quite similar effects across the three index variables. The GDP adjustment processes across the three index variables tend to be fastest for the LDCs, and relatively slowest for the OECD economies. For HDI, the half-lives do not just vary across country groupings, but also vary noticeably across the different specifications of state dependence. This reinforces the point that Barro regressions mask sizeable variation of half-lives, and that half-lives will change as the overall development environment within which economic policies are pursued is evolving. For example, the half-life for HDI in Sub-Saharan Africa when conditioning long-run development on institutional quality (six years) is about half as long than when conditioning long-run development on gender inequality (twelve years). Thus, HDI adjustments for Sub-Saharan Africa are slowed down notably more strongly by cross-country differences in institutional quality than in gender inequality. While the difference with the exception of the LDCs is less pronounced for other country groupings, differences in institutional quality generally appear to be delaying long-run adjustment more sizeably than differences in gender inequality. Differences in the development conduciveness of the religious environment are a major factor for such delay also, for some country groupings (most pronouncedly Asia) in even more accentuated form than institutional quality issues.

Concerning the estimated long-run coefficient functionals for the state-dependent panel model in Equation (14) several observations stand out, as displayed in Figures 9 to 11. First, the figures, most strongly for GDP, but on a diminished scale also for HDI, indicate strong state dependence of the development effects of economic policy changes, as the estimated long-run coefficient functionals exhibit sizeable variation across different values of the conditioning state indices. The degree of state dependence highlights the cost of (erroneously) imposing cross-country homogeneity of the long-run development effects of changes in economic policy. Let us turn second to specific policy variables and conditioning state indices. Considering among the latter first institutional development, the sign of the long-run effects of a fiscal (government consumption) stimulus varies for both HDI and GDP across different levels of institutional quality. For countries with low institutional quality, government consumption stimuli positively affect long-run HDI and GDP, but for countries with high institutional quality, the long-run development effects are negative, as for the Barro regression model. The scope of fiscal policy in the form of government consumption is much more limited for countries in which institutions are highly developed already. Strong institutional development, on the other hand, increases the long-run development effects of both investment in physical capital and of trade globalization, both for HDI and GDP, but again the stronger effects materializing for GDP. Taken together, the fiscal (government consumption) stimulus and physical capital investment effects suggest that while government consumption expenditure in countries with strong institutional development is not a suitable vehicle for long-run growth, a different assessment may hold for government investment expenditure. With respect to gender inequality, state variation of HDI development effects of economic policy changes is actually more pronounced across different stages of gender (in-)equality than across different stages of institutional development. The strongest variation is observed for the long-run HDI effects of changes in investment in physical capital, with these being about half a percentage point higher in countries exhibiting (relative) success at moving towards gender equality. The scale with which variations in gender inequality affect long-run GDP development is small when compared with the corresponding scale for institutional development. Also, as indicated by the standard error bands in Figure 10, there is uncertainty regarding how the long-run GDP effects of physical capital investment vary across stages of gender (in-)equality. Turning finally to development conduciveness of the religious environment, while the scale of state variation of the policy effects is large for GDP and relatively large for HDI, the individual policy effect variations seem at best difficult to rationalize. Why, for example, would the long-run increase of GDP per capita be about one whole percentage point larger in an environment in which the mix of religious affiliations is slightly more growth conducive? From our perspective, the magnitude with which the development effects of macroeconomic policies vary across different religious environments make yet more transparent than for the Barro regressions that the religious affiliation variables proxy for other societal characteristics, possibly including social trust, and thus should not be taken at face value. For the remainder of this paper, therefore, we do not further pursue models that contain the religious environment index.

Exploiting the rich dynamic structure of our state-dependent panel model, we next compute dynamic multipliers depicting the full adjustment paths of HDI and of GDP per capita in response to a permanent ten percentage points increase in one of the economic policy variables. We compare the dynamic multipliers obtained from our state-dependent dynamic panel model with the time path of the effect of the corresponding change in the economic policy variables in period $t = 0$ obtained from the Barro regression framework.[23] To be specific about the computation of the dynamic multipliers, consider first the Barro regression model in Equation (7),

$$T^{-1} \cdot (y_{iT} - y_{i0}) = \beta_0 + \beta_1 \cdot y_{i0} + \boldsymbol{\gamma}' \cdot \boldsymbol{x}_i + \boldsymbol{\delta}' \cdot \boldsymbol{z}_i + u_i.$$

Neglecting any transitional dynamics, a policy change in the ℓ-th $\boldsymbol{x}$ regressor implies a

[23] It is certainly sensible to argue that changes in, say, government consumption will in general also induce changes in physical capital investment and in international trade. However, as here we wish to emphasize the comparison between intertemporal adjustments as conventionally computed for the Barro regression model and those implied by our state-dependent panel model, we stick to computing orthogonal dynamic multipliers.

change in the long-run level of the dependent variable given by

$$\widetilde{y}_{iT}^{\ell} - y_{iT} = T \cdot \gamma_{\ell} \cdot (\widetilde{x}_{i\ell} - x_{i\ell}), \tag{15}$$

where $\widetilde{x}_{i\ell}$ denotes the value of the ℓ-th regressor after the policy change, and $\widetilde{y}_{iT}^{\ell}$ the corresponding new long-run level of y_i. In case the dependent variable is HDI, $\widetilde{y}_{iT}^{\ell} - y_{iT}$ reflects the level change of HDI relative to its baseline level after all adjustment has taken place. In case the dependent variable is the logarithm of GDP per capita, $\widetilde{y}_{iT}^{\ell} - y_{iT}$ reflects the percentage change of GDP per capita relative to its baseline level after all adjustment has taken place.[24] Recall that in the Barro regression model the $\boldsymbol{x}$ variables are measured as shares of GDP, while the $\boldsymbol{x}$ variables in the state-dependent panel data model are measured as per capita quantities. In order to work with comparable shocks in the two models, for each country we calculate the increase in the share of x_{ℓ} in GDP implied by a ten percent increase in x_{ℓ} in the state-dependent panel model, and use the implied change in the share of x_{ℓ} in GDP as the shock to the Barro regression model. Turning now to transitional dynamics, as follows from Appendix C.1, the transition path leading to the new long-run level of the dependent variable in the Barro regression model is given by

$$y_{it} - y_{i0} = (1 - e^{-\lambda t}) \cdot (\widetilde{y}_{iT}^{\ell} - y_{i0}), \tag{16}$$

with $\lambda = -log(1 + T\beta_1)/T$. For the calculation of the dynamic multipliers in the state-dependent panel model, see Appendix D. The dynamic multipliers in Figure 13 display for all 84 countries in our sample the percentage change of HDI and of GDP per capita in response to a ten percentage points increase in one of the economic policy variables. To structure the large number of multipliers we compute, we decided to assign countries to one of three cross-country clusters, based on their observed average values of the condi-

[24]See Appendix D for further details concerning the computation of the dynamic multipliers.

tioning state indices institutional development and gender inequality, and with the clusters constructed to create relatively homogenous country groupings according to the two state indices institutional development and gender inequality. We assign each country to one of these clusters: Cluster 1 containing all countries scoring well below average on gender inequality and at most average on institutional development; Cluster 2 containing all countries scoring in the extended medium range of values for institutional development and close to average or better on gender inequality; and Cluster 3 finally containing all countries scoring at least in the 80% percentile on institutional development - all these countries happen to have an average or higher score on gender inequality. See Figure 12 for a graphical illustration that these three clusters naturally emerge when considering the two state indices institutional development and gender inequality, and Table 7 for a listing of the countries within these three clusters. Each dynamic multiplier trajectory in Figure 13 corresponds to the average trajectory across the conditioning state indices institutional development and gender inequality: For each of these two indices, we trace the in-sample effects of a period $t = 0$ (ten percent) increase of the $\boldsymbol{x}$ variable in question if the state index had evolved as it actually did in sample.[25] The Barro regression based multipliers are, of course, state invariant and thus do not involve averaging across state indices. The left column in Figures 13 and 14 depicts the dynamic multipliers for all three clusters and all three economic policy variables under HDI being the dependent variable, and the right column depicts the dynamic multipliers under the logarithm of GDP per capita being the dependent variable. In each panel, the solid lines depict dynamic multipliers obtained from the state-dependent panel model in Equation (14), and the starred lines depict the dynamic multipliers implied by the Barro regression model as given by Equation (16). Figure 13 depicts for the state-dependent panel model the dy-

[25]As the dynamic multipliers for our dynamic panel model are state dependent, there are other possibilities to compute dynamic multipliers, including integrating out the state dependence. See Koop, Pesaran and Potter (1996) for a general discussion in the time-series context.

namic multipliers for each country within a given cluster, whereas Figure 14 displays the averages of these dynamic multipliers across countries in a given cluster. Finally in Figure 14, the dash-dot line depicts the long-run effects as implied by the state-dependent panel model. Several observations stand out upon inspection of Figures 13 and 14. First, there is considerable heterogeneity across clusters in both the short- and the long-run effects of the policy changes on both HDI and GDP per capita as implied by the state-dependent panel model. As just one example, while for countries in Cluster 3 GDP per capita grows strongly after an increase in investment in physical capital, the effects of such a stimulus are concentrated around zero for countries in Cluster 1. This heterogeneity of the dynamic multipliers in part reflects, of course, the state dependence of the long-run coefficient functionals discussed earlier in this section. It also reflects the country-specific short-run dynamics inherent in our state-dependent panel model. The latter two sources of cross-country heterogeneity are also prominently present in the dynamic multipliers reflecting the GDP effects of a fiscal (government consumption) stimulus: While the average long-run effects after a modest initial GDP gain are negative for Cluster 3, they are positive for Clusters 1 and 2, though for these clusters also the short-run effects are larger in magnitude than the long-run effects. Even in countries with limited institutional development, therefore, the development scope of fiscal policy (in the form of government consumption stimuli) is limited. Second, the policy effects on HDI implied by the state-dependent panel model generally tend to be quantitatively, but in some instances also qualitatively different from those on GDP per capita. For example, while an increase in trade openness leads to an accumulating gain in GDP per capita across all clusters, the same stimulus across all clusters negatively affects HDI. The dynamic multipliers generally make clear that the range of macroeconomic policies we consider impact HDI on a scale often about one tenth of that for the GDP impacts, both in the short and in the long run. Third, both the short- and the long-run development effects in the state-dependent panel model are generally different from the corresponding effects in the Barro regression model, not least because the Barro model implies homogenous effects across all countries and features linear adjustment processes. Only for specific cases are the multiplier effects implied by the Barro regression model similar to the multiplier effects implied by the state-dependent panel model. In general, even if one is interested in average effects across certain societal characteristics, these cannot be well measured by a model neglecting prevailing key heterogeneities.

Tables 8 and 9 focus on the long-horizon effects of the various economic policy changes depicted in Figures 13 and 14, with Table 8 providing the development effects after 20 years, and Table 9 providing these effects in the steady state.[26] The two tables highlight some commonalities in the long-horizon development effects of changes in our three economic policy variables. Stimuli in investment in physical capital across all three country clusters and for both HDI and GDP have positive long-horizon effects - though the GDP effects are significantly larger than those for HDI. For both HDI and GDP these effects appear noticeably smaller, though, than suggested by the Barro regression model. For fiscal (government consumption) stimuli, as noted earlier, state conditioning plays a particulary pronounced role, in that for both HDI and GDP the long-horizon effects diminish with advances in institutional development (and for HDI also with advances in gender inequality) - for the GDP effects, these even turn negative, as also noted earlier. The Barro regression model, though, seems to overstate the extent to which government consumption stimuli may have detrimental long-term development effects. Last in terms of commonalities of long-horizon effects, it is notable that across all three of our country clusters the long-horizon effect of increased international trade are negative for HDI, and (sizeably) positive for GDP.

[26]Table 9 also lists the steady state effects implied by the Barro regression models that were not plotted in Figures 13 and 14.

Let us finally discuss the relation between our findings in this section and those in Section 2. In Section 2, we had found evidence (see in particular Figures 1, 3 and 5) that HDI would exhibit unconditional convergence features not present in GDP. In this section, we found evidence that countries' long-run development paths are state dependent, and that the *conditional* convergence process for HDI tends to be much more drawn out than that for GDP. Table 10 indicates a likely source for this apparent discrepancy of findings: At least for Africa and Asia, but to a weaker degree also for the OECD countries, there is (panel unit root test based) evidence that HDI is a unit root process; also, GDP appears to be a unit root process across all country groupings. While the (popular) methodology employed in Section 2 is not valid in the presence of a unit root (bounded second moments then do not exist; a regression of the level of a variable on its growth rate is unbalanced and yields inconsistent parameter estimates), our state-dependent panel model is applicable even in the presence of unit roots. The latter model's implications that both HDI and GDP converge conditionally to state-dependent development paths, with HDI adjustment significantly more drawn out than GDP adjustment therefore need to be taken at face value. In Section 2, we had also found evidence that long-run levels development of HDI is quite closely aligned with that for GDP, but that such close alignment is not present in growth rates, even at a 35 years horizon. These findings are consistent with the empirical evidence accumulated in this section: While HDI and GDP may feature a common stochastic trend, some core economic policies have notably different effects on HDI vs. GDP growth even at extended horizons. It remains a question that is beyond the scope of this paper, though, to characterize the key factors underlying a common stochastic trend in HDI and GDP.

5 Conclusion

In this paper, we have applied a novel dynamic panel data model with state-dependent coefficients to study the effects of a set of macroeconomic policies - investment in physical capital, government consumption and trade openness - on the development of HDI and GDP per capita. In contrast to the Barro regression model framework, the panel data model we apply does not require to *a priori* impose a decomposition of the data into short- and long-run dynamics, is able to account for potential endogeneity of the policy variables, allows for a high degree of cross-country heterogeneity in the development process, and is able to assess the quantitative role of countries' persistent characteristics such as institutional quality, gender (in-)equality and religious environment. Among the key insights that have emerged from our analysis are: First, HDI development on various counts differs notably from that of GDP. While both HDI and GDP exhibit conditional (though not unconditional) cross-country convergence properties, the HDI adjustment process is slower than that for GDP. Realizing gains in HDI development requires more patience than in the case for GDP development policies. Also, macroeconomic policies such as international trade integration, stimulation of investment in physical capital and government consumption stimuli that may spur GDP development relatively notably will have less pronounced effects for HDI. HDI development policies should look beyond the realm of GDP development policies. Second, there are sizeable and important heterogeneities in the development effects of macroeconomic policies across countries. Cross-country differences in social norms and institutions may translate into differences in both the transitional dynamics and the long-run effects implied by economic policy changes. Our findings in this regard underline the fallacy of "one size fits all" recipes, and highlight the importance of observing local conditions for the formulation of development strategies. One key example of this is that fiscal stimuli in the form of government consumption positively affect GDP in countries with low institutional quality, but negatively affect long-run GDP in countries with high institutional quality. The range of economic policies and societal characteristics rendering the development effects of changes in such policies state dependent we have considered in this paper is rather limited. This is primarily due to data limitations that can hinder estimation of the state-dependent panel model even when a corresponding Barro regression model can be estimated. Much work on data measurement thus remains, and some of our other current work (see Binder and Georgiadis, 2010) is making start to remedy such limitations.

References

[1] Acemoglu, D., S. Johnson and J.A. Robinson (2001) "The Colonial Origins of Comparative Development: An Empirical Investigation," *American Economic Review*, 91, 1369-1401.

[2] Acemoglu, D., S. Johnson and J.A. Robinson (2005) "Institutions as the Fundamental Cause of Long-Run Growth," in P. Aghion and S. Durlauf (Eds.): *Handbook of Economic Growth*, Elsevier Science, 385-472.

[3] Barro, R.J. (1991), "Economic Growth in a Cross Section of Countries," *Quarterly Journal of Economics*, 106, 407-443.

[4] Barro, R.J. and X. Sala-i-Martin. (2004), "*Economic Growth*," MIT Press.

[5] Barro, R.J. and R. McCleary (2003), "Religion and Economic Growth," NBER Working Papers, 9682.

[6] Binder, M. and M.H. Pesaran (1999), "Stochastic Growth Models and Their Econometric Implications," *Journal of Economic Growth*, 4, 139-183.

[7] Binder, M. and C.J. Offermanns (2007), "International Investment Positions and Exchange Rate Dynamics: A Dynamic Panel Analysis," Center for Financial Studies Working Paper No. 2007/23.

[8] Binder, M. and G. Georgiadis (2010), "Institutional and Financial Market Development of Nations: New Measures for a Large Panel," Mimeo, Goethe University Frankfurt.

[9] Binder, M., G. Georgiadis and S. Sharma (2010), "Growth Effects of Financial Globalization," Mimeo, Goethe University Frankfurt.

[10] Brandolini, A. (2007), "On Applying Synthetic Indices of Multidimensional Well-Being: Health and Income Inequalities in Selected EU Countries," Bank of Italy Economic Working Papers No. 668.

[11] Decancq, K. and M.A. Lugo (2008), "Setting Weights in Multidimensional Indices of Well-Being and Deprivation," OPHI Working Paper No. 18.

[12] Evans, P. (1996), "Using Cross-Country Variances to Evaluate Growth Theories," *Journal of Economic Dynamics and Control*, 20, 1027-1049.

[13] Freedomhouse (2009), "Freedom in the World 2009," Freedom House, Inc., Washington, D.C.

[14] Gray Molina, G. and M. Purser (2010), "Human Development Trends since 1970: A Social Convergence Story," HDRO Working Paper, 01/2010.

[15] Hauk, W.R. and R. Wacziarg (2009), "A Monte Carlo Study of Growth Regressions," *Journal of Economic Growth*, 14, 103-147.

[16] Heston, A., R. Summers and B. Aten (2009), "Penn World Table Version 6.3," Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania.

[17] Im, K.S., M.H. Pesaran and Y. Shin (2003), "Testing for Unit Roots in Heterogenous Panels," *Journal of Econometrics*, 115, 53-74.

[18] Islam, N. (1995), "Growth Empirics: A Panel Data Approach," *Quarterly Journal of Economics*, 110, 1127-1170.

[19] Koop, G., M.H. Pesaran, and S.M. Potter (1996), "Impulse Response Analysis in NOnlinear Multivariate Models," *Journal of Econometrics*, 74, 119-147.

[20] Lee, K., M.H. Pesaran and R.P. Smith (1997), "Growth and Convergence in a Multi-Country Empirical Stochastic Solow Model," *Journal of Applied Econometrics*, 12, 357-392.

[21] Marshall, M.G. and K. Jaggers (2009), "Polity IV Project: Political Regime Characteristics and Transitions, 1800-2002," Center for International Development and Conflict Management, University of Maryland.

[22] Mayer-Foulkes, D. (2010), "Divergences and Convergences in Human Development," HDRO Background Paper 2010.

[23] Pesaran, M.H. and Y. Shin (1999), "An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis," In: S. Strom (Ed.), *Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium*, Cambridge: Cambridge University Press.

[24] Pesaran, M.H., Y. Shin and R.P. Smith (1999), "Pooled Estimation of Long-Run Relationships in Dynamic Heterogeneous Panels," *Journal of the American Statistical Association*, 94, 621-634.

[25] Political Risk Services Group (2008), "*International Country Risk Guide 2008*,".

[26] Rodrik, D., A. Subramanian and F. Trebbi (2004), "Institutions Rule: The Primacy of Institutions over Geography and Integration in Economic Development," *Journal of Economic Growth*, 9, 131-165.

[27] Rodríguez, F.R. (2007), "Cleaning Up the Kitchen Sink: Growth Empirics When the World Is Not Simple," Weslayan Economic Working Papers No. 2006-004.

[28] Sala-i-Martin, X., G. Doppelhofer and R.I. Miller (2004), "Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach," *American Economic Review*, 94, 813-835.

[29] Sen, A.K. (1999), "*Development As Freedom*", New York: Random House.

[30] Sen, A.K. (2001), "Many Faces of Gender Inequality", *Frontline*, 18.

[31] United Nations (1990), "*Human Development Report 1990*," United Nations, New York.

[32] United Nations (1995), "*Human Development Report 1995*," United Nations, New York.

[33] World Bank (2008), "*World Development Indicators (WDI) 2008*," International Bank for Reconstruction and Development/The World Bank.

A Data for Dynamic Panel Model's Dependent and Explanatory Variables

Data for GDP, government consumption, investment in physical capital, and imports plus exports are taken from the Penn World Tables Mark 6.3. Data for HDI are taken from the Gray Molina and Purser (2010) data set.

B Construction of the State Indices

B.1 Institutional Development

The institutional development index is taken from Binder and Georgiadis (2010), and is based on data on corruption, law and order, bureaucracy quality, investment profile and internal conflict, all drawn from the Political Risk Services Group's International Country Risk Guide.

B.2 Gender Inequality

Our gender inequality index is obtained on the basis of (i) the difference between the ratio of a country's female to male gross enrollment in primary schooling and the cross-country grand average of this ratio and of (ii) the difference between the ratio of female to male life expectancy and the cross-country grand average of this ratio, with both series obtaining equal weight in index construction. The data are taken from the World Bank's World Development Indicators 2008.

B.3 Development Conduciveness of Religious Environment

Our index of the development conduciveness of the religious environment is obtained by summing up the products of (i) a population's proportion being muslim, protestant, buddhist, catholic, orthodox, hindu and believing in eastern religions and of (ii) the coefficient estimate of the latter variable in the growth regressions of Sala-i-Martin, Doppelhofer and Miller (2004). The data on religious affiliations we use are updates of a data set originally compiled by Barro and McCleary (2003).

B.4 Extracting the Trend Component

To extract the trend component from each of the series for $\{z_{i,t-1}\}_{i=1,2,\ldots,N;\, t=1,2,\ldots,T}$, while ensuring that the trend component remains pre-determined and thus not complicating estimation of our state-dependent panel model, we

(i) keep the first four observations $z_{i,t-1}$, $t = 1, 2, 3, 4$, and set $t = 5$;

(ii) apply a Hodrick-Prescott filter to $\{z_{i0}, z_{i1}, \ldots, z_{i,t-1}\}$;

(iii) extract the trend component $z^{TR}_{i,t-1}$;

(iv) save $z^{TR}_{i,t-1}$ and set $t = t + 1$;

(v) repeat steps (ii) to (iv) until $t = T$.

The conditioning state variable we use for estimation of our state-dependent panel model is given by the vector $(z_{i0}, z_{i1}, z_{i2}, z_{i3}, z^{TR}_{i4}, z^{TR}_{i5}, \ldots, z^{TR}_{i,T-1})'$. To keep the notation simple, while using the trend components of the conditioning state variables for estimation purposes, elsewhere in the paper we drop the "TR" superscript even when referring to the trend component of the conditioning state variable.

C Speeds of Adjustments and Half Lives in the Barro Regression and State-Dependent Dynamic Panel Models

C.1 Barro Regression Model

In the deterministic continuous-time Solow-Swan growth model, the rate of change of output in per capita efficiency units, $y^E_{it} = Y_{it}/(A_{it}L_{it})$, with Y_{it} denoting output (GDP), L_{it} the size of the labor force, and A_{it} the level of technology, is a decreasing function of the level of output in per capita efficiency units, that is $\dot{y}^E/y^E = \dot{y}^E(i,t,y^E)/y^E$, $\partial(\dot{y}^E/y^E)/\partial y^E < 0$, and at the steady-state the change is zero so that $\dot{y}^E(i,t,y^{E*}_i)/y^E = 0$. Noting that $\dot{y}^E/y^E = dlog(y^E)/dt := \dot{ly}^E$, a first-order Taylor approximation of the rate of change of output in per capita efficiency units around the steady-state level y^{E*}_i is given by

$$
\begin{aligned}
\dot{ly}^E(i,t,y^E) &\approx \dot{ly}^E(i,t,y^{E*}_i) + \frac{\partial \dot{ly}^E(i,t,y^E)}{\partial ly^E(i,t)}\Big|_{y^E(i,t)=y^{E*}_i} \cdot [ly^E(i,t) - ly^{E*}_i] \\
&\equiv -\lambda \cdot [ly^E(i,t) - ly^{E*}_i]. \qquad \text{(C.1)}
\end{aligned}
$$

The solution to this differential equation with boundary condition at $t = 0$ is given by

$$
\begin{aligned}
ly^E(i,t) &= ly^{E*}_i + e^{-\lambda t} \cdot \left[ly^E(i,0) - ly^{E*}_i\right] \\
&= (1 - e^{-\lambda t}) \cdot ly^{E*}_i + e^{-\lambda t} \cdot ly^E(i,0). \qquad \text{(C.2)}
\end{aligned}
$$

Moving to a model in discrete time for which data are observable, with $A_{it} \equiv A_{i0} \cdot exp(g \cdot t)$, $L_{it} \equiv L_{i0} \cdot exp(n \cdot t)$, and $y_{it} = Y_{it}/L_{it}$, Equation (C.2) can be written as

$$
T^{-1} \cdot [log(y_{iT}) - log(y_{i0})] = g + \beta_1 \cdot [log(y_{i0}) - log(y^*_i) - log(A_{i0})]\,, \qquad \text{(C.3)}
$$

where $\beta_1 = -T^{-1} \cdot [1 - exp(-\lambda T)]$. Tacking on a stochastic disturbance term v_i,[27] assuming $log(A_{i0}) = \boldsymbol{\pi}' \cdot \mathbf{z}_i + log(A_0) + e_i$, where $\mathbf{z}_i$ is a vector of variables capturing predictable heterogeneity in initial technology, $log(A_{i0})$, and using the steady-state solution for the standard Solow growth model with saving rate s and $Y_{it} = K_{it}^{\alpha}(A_{it}L_{it})^{1-\alpha}$ gives

$$\begin{aligned} T^{-1} \cdot [log(y_{iT}) - log(y_{i0})] \quad = \quad & g + \beta_1 \cdot log(y_{i0}) + \beta_1 \cdot \left(\frac{\alpha}{1-\alpha}\right) \cdot log(n + \delta + g) \\ & -\beta_1 \cdot \left(\frac{\alpha}{1-\alpha}\right) \cdot s - \beta_1 \cdot [log(A_0) + \boldsymbol{\pi}' \cdot \mathbf{z}_i] + \epsilon_i, \end{aligned} \tag{C.4}$$

where $\epsilon_i = v_i - \beta_1 \cdot e_i$.[28] The coefficient β_1 in the Barro regression model in Equation (7) is thus related to the parameter λ in an underlying Solow growth model according to

$$\lambda = -\frac{log(1 + T \cdot \beta_1)}{T}. \tag{C.5}$$

The parameter λ determines the half-life of deviations from a country's steady-state, as from Equation (C.2) we have that

$$\frac{ly^E(i, t^{HL}) - ly_i^{E*}}{ly^E(i, 0) - ly_i^{E*}} = \frac{ly(i, t^{HL}) - log(A_{it}) - ly_i^* + log(A_{it})}{ly(i, 0) - log(A_{it}) - ly_i^* + log(A_{it})} = e^{-\lambda t^{HL}} \stackrel{!}{=} \frac{1}{2}, \tag{C.6}$$

and

$$t^{HL} = \frac{log(2)}{\lambda}. \tag{C.7}$$

C.2 State-Dependent Dynamic Panel Model

To derive the half-life in our state-dependent panel model, consider an autoregressive representation of $w_{it} = log(y_{it})$, assuming for simplicity of exposition a deterministic

[27] It may not be innocuous to additively tack on a stochastic disturbance term to the solution of a deterministic growth model; see Binder and Pesaran (1999).

[28] See Rodríguez (2007) for how the effects of the variables capturing predictable heterogeneity in initial technology could enter the Barro regression model in a non-linear form.

model with a first-order lag structure,

$$
\begin{aligned}
w_{it} &= d_i + \rho_i \cdot w_{i,t-1} \\
&= \rho_i^t \cdot w_{i0} + \frac{1-\rho_i^t}{1-\rho_i} \cdot d_i \\
&= w_i^* + \rho_i^t \cdot (w_{i0} - w_i^*). \qquad \text{(C.8)}
\end{aligned}
$$

From Equation (C.8) it is easy to see that

$$
\frac{w_{it}^{HL} - w_i^*}{w_{i0} - w_i^*} = \frac{1}{2} \quad \Longrightarrow \quad t^{HL} = \frac{log(0.5)}{log(\rho_i)}. \qquad \text{(C.9)}
$$

In the state-dependent panel model considered in Equation (6), $w_i^* = \boldsymbol{\theta}(z_i^*)' \cdot \boldsymbol{x}_i^*$ and $\rho_i = 1 + \alpha_i$.

D Computation of Dynamic Multipliers in the State-Dependent Dynamic Panel Data Model

Let us rewrite the state-dependent dynamic panel model in Equation (6) as

$$
\begin{aligned}
y_{it} &= \mu_i + \varphi_i \cdot t + (\rho_{i1} + \rho_{i2} + \ldots + \rho_{ip}) \cdot y_{i,t-1} + (\varrho_{i0} + \varrho_{i1} + \ldots + \varrho_{iq})' \cdot \boldsymbol{x}_{it} \\
&\quad + \sum_{\ell=1}^{p-1} \left(- \sum_{s=\ell+1}^{p} \rho_{is} \right) \cdot \Delta y_{i,t-\ell} + \sum_{\ell=0}^{q-1} \left(- \sum_{s=\ell+1}^{q} \varrho_{is} \right)' \cdot \Delta \boldsymbol{x}_{i,t-\ell} + \epsilon_{it} \qquad \text{(D.1)}
\end{aligned}
$$

$$
\begin{aligned}
&= \mu_i + \varphi_i \cdot t + (\alpha_i + 1) \cdot y_{i,t-1} - \alpha_i \cdot \boldsymbol{\theta}'(z_{i,t-1}) \cdot \boldsymbol{x}_{it} \\
&\quad + \sum_{\ell=1}^{p-1} \delta_{i\ell} \cdot \Delta y_{i,t-\ell} + \sum_{j=0}^{q-1} \boldsymbol{\gamma}_{i\ell}' \cdot \Delta \boldsymbol{x}_{i,t-\ell} + \epsilon_{it}. \qquad \text{(D.2)}
\end{aligned}
$$

Estimates of the slope coefficients in Equation (D.2) can be used to compute estimates of $\rho_{ik},\ k = 1, 2, \ldots, p,\ \varrho_{ik},\ k = 0, 1, \ldots, q,$ from Equation (D.1) as

$$\begin{bmatrix}\rho_{i1}\\ \rho_{i2}\\ \vdots\\ \rho_{ip}\end{bmatrix} = \begin{bmatrix}\alpha_i + 1\\ 0\\ \vdots\\ 0\end{bmatrix} + \begin{bmatrix}1 & 0 & 0 & \cdots & 0 & 0\\ -1 & 1 & 0 & \cdots & 0 & 0\\ 0 & -1 & 1 & \cdots & 0 & 0\\ \vdots & & \ddots & & \vdots & \vdots\\ \vdots & & & \ddots & 1 & 0\\ \vdots & & & & -1 & 1\\ 0 & 0 & 0 & \cdots & 0 & -1\end{bmatrix} \cdot \begin{bmatrix}\delta_{i1}\\ \delta_{i2}\\ \vdots\\ \delta_{i,p-1}\end{bmatrix}, \tag{D.3}$$

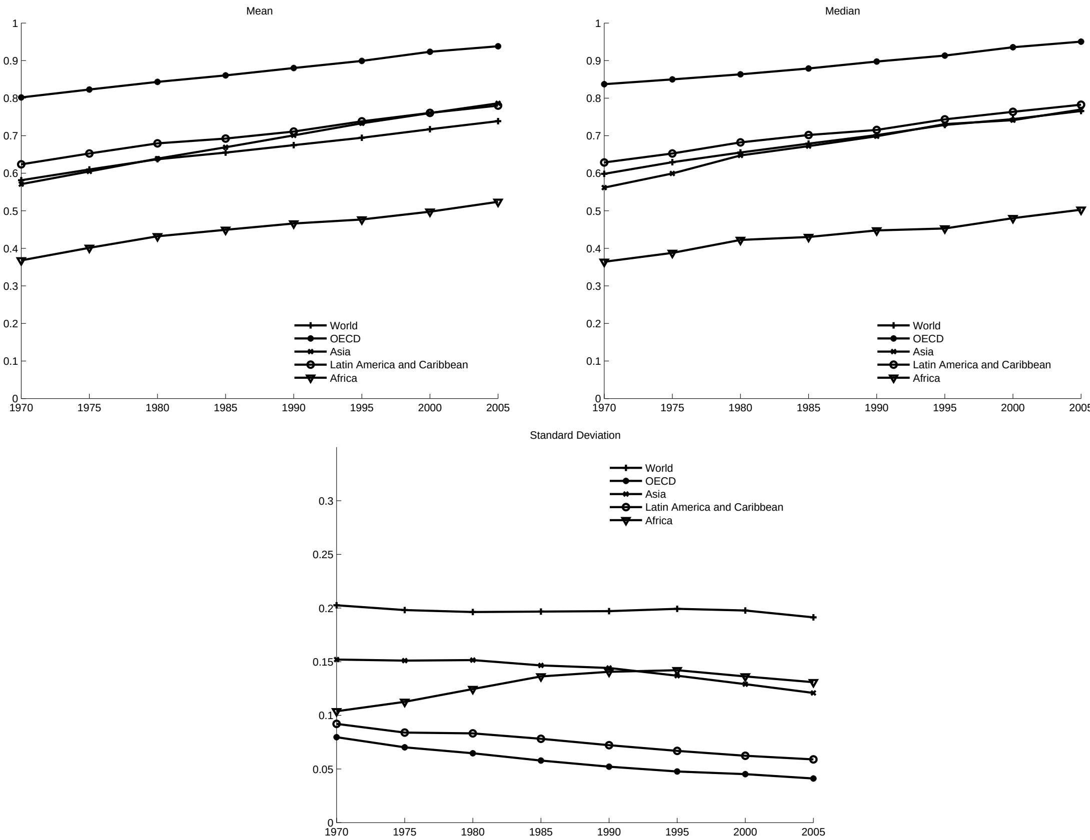
and

$$\begin{bmatrix}\varrho_{i\ell 1}\\ \varrho_{i\ell 2}\\ \vdots\\ \varrho_{i\ell p}\end{bmatrix} = \begin{bmatrix}-\alpha_i \cdot \theta_\ell(z_{i,t-1})\\ 0\\ \vdots\\ 0\end{bmatrix} + \begin{bmatrix}1 & 0 & 0 & \cdots & 0 & 0\\ -1 & 1 & 0 & \cdots & 0 & 0\\ 0 & -1 & 1 & \cdots & 0 & 0\\ \vdots & & \ddots & & 1 & 0\\ \vdots & & & \ddots & \vdots & \vdots\\ \vdots & & & & -1 & 1\\ 0 & 0 & 0 & \cdots & 0 & -1\end{bmatrix} \cdot \begin{bmatrix}\gamma_{i\ell 0}\\ \gamma_{i\ell 1}\\ \vdots\\ \gamma_{i,\ell,q-1}\end{bmatrix}, \tag{D.4}$$

for $\ell = 1, 2, \ldots, m$. Using $\rho_{ik},\ k = 1, 2, \ldots, p,\ \varrho_{ik},\ k = 0, 1, \ldots, q,$ a simulated series $\{\widetilde{y}_{it}\}$ for which $\widetilde{x}_{\ell ir} = x_{\ell ir} + impulse,\ t \geq r,$ is generated, and the dynamic multipliers for $\ell = 1, 2, \ldots, m,\ t = r, r + 1, \ldots, T_i,$ are obtained by subtracting $\{y_{it}\}$ from $\{\widetilde{y}_{it}\}$. We set $impulse = 0.1$ and for $\{x_{\ell ir}\}$ we use country i's actual values of *lgovpc*, *linvpc*, and *lopennpc*.

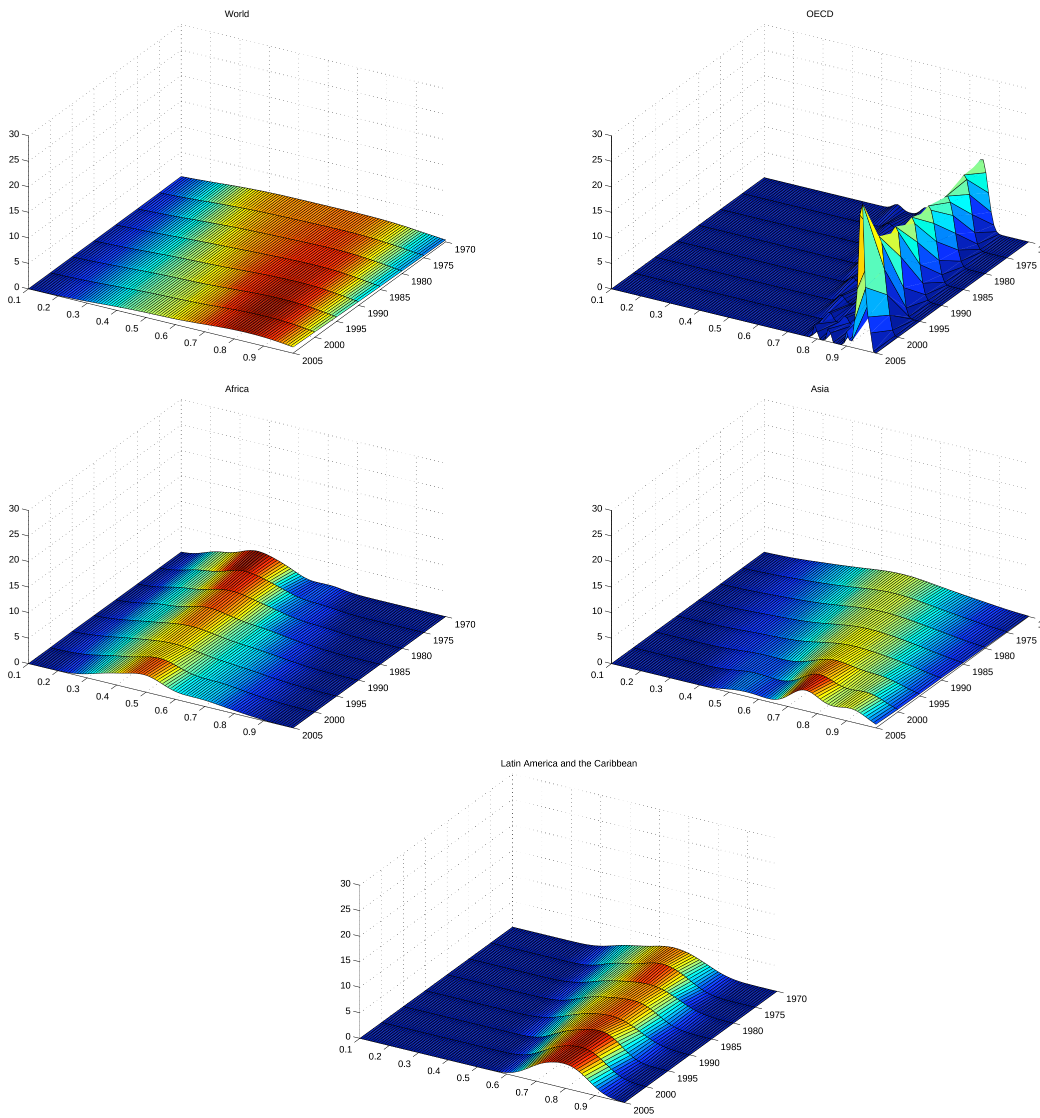
E Figures

Figure 1: Evolution of the Moments of HDI in the Gray Molina and Purser (2010) Data Set



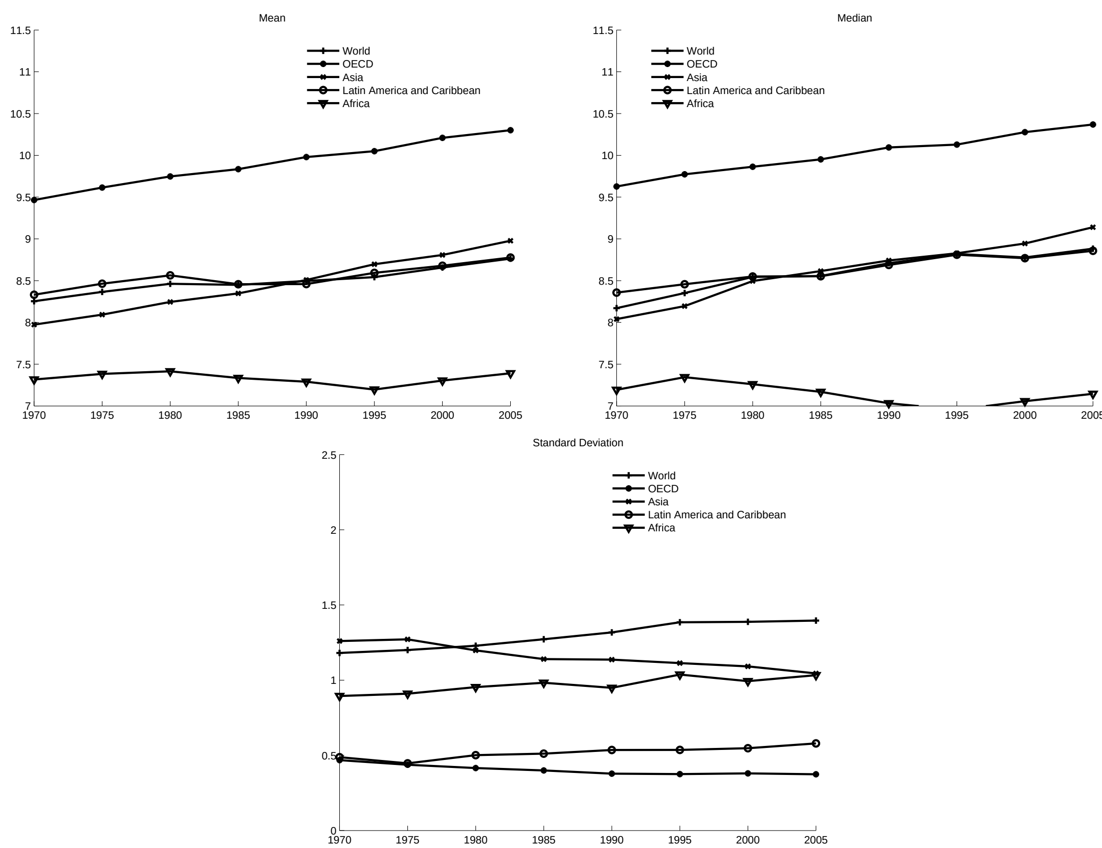
Note: The graphs depict the evolution of the cross-country mean, median and standard deviation of HDI for $N = 84$ countries from the Gray Molina and Purser (2010) data set for the time period from 1970 to 2005. The upper left-hand panel plots the evolution of the mean, the upper right-hand panel plots the evolution of the median, and the lower panel plots the evolution of the standard deviation. In each panel, the evolution of the mean, the median, and the standard deviation is plotted for the full sample ("world"), as well as the OECD, Asian, African, and Latin American and Caribbean countries that are part of this "world" sample.

Figure 2: Evolution of the Cross-Sectional Distribution of HDI in the Gray Molina and Purser (2010) Data Set



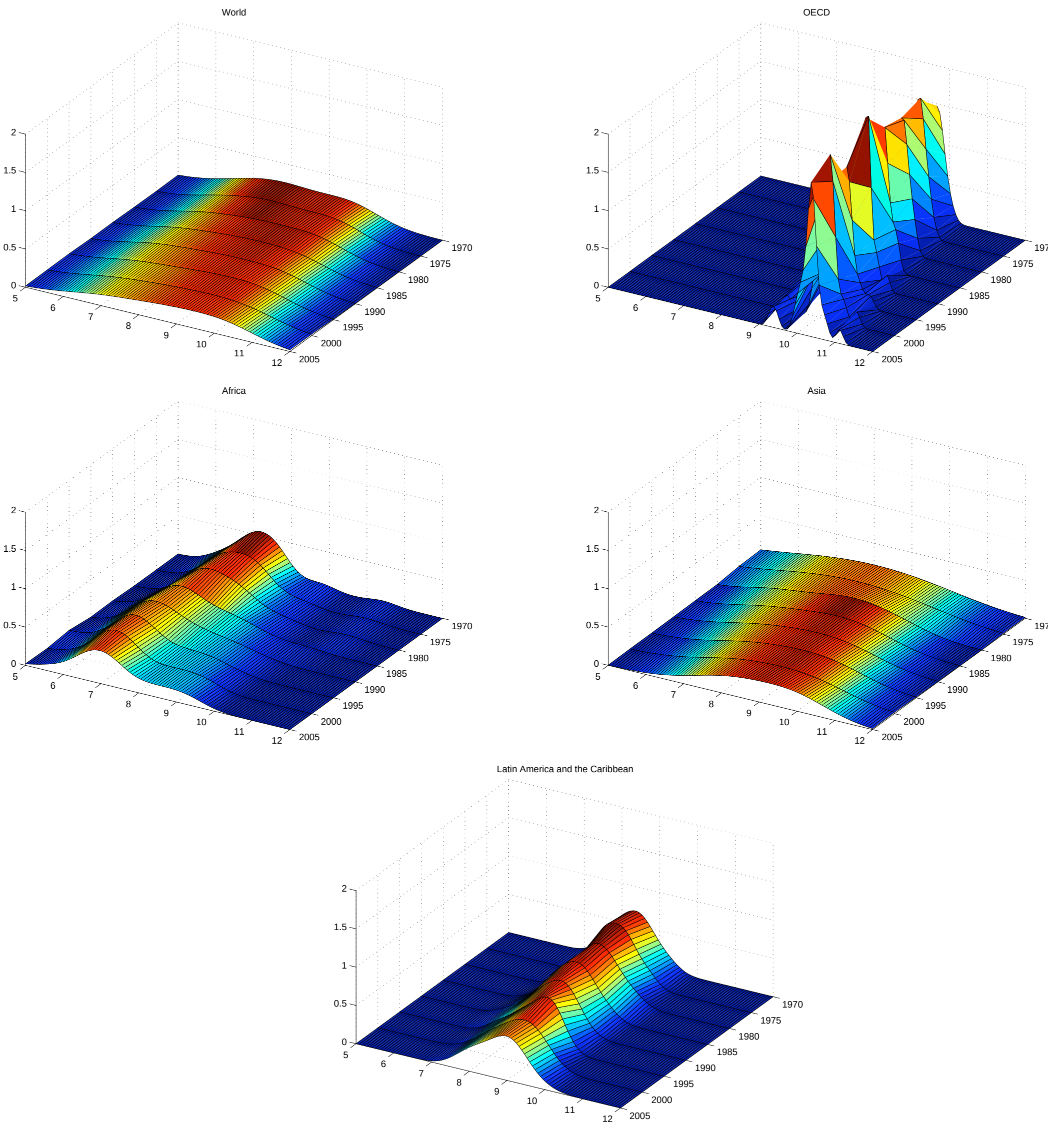
Note: The graphs depict the evolution of the cross-sectional distribution of HDI for $N = 84$ countries from the Gray Molina and Purser (2010) data set for the time period from 1970 to 2005. The upper left-hand panel plots the evolution of the cross-sectional distribution of HDI for the full sample ("world"), the upper right-hand panel plots this distribution for the OECD, the middle left-hand panel plots this distribution for the African countries, the middle right-hand panel plots this distribution for the Asian countries, and the lower panel plots this distribution for the Latin American and Caribbean countries that are part of this "world" sample. In each panel, the horizontal axes display the time period and the scale for HDI, and the vertical axis displays the estimated density.

Figure 3: Evolution of the Moments of the Logarithm of GDP per Capita in the Penn World Tables 6.3



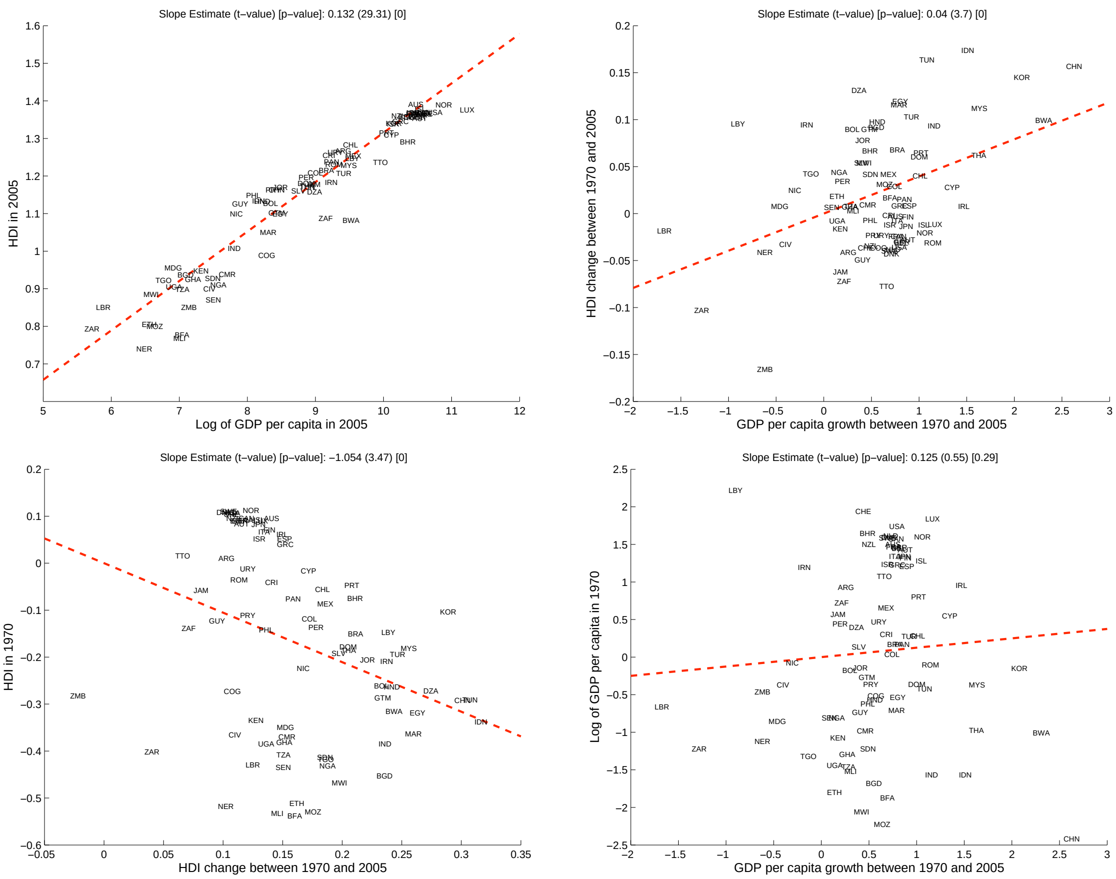
Note: The graphs depict the evolution of the cross-country mean, median, and standard deviation of the logarithm of GDP per capita for $N = 84$ countries from the Gray Molina and Purser (2010) data set for the time period from 1970 to 2005. See the Note to Figure 1.

Figure 4: Evolution of the Cross-Sectional Distribution of the Logarithm of GDP per Capita in the Penn World Tables 6.3



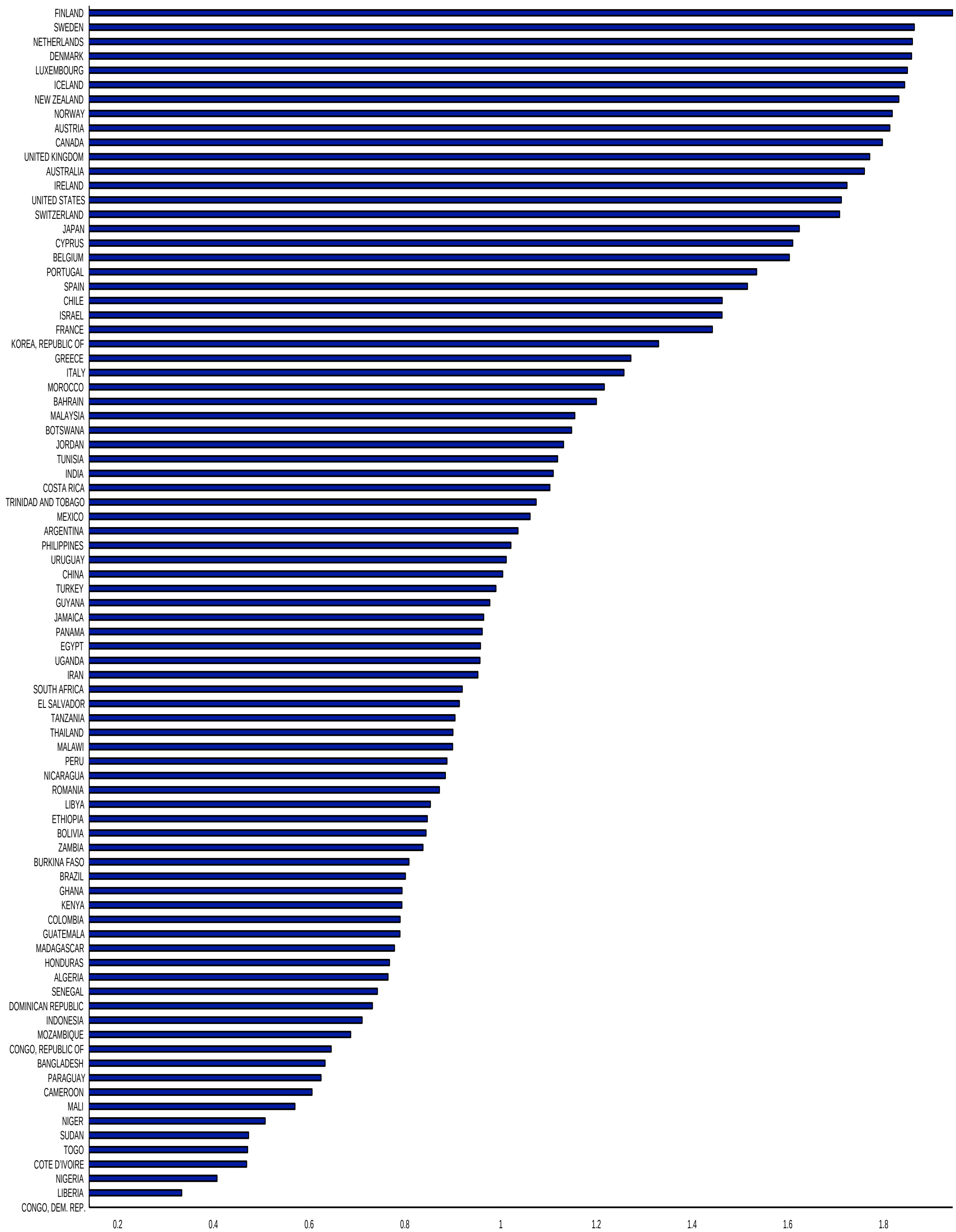
Note: The graphs depict the evolution of the cross-sectional distribution of the logarithm of GDP per capita for $N = 84$ countries from the Gray Molina and Purser (2010) data set for the time period from 1970 to 2005. See the Note to Figure 2.

Figure 5: Correlation Between Trends in HDI and GDP per Capita Between 1970 and 2005



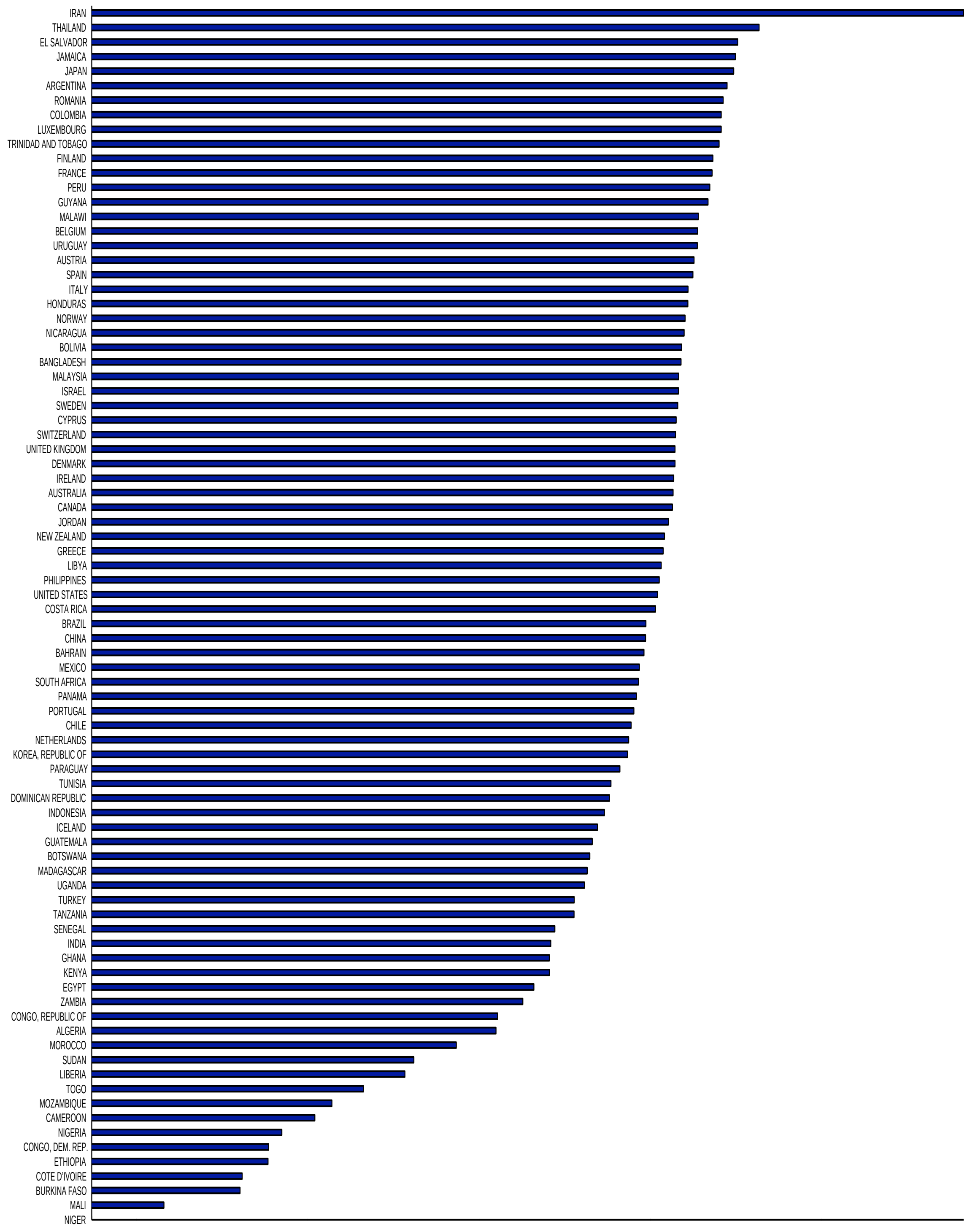
Note: The graphs depict correlations between HDI in 2005 and the logarithm of GDP per capita in 2005 (upper left-hand panel), the change in HDI and in GDP per capita growth between 1970 and 2005 (upper right-hand panel), HDI in 1970 and the change in HDI between 1970 and 2005 (lower left-hand panel), and the logarithm of GDP per capita in 1970 and GDP per capita growth between 1970 and 2005 (lower right-hand panel). In each panel, the dashed line shows fitted values from an OLS regression of the variable displayed on the vertical axis on the variable displayed on the horizontal axis after controlling for an intercept in both variables.

Figure 6: Country Rankings for the Institutional Development Index in 2005



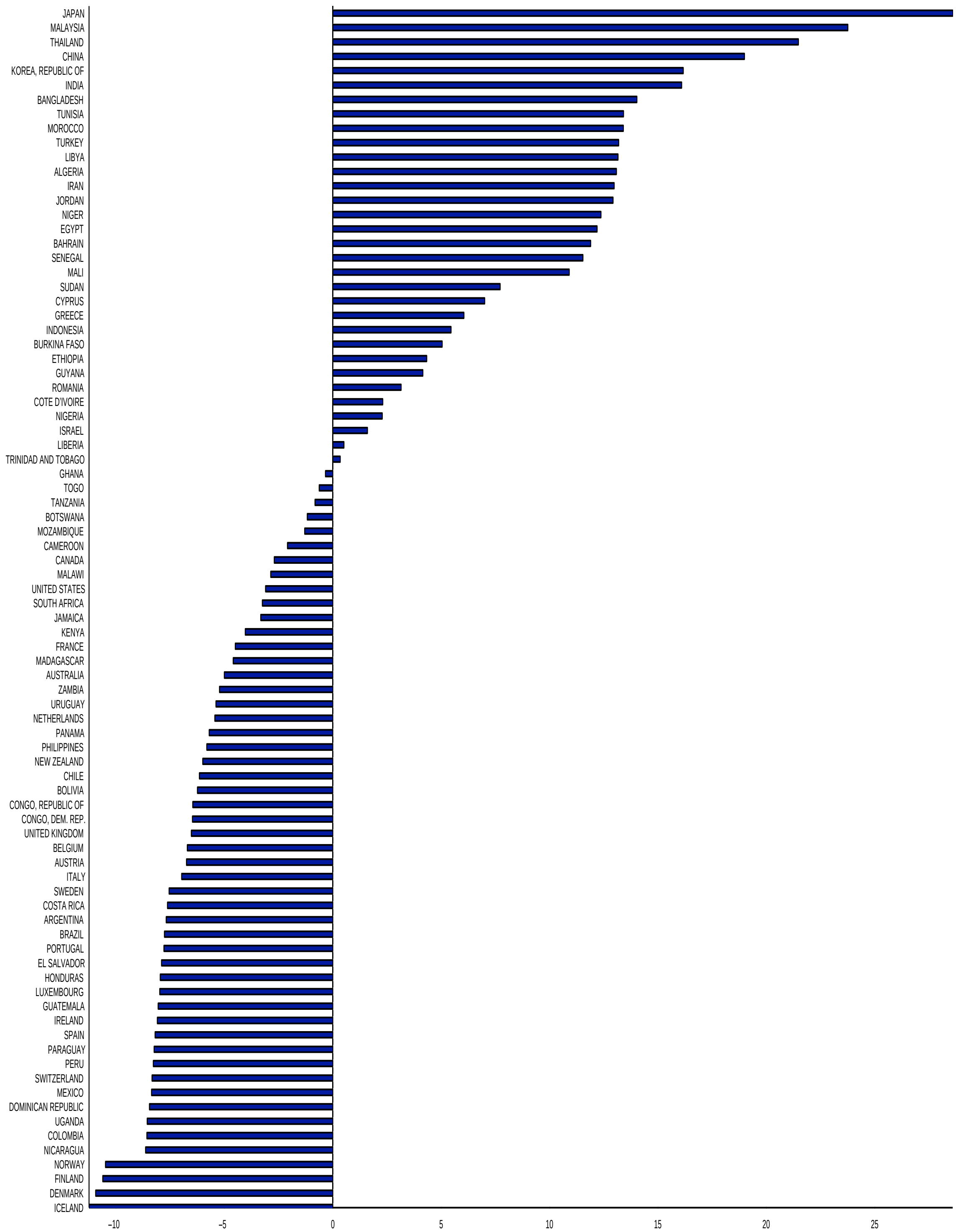
Note: The graph depicts the cross-country ranking of institutional development for 2005. The countries are sorted from highest to lowest ranks of institutional development. The length of each bar reflects the value of the institutional development index in 2005.

Figure 7: Country Rankings for the Gender Inequality Index in 2005



Note: The graph depicts the cross-country ranking of gender inequality for 2005. The countries are sorted from lowest to highest degrees of gender inequality. The length of each bar reflects the degree to which a country has achieved gender equality.

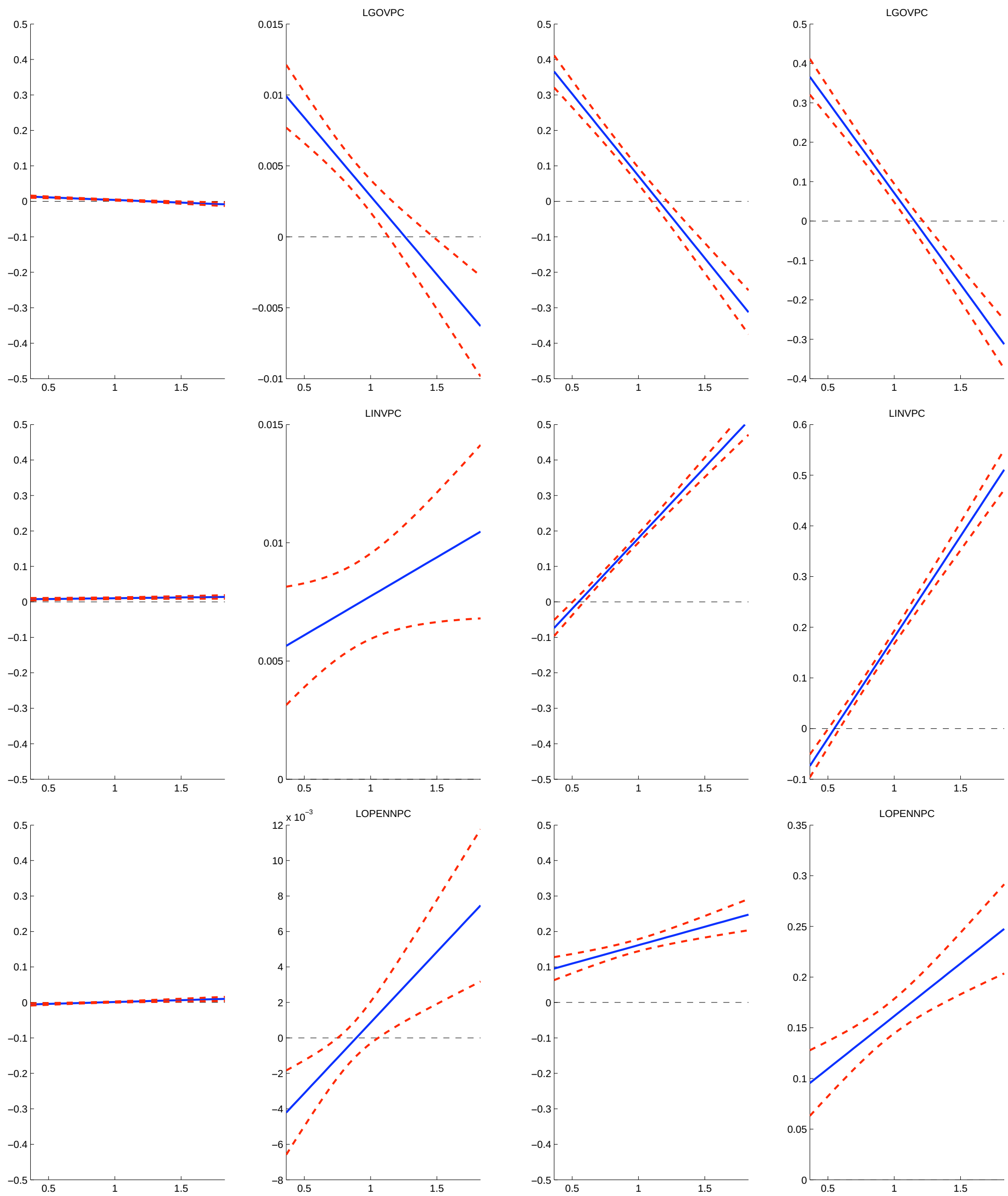
Figure 8: Country Rankings for the Development Conduciveness of the Religious Environment in 2005



Note: The graph depicts the cross-country ranking of the index of development conduciveness of the religious environment for 2005. The countries are sorted from highest to lowest degrees of development conduciveness of the religious environment. The length of each bar reflects the degree to which a country's religious environment is conducive for development.

Figure 9: Institutional Development Index

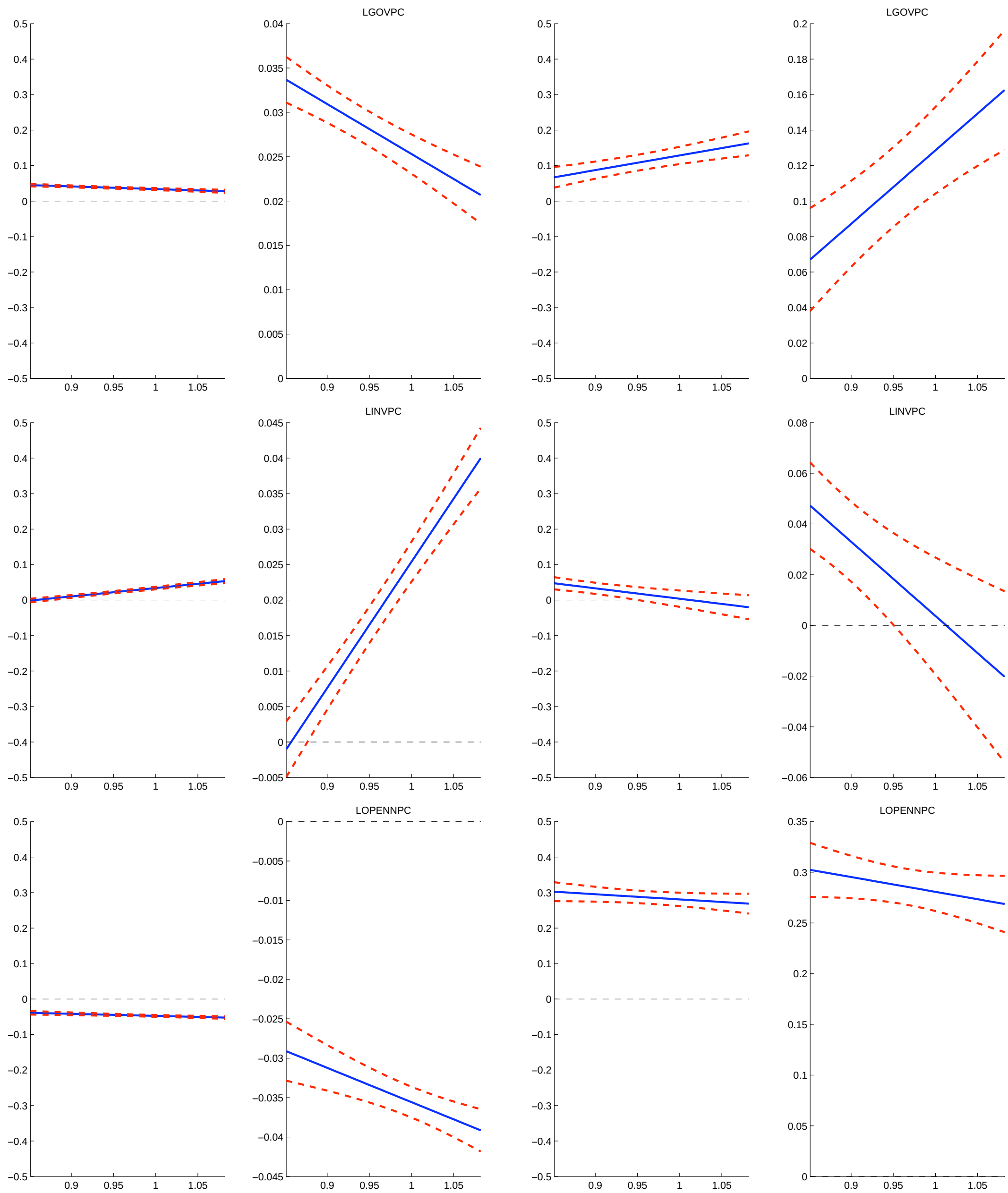
HDI | Logarithm of GDP Per Capita



Note: The graph depicts the estimated long-run multiplier functionals $\widehat{\theta}_k(z_{i,t-1})$ from Equation (14) with the conditioning index $z_{i,t-1}$ being institutional development. For each choice of the dependent variable the graph presents two sets of results. First, in the left column for HDI the long-run percentage change of HDI in response to a one basis point increase in the corresponding explanatory variable is depicted (as the long-run coefficient in case of HDI being the dependent variable does not represent an elasticity, the reported percentage change is evaluated at each country's initial value of HDI). Second, in the right column for HDI, the long-run coefficient functional estimates themselves are depicted. For GDP per capita, the left column depicts the long-run percentage change of GDP per capita in response to a one percentage change in the corresponding explanatory variable, and the right column the long-run coefficient functional estimates. In each panel, the solid line depicts the point estimates, and the dashed lines depict 95% confidence bands. The scales in the first and third columns from the left are adjusted to be the same for the HDI and GDP per capita graphs.

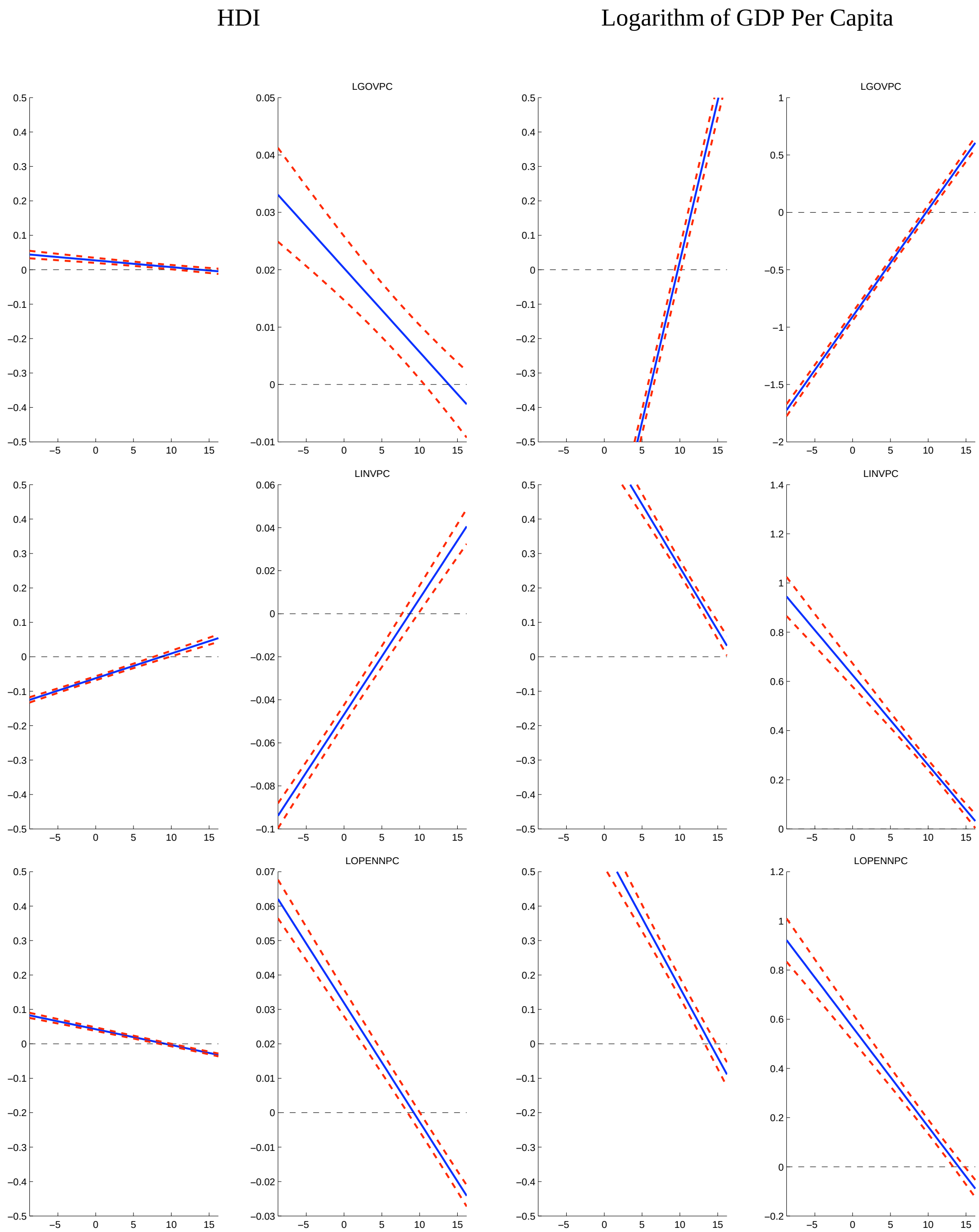
Figure 10: Gender Inequality

HDI   Logarithm of GDP Per Capita



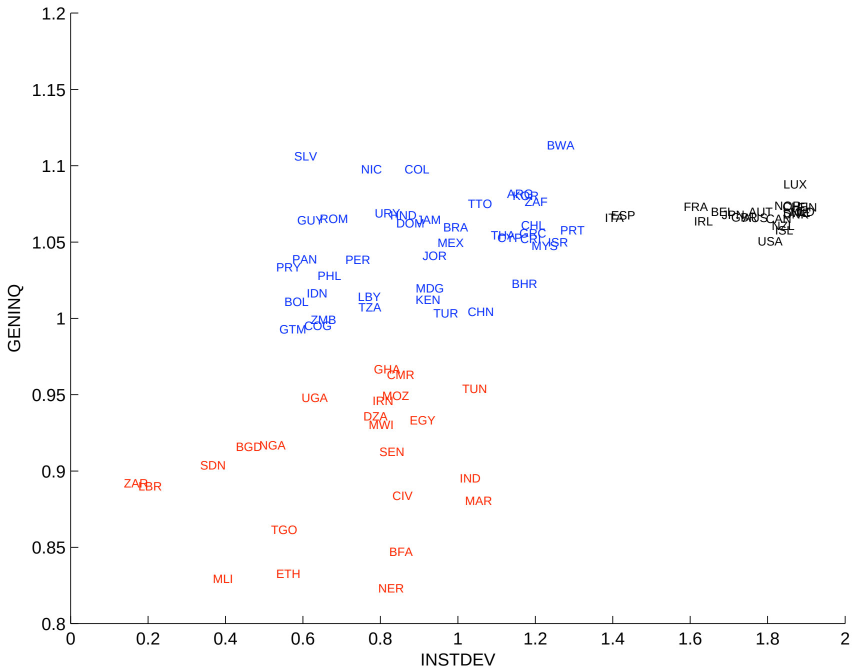
Note: The graph depicts the estimated long-run multiplier functional $\widehat{\theta}_k(z_{i,t-1})$ from Equation (14) with the conditioning index $z_{i,t-1}$ being gender inequality. Recall, that the higher the index value for gender inequality, the more successful a country has been in moving towards gender equality. For further details, see the Note to Figure 9.

Figure 11: Development Conduciveness of the Religious Environment



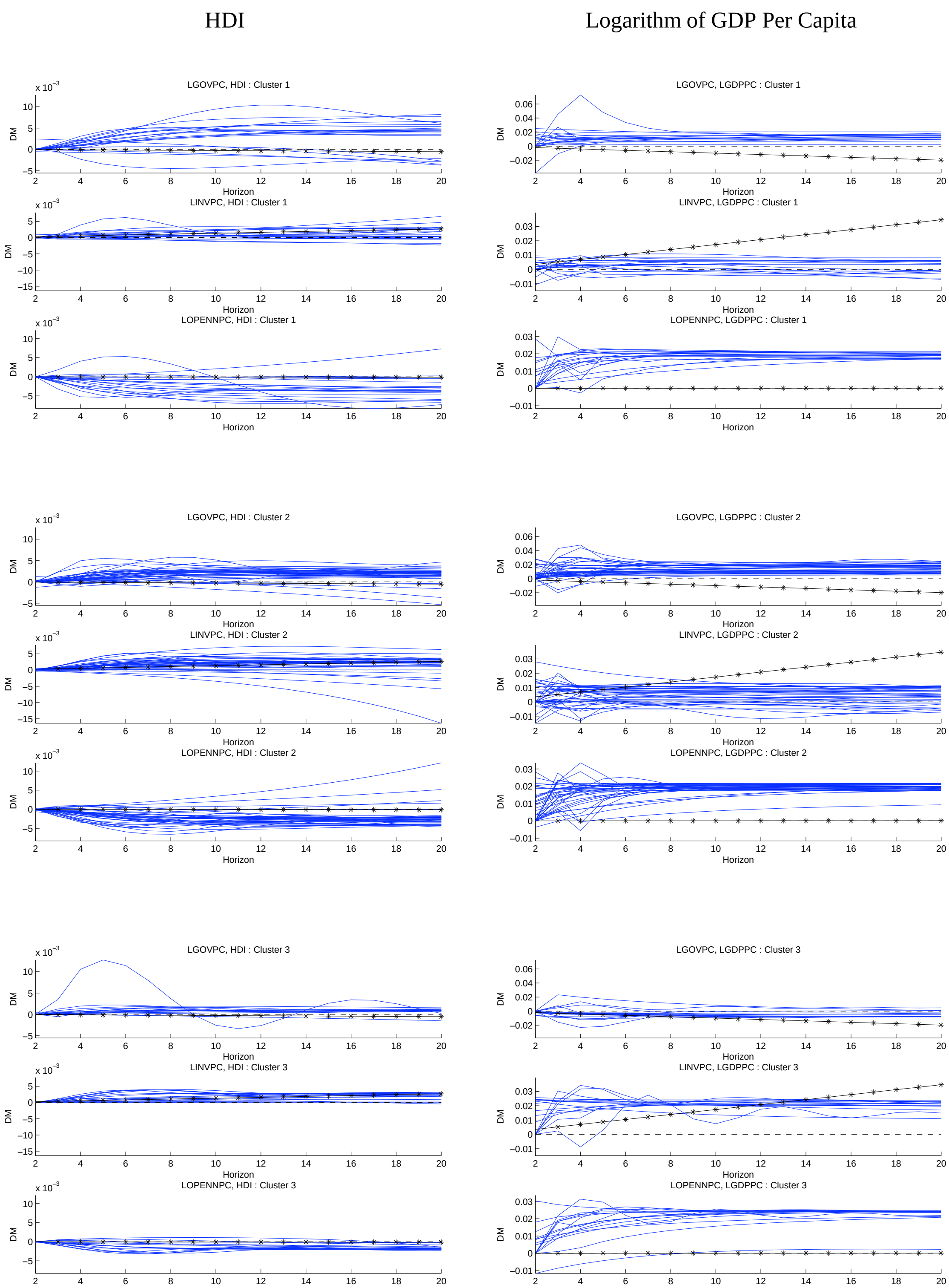
Note: The graph depicts the estimated long-run multiplier functional $\widehat{\theta}_k(z_{i,t-1})$ from Equation (14) with the conditioning index $z_{i,t-1}$ being the development conduciveness of the religious environment. For further details, see the Note to Figure 9.

Figure 12: The Country Clusters



Note: The graph depicts a scatter plot of countries' average institutional development index values against countries' average gender inequality index values. The brightness of the country codes indicates the adherence of the countries to our three country clusters.

Figure 13: Dynamic Multipliers Across Clusters

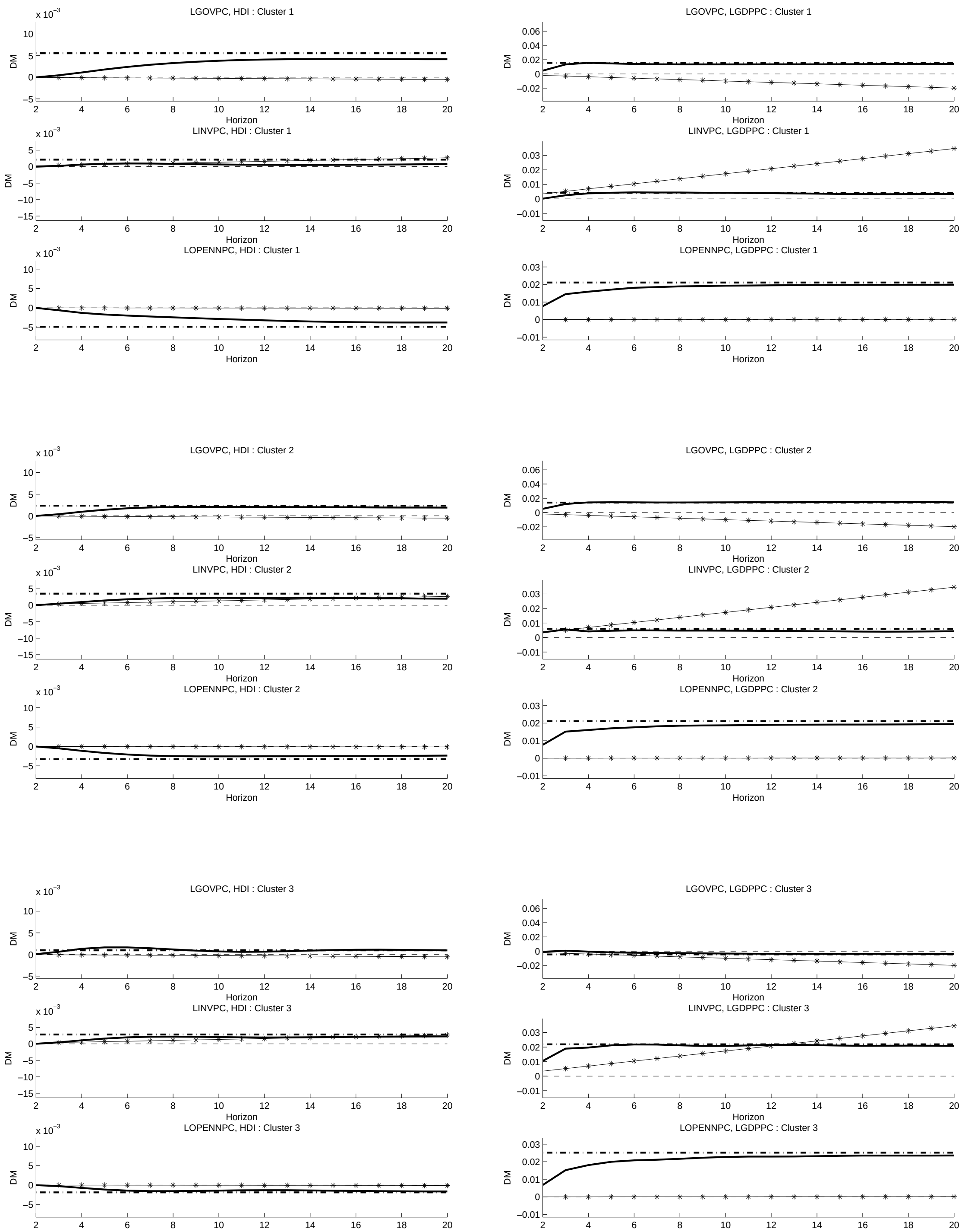


Note: Each sub-panel displays the dynamic multipliers (solid lines) for a permanent ten basis points increase for a given explanatory variable and given choice of the dependent variable in a given cluster. Also depicted in each sub-panel is the corresponding multiplier (transition path) implied by the Barro regression model (starred line). For example, the upper left-hand panel depicts the dynamic responses of HDI for all countries in Cluster 1 for a permanent ten basis points increase in government consumption expenditure as implied by the state-dependent panel model in Equation (14) and the Barro regression model.

Figure 14: Cluster-Average Dynamic Multipliers

HDI

Logarithm of GDP Per Capita



Note: Each sub-panel depicts the cluster average of the dynamic multipliers for the state-dependent panel model as plotted in Figure 13. Also depicted in each sub-panel is the corresponding multiplier (transition path) implied by the Barro regression model. For example, in the upper left-hand panel the average dynamic responses for HDI of all countries in Cluster 1 (solid line) to a permanent ten basis points increase in government consumption expenditure is graphed together with the corresponding quantity implied by the Barro regression model (starred line) and the long-run effect implied by the state-dependent panel model (dash-dot line).

F Tables

Table 1: Countries Included

Algeria	Jordan
Argentina	Kenya
Australia	Korea, Republic of
Austria	Liberia
Bahrain	Libya
Bangladesh	Luxembourg
Belgium	Madagascar
Bolivia	Malawi
Botswana	Malaysia
Brazil	Mali
Burkina Faso	Mexico
Cameroon	Morocco
Canada	Mozambique
Chile	Netherlands
China	New Zealand
Colombia	Nicaragua
Congo, Dem. Rep.	Niger
Congo, Republic of	Nigeria
Costa Rica	Norway
Cote d'Ivoire	Panama
Cyprus	Paraguay
Denmark	Peru
Dominican Republic	Philippines
Egypt	Portugal
El Salvador	Romania
Ethiopia	Senegal
Finland	South Africa
France	Spain
Ghana	Sudan
Greece	Sweden
Guatemala	Switzerland
Guyana	Tanzania
Honduras	Thailand
Iceland	Togo
India	Trinidad and Tobago
Indonesia	Tunisia
Iran	Turkey
Ireland	Uganda
Israel	United Kingdom
Italy	United States
Jamaica	Uruguay
Japan	Zambia

Note: The table lists the sub-set of countries in the Gray Molina and Purser (2010) data set included in our empirical analysis.

Table 2: Barro Regression with Δhdi as Dependent Variable

Variable	Model 1	Model 2	Model 3	Model 4
Const	0.0064*** (8.88)	0.0004 (0.13)	0.0057*** (9.18)	-0.004 * (1.42)
*hdi*0	-0.0066*** (4.42)	-0.0076*** (4.81)	-0.003 ** (1.97)	-0.0068*** (4.24)
govgdp	-0.0016 (0.55)	-0.0016 (0.59)	-0.0023 (1.04)	-0.0024* (1.29)
invgdp	0.0084*** (2.88)	0.008 *** (2.55)	0.0044* (1.5)	0.0037* (1.29)
openngdp	-0.0003 (0.55)	-0.0004 (0.78)	-0.0002 (0.52)	-0.0003 (0.85)
instdev	0.0006 (0.94)	-	-	0.0005 (1.09)
geninq	-	0.0072** (2.12)	-	0.0115*** (3.57)
condrel	-	-	0.0001*** (2.83)	0.0001*** (3.3)
R-Squared	0.24	0.26	0.34	0.41
Implied λ	0.0076	0.0089	0.0032	0.0078
Half-Life	91.6	78.1	> 100	88.8
N	84	84	84	84

Note: Absolute *t*-values in parenthses. *,** and *** indicate statistical significance at the 10, 5 and 1 percent significance level, respectively.

Table 3: Barro Regression with $\Delta lgdppc$ as Dependent Variable

Variable	Model 1	Model 2	Model 3	Model 4
Const	0.0781*** (5.1)	-0.0366 (1.24)	0.029 * (1.45)	-0.0249 (1.12)
*lgdppc*0	-0.0121*** (4.82)	-0.0069*** (2.3)	-0.0027 (0.88)	-0.0131*** (5.86)
govgdp	-0.0401*** (2.3)	-0.0443*** (2.25)	-0.0511*** (2.56)	-0.0438*** (3.02)
invgdp	0.0733*** (2.93)	0.0708*** (2.25)	0.084 *** (2.48)	0.0317* (1.38)
openngdp	0.0014 (0.35)	-0.0022 (0.4)	-0.0004 (0.07)	0.0004 (0.1)
instdev	0.0284*** (5.21)	-	-	0.0282*** (6.43)
geninq	-	0.1013*** (2.91)	-	0.1191*** (4.44)
condrel	-	-	0.0003* (1.31)	0.0006*** (3.33)
R-Squared	0.5	0.33	0.27	0.63
Implied λ	0.0162	0.0079	0.0028	0.0177
Half-Life	42.8	87.9	> 100	39.2
N	84	84	84	84

Note: Absolute *t*-values in parenthses. *,** and *** indicate statistical significance at the 10, 5 and 1 percent significance level, respectively.

Table 4: Speed of Adjustment Parameters, z_{it}: INSTDEV

	y_{it}: *HDI*				y_{it}: *LGDPPC*				
Country Group	Mean	Median	H-L	N	Mean	Median	H-L	H-L (Months)	N
All Countries	-0.12	-0.09	6	83	-0.54	-0.56	1	11	83
OECD	-0.1	-0.06	7	24	-0.45	-0.42	1	14	24
Sub-Saharan Africa	-0.11	-0.05	6	24	-0.62	-0.61	1	9	24
Latin America and Caribbean	-0.2	-0.2	3	19	-0.53	-0.56	1	11	19
Asia	-0.06	-0.08	12	15	-0.54	-0.61	1	11	15
LDCs	-0.1	-0.05	7	16	-0.64	-0.62	1	8	16

Note: The table reports the speed of adjustment parameter estimates, $\widehat{\alpha}_i$ from Equation (14) for the full sample, the OECD, the Sub-Saharan African, the Latin American and Caribbean, the Asian and the Least Developed (LDCs) countries. In the left results column of the table, the dependent variable is HDI, and in the right results column it is the logarithm of GDP per capita. For a given choice of the dependent variable, the table reports the mean and the median across countries within a given country group, the implied half life as well as the number of countries within the country group in question.

Table 5: Speed of Adjustment Parameters, z_{it}: GENINQ

	y_{it}: *HDI*				y_{it}: *LGDPPC*				
Country Group	Mean	Median	H-L	N	Mean	Median	H-L	H-L (Months)	N
All Countries	-0.1	-0.09	7	83	-0.52	-0.51	1	11	83
OECD	-0.09	-0.08	7	24	-0.41	-0.4	1	16	24
Sub-Saharan Africa	-0.06	-0.07	12	24	-0.61	-0.55	1	9	24
Latin America and Caribbean	-0.15	-0.14	4	19	-0.48	-0.43	1	13	19
Asia	-0.04	-0.09	17	15	-0.54	-0.51	1	11	15
LDCs	-0.04	-0.08	16	16	-0.64	-0.55	1	8	16

Note: The table reports the speed of adjustment parameter estimates, $\widehat{\alpha}_i$ from Equation (14) for the full sample, the OECD, the Sub-Saharan African, the Latin American and Caribbean, the Asian and the Least Developed (LDCs) countries. In the left results column of the table, the dependent variable is HDI, and in the right results column it is the logarithm of GDP per capita. For a given choice of the dependent variable, the table reports the mean and the median across countries within a given country group, the implied half life as well as the number of countries within the country group in question.

Table 6: Speed of Adjustment Parameters, z_{it}: CONDREL

	y_{it}: *HDI*				y_{it}: *LGDPPC*				
Country Group	Mean	Median	H-L	N	Mean	Median	H-L	H-L (Months)	N
All Countries	-0.14	-0.14	5	83	-0.53	-0.52	1	11	83
OECD	-0.16	-0.16	4	24	-0.47	-0.48	1	13	24
Sub-Saharan Africa	-0.08	-0.1	8	24	-0.57	-0.51	1	10	24
Latin America and Caribbean	-0.16	-0.13	4	19	-0.49	-0.4	1	12	19
Asia	-0.16	-0.18	4	15	-0.57	-0.53	1	10	15
LDCs	-0.06	-0.08	11	16	-0.65	-0.57	1	8	16

Note: The table reports the speed of adjustment parameter estimates, $\widehat{\alpha}_i$ from Equation (14) for the full sample, the OECD, the Sub-Saharan African, the Latin American and Caribbean, the Asian and the Least Developed (LDCs) countries. In the left results column of the table, the dependent variable is HDI, and in the right results column it is the logarithm of GDP per capita. For a given choice of the dependent variable, the table reports the mean and the median across countries within a given country group, the implied half life as well as the number of countries within the country group in question.

Table 7: The Clusters

	Cluster 1	Cluster 2	Cluster 3
	Algeria	Argentina	Australia
	Bangladesh	Bahrain	Austria
	Burkina Faso	Bolivia	Belgium
	Cameroon	Botswana	Canada
	Congo, Dem. Rep.	Brazil	Denmark
	Cote d'Ivoire	Chile	Finland
	Egypt	China	France
	Ethiopia	Colombia	Iceland
	Ghana	Congo, Republic of	Ireland
	India	Costa Rica	Italy
	Iran	Cyprus	Japan
	Liberia	Dominican Republic	Luxembourg
	Malawi	El Salvador	Netherlands
	Mali	Greece	New Zealand
	Morocco	Guatemala	Norway
	Mozambique	Guyana	Spain
	Niger	Honduras	Sweden
	Nigeria	Indonesia	Switzerland
	Senegal	Israel	United Kingdom
	Sudan	Jamaica	United States
	Togo	Jordan	
	Tunisia	Kenya	
	Uganda	Korea, Republic of	
		Libya	
		Madagascar	
		Malaysia	
		Mexico	
		Nicaragua	
		Panama	
		Paraguay	
		Peru	
		Philippines	
		Portugal	
		Romania	
		South Africa	
		Tanzania	
		Thailand	
		Trinidad and Tobago	
		Turkey	
		Uruguay	
		Zambia	
Mean			
INSTDEV	0.67	0.89	1.73
GENINQ	0.9	1.05	1.07

Note: The table details the division of the full sample into three clusters of countries based on their average institutional development and gender inequality scores. See also Figure 12.

Table 8: Development Effects of Policy Changes for Our Three Clusters of Countries: 20 Year Time Horizon

	HDI			LGDPPC		
	LGOVPC	LINVPC	LOPENNPC	LGOVPC	LINVPC	LOPENNPC
Cluster 1	0.42	0.08	-0.38	1.40	0.34	1.99
Cluster 2	0.19	0.20	-0.24	1.44	0.43	1.94
Cluster 3	0.09	0.23	-0.16	-0.39	2.08	2.35
Barro	-0.05	0.27	-0.01	-1.98	3.47	0.01

Note: The table displays in the rows labelled “Cluster 1”, “Cluster 2” and “Cluster 3” the average percentage change in HDI/GDP per capita after 20 years across all countries in a given cluster implied within the state dependent panel model by a ten percentage points increase in government consumption, in investment in physical capital, and in trade openness (exports plus imports). In the last row labelled “Barro”, we report the corresponding effects implied by the Barro regression model.

Table 9: Long-Run Development Effects of Policy Changes for Our Three Clusters of Countries

	HDI			LGDPPC		
	LGOVPC	LINVPC	LOPENNPC	LGOVPC	LINVPC	LOPENNPC
Cluster 1	0.55	0.21	-0.49	1.55	0.42	2.11
Cluster 2	0.24	0.35	-0.33	1.39	0.60	2.11
Cluster 3	0.10	0.28	-0.19	-0.46	2.19	2.52
Barro	-0.37	1.39	-0.06	-8.66	16.36	-0.07

Note: See the Note to Table 8. Rather than reporting development effects for a time horizon of 20 years as Table 8 does, this table reports the long-run (steady state) development effects.

Table 10: Panel Unit Root Tests for HDI Series and the Logarithm of GDP per Capita

	$p = 1$		$p = 2$	
	HDI	log GDP	HDI	log GDP
World	0.02	0.42	0.01	0.94
OECD	0.02	0.03	0.01	0.09
Latin America and Caribbean	0.00	0.15	0.00	0.06
Africa	0.91	0.99	0.90	1.00
Asia	0.57	0.53	0.71	0.83

Note: The table reports *p*-values from panel unit root tests for HDI and the logarithm of GDP per capita. Under the null hypothesis of the Im, Pesaran and Shin (2003, IPS) test, the series under investigation has a unit root for each individual unit in the panel. The IPS test allows for country level fixed effects and fixed effects type linear time trends, as well as country-specific (systematically varying) slope coefficients under the alternative hypothesis of mean reversion in the individual series.