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Determinants of Human Development: Capturing the Role of Institutions

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Abstract

In this paper, we study development in a panel of 87 countries from 1970 to 2005. We focus on characterizing institutionally driven 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 development, and that can capture the dependence of the development effects of macroeconomic policies on differences in countries' persistent characteristics, such as their institutions. Among our findings are that macroeconomic policies affect 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 expansions positively affect long-run GDP in countries with low institutional quality, but negatively affect long-run GDP in countries with high institutional quality.

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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 latter issues are (i) how the contributions of macroeconomic development policies to advances in economic prosperity may depend on a country's persistent characteristics such as its institutions, (ii) how considering measures of development other than income affects development policy advice, and (iii) how to ensure that estimates of development policy effects take into account the specifics of cross-country panel data. Taking up these issues in this paper, we study economic development in a panel of 87 countries from 1970 to 2005. We investigate institutionally driven 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 (i) account for crucial aspects of both the cross-sectional and intertemporal features of the observed process of development, and (ii) characterize a possible state dependence of the development effects of macroeconomic policies on differences in countries' persistent characteristics such as their institutions.

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 the Barro regression framework, however, which limit its usefulness for empirical analysis.[2] A first issue casting doubt on the appropriateness of the default Barro regression framework is that - random intercept effects apart - all cross-country heterogeneities of the output growth process are assumed to be fully captured by different realiza-

[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 econometric issues arising in the empirical output growth literature. 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.

tions of the regression's explanatory variables. This is, however, extremely unlikely to be satisfied in practice, as due to finite sample size issues only a limited number of explanatory variables - capturing only a small 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 empirical output growth literature to consider panel fixed effects models, with the fixed effects accounting for all time-invariant factors, including those that exhibit systematic (as opposed to purely random) variation across countries. Pursuing this line of thought further, however, countries' systematically differing societal characteristics are still unlikely to be fully captured by incorporating fixed effects intercept terms, but would seem to require also incorporating systematically varying slope coefficients. As has been argued by Lee, Pesaran and Smith (1997), assuming that the marginal effects of development policies are the same across countries when in fact they differ, leads to serious fallacies in empirical inference. A second issue of concern 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 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 causal for output growth. For purposes of policy analysis, it is clearly desirable, however, to work with an econometric framework that can distinguish between correlates and causes of economic growth.[3] Third in terms of concerns with the default Barro regression is that it does not feature a country-specific 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 (2006) and Binder, Georgiadis and Sharma (2011). Considering these four issues, there is a clear need for empirical work on economic development to move beyond default econometric techniques as typically used in the empirical output growth literature.

[3]We should mention that there has been important work tackling this endogeneity issue in models that otherwise stick to the framework of Barro regressions. See, for example, Acemoglu, Johnson and Robinson (2001).

Beyond giving careful consideration to empirical modelling issues, in this paper we also go beyond an output-/income-only based analysis of the development process. As prominently advocated by Sen (1999), the ultimate goal of economic development policies should be to enhance the set of people's opportunities. The empirical growth literature to date has, however, primarily focused on investigating the determinants of the long-run level of output 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, an exclusive focus on output 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 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 the empirical modelling and data-measurement considerations highlighted in the previous paragraphs, in this paper, then, we move beyond a Barro regression based analysis of output growth. We take advantage of newly compiled 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 state-dependent long-run coefficients, as proposed by Binder and Offermanns (2007) as well as Binder, Georgiadis and Sharma (2011). The model introduced in these papers, in what follows

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

referred to as the conditional pooled mean group (CPMG) state-dependent panel model, appears to be strongly suited for the analysis of the determinants of GDP and HDI, as it can capture crucial aspects of both the cross-sectional as well as intertemporal features of the GDP and HDI development processes, and can overcome the problems associated with the Barro regression approach detailed above. In particular, the CPMG state-dependent panel model (i) features a country-specific distinction between short- and long-run dynamics, (ii) allows for systematic cross-country heterogeneity in intercepts and slope coefficients while also identifying features of the development process that are common across countries, (iii) allows for the explanatory variables to be 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 institutional environments. Modelling the development effects that macroeconomic policies have on HDI (GDP) as a function of state variables measuring a country's institutions (with the state variables capturing that institutions typically are persistent, yet, when appropriately aggregated, feature slow time variation), appears to be a novel and promising way to reconcile a fixed effects empirical growth model with an analysis of institutions and other societal characteristics as often emphasized in analyses using the random effects-based Barro regression framework.[5] Our approach to modelling state dependence of the development effects of macroeconomic policies involves determining how these effects vary as a function of indices reflecting various of those aspects of countries' institutions that in the recent empirical growth literature have been found to robustly affect economic development.

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 Section 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 as a function of countries' institutional characteristics. We also discuss in Section 3 our state variables measuring such institutional characteristics. 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

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

measurement and computational/econometric issues.

2 Some Stylized Facts About HDI Trends

We make use in this paper of newly compiled data on human development for a large panel of countries. In particular, we use data on hybrid HDI for 87 countries from 1970 to 2010.[6] Table 1 provides a listing of all 87 countries that we consider in this paper.[7]

In this section, we begin or data analysis by outlining some stylized facts about trends in the cross-country HDI and GDP development processes.[8] Figure 1 provides the evolution of key first and second moments of the cross-sectional distributions of HDI for sub-sets of countries, and Figure 2 plots the evolutions of estimates of the

[6]While the United Nations for the 2010 Human Development Report introduced a change of some of the variables and the method of aggregation employed in the calculation of HDI, in this paper we use the hybrid HDI, which is based on the variables contained in the HDI data prior to the 2010 Human Development Report, but aggregating these variables using geometric averages, as per the aggregation methodology introduced in the 2010 Human Development Report. Our use of hybrid HDI is motivated by data availability considerations. Denoting by $lgdp_{it}$ the logarithm of GDP per capita in U.S. \$ at purchasing power parity exchange rates, by $life_{it}$ life expectancy at birth, by $cger_{it}$ the combined gross school enrolment rate, and by $liter_{it}$ the adult literacy rate, the hybrid HDI is computed as follows:

$$hdi_{it} = (gdpx_{it} \cdot lifex_{it} \cdot educx_{it})^{1/3}, \quad (1)$$

where

$$educx_{it} = (cgerx_{it} \cdot literx_{it})^{1/2}, \quad (2)$$

$$cgerx_{it} = cger_{it}/115.82, \quad (3)$$

$$literx_{it} = liter_{it}/99, \quad (4)$$

$$lifex_{it} = \frac{life_{it} - 20}{83.166 - 20}, \quad (5)$$

and

$$gdpx_{it} = \frac{lgdp_{it} - log(163.28)}{log(106,769.74) - log(163.28)}. \quad (6)$$

[7]The composition of our sample is driven by our requirement (imposed to ensure adequate reliability of our panel model estimates) that in order to incorporate a country in our sample, we have at least 30 consecutive time-series observations available for all variables entering our panel model. See Section 3 and Appendix A for further details.

[8]For this stylized facts analysis, we exploit the full time-series dimension of the newly compiled UNDP data on HDI and GDP per capita, namely 1970 to 2010. For the remainder of the paper we will need to drop observations after 2005, due to restrictions on the availability of some of the additional variables we make use of in our panel model estimation, see Section 3.

cross-sectional distributions themselves. When interpreting the plots of (the moments of) these distributions, it should be kept in mind that HDI and the logarithm of GDP per capita may not be ergodic variables - that is, they may not converge to time-invariant steady-state distributions, and their 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. Figure 1 also conveys that unconditional convergence of HDI with respect to initial values has taken place, in the sense that HDI has grown stronger for less-developed groupings of countries than for the OECD countries. The median of HDI in the OECD countries from 1970 to 2010 rose by 17%, whereas it rose by 46% in Africa, by 45% in Asia, and by 33% in Latin America and the Caribbean. Furthermore, within each country group/region except for Africa, the standard deviation of the cross-sectional distribution of HDI has decreased from 1970 to 2010: The standard deviation for the OECD countries from 1970 to 2010 fell by 39%, for the Latin American and Caribbean countries by 30%, and for the Asian countries by 18%, whereas it rose for the African countries by 44%.

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 estimates of the cross-sectional distributions themselves. Comparing Figure 3 for the logarithm of GDP per capita with Figure 1 for HDI, three observations stand out: First, while all regions have experienced notable improvements in HDI from 1970 to 2010, 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 the OECD, Asian as well as Latin American and Caribbean countries' mean and median. Second, for the Latin American and Caribbean as well as African countries' mean and median, 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 2010 rose by 8%, also rising by 8% in Latin America and the Caribbean, by 1% in Africa, yet by 16% in Asia.[9] Third, while for HDI

[9]The average annual growth rate of the *level* of GDP per capita in the OECD countries from 1970 to 2010 amounted to 1.9%, to 1.7% in Latin America and the Caribbean, to 0.2% in Africa, and to 3.2% in Asia.

countries within a given region appear to unconditionally converge to a common long-run level (with the exception of Africa countries), a long-term decline of the within-region standard deviations is absent for the logarithm of GDP per capita, with the exception of the Asian countries. The region/country group standard deviation rose by 2% for the OECD, by 13% for Latin America and the Caribbean, and by 18% for Africa; only for Asia it declined by 20%.[10]

Comparison of the estimates of the cross-sectional distributions of HDI (in Figure 2) and the logarithm of GDP per capita (in Figure 4) further illustrates the relative strength of the unconditional convergence patterns. Unconditional convergence for HDI is apparent for the OECD countries, Asia as well as Latin America and the Caribbean; but tends to be absent for the logarithm of GDP per capita.

Finally in terms of stylized facts for our data, Figure 5 provides scatter plots of the HDI levels in 2010 against the logarithm of GDP per capita in 2010, of the 1970 to 2010 changes in HDI against GDP per capita growth rates during this time period, and scatter plots of the change in (growth of) HDI (GDP per capita) between 1970 and 2010 against initial HDI (logarithm of 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 0.97) between the levels of HDI and of the logarithm of GDP per capita in 2010. The relationship between the 1970 to 2010 change of HDI and the growth rate of GDP per capita during the same time period also is positive, though with a slope only about half as large as for the corresponding levels relationship. While there appears to be a negative, statistically significant, relationship between the initial level of HDI in 1970 and the change of HDI between 1970 and 2010, pointing to the presence of unconditional convergence for HDI, the same does not appear to be the case for GDP per capita. As remarkable as some of these stylized facts concerning convergence are, to move beyond a simplistic 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 turn to our panel-econometric analysis.

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

3 Econometric Model

We consider a panel autoregressive distributed lag model, where in departure from a heterogenous dynamic panel data model such as the one in Lee, Pesaran and Smith (1997) we allow the key slope coefficients to be state dependent, varying as a function of a (pre-determined) conditioning state variable, $z_{i,t-1}$:

$$\begin{aligned} y_{it} &= \mu_i + \varphi_i \cdot t + \sum_{k=1}^{p} \rho_{ik}(z_{i,t-1}) \cdot y_{i,t-k} \\ &\quad + \sum_{k=0}^{q} \boldsymbol{\varrho}'_{ik}(z_{i,t-1}) \cdot \boldsymbol{x}_{i,t-k} + \epsilon_{it}, \quad t = r, r+1, \ldots, T, \end{aligned} \tag{7}$$

where y_{it} denotes the dependent variable of country i at time t (hdi_{it} or $lgdp_{it}$), 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 $\boldsymbol{\varrho}'_{ik}(z_{i,t-1})$ denote state-dependent slope coefficients, $r = max(p, q)$, the disturbance term ϵ_{it} is distributed as $\epsilon_{it} \sim \big(0, \sigma_i^2\big)$, $i.i.d.$ across t, and with the disturbance terms in addition being independent across i.[11]

The principal idea underlying our consideration of a model with state-dependent slope 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 in empirical practice is rather implausible, as many of the time-invariant aspects of development that together enter the country-specific effects vary systematically (not just randomly) across countries. It thus seems imperative to allow for fixed-effects intercepts, as we have in our specification of the μ_i's in Equation (7). Of course, having introduced such fixed-effects intercepts, 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, represent indices composed of variables that reflect similar aspects of a country's institutions. Carefully designing

[11]For ease of exposition we assume in Equation (7) 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 allow for variable- and country-specific lag orders p_i and q_{ik}, for $k = 1, 2, \ldots, m$ and $i = 1, 2, \ldots, N$, as well as for an unbalanced panel of observations.

the composition of each index variable, we ensure that our $z_{i,t-1}$'s feature sufficient (if relatively small) time variation. Our model thus overcomes the random effects restriction of the Barro regression framework, without having to pass on examining the quantitative importance of various elements of a country's institutions.[12]

The error-correction representation of Equation (7), explicitly separating short- and long-run dynamics, is given by:

$$\begin{aligned}\Delta y_{it} &= \mu_i + \varphi_i \cdot t + \alpha_i(z_{i,t-1}) \cdot y_{it-1} + \boldsymbol{\beta}_i'(z_{i,t-1}) \cdot \boldsymbol{x}_{i,t-1} + \boldsymbol{\psi}_i'(z_{i,t-1}) \cdot \boldsymbol{h}_{it} + \epsilon_{it} \\ &= \mu_i + \varphi_i \cdot t + \alpha_i(z_{i,t-1}) \cdot \left[y_{i,t-1} - \boldsymbol{\theta}_i'(z_{i,t-1}) \cdot \boldsymbol{x}_{i,t-1}\right] + \boldsymbol{\psi}_i'(z_{i,t-1}) \cdot \boldsymbol{h}_{it} + \epsilon_{it}, \quad (8)\end{aligned}$$

where

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

$$\begin{aligned}\boldsymbol{\psi}_i(z_{i,t-1}) = \Big[&-\sum\nolimits_{k=2}^{p} \rho_{ik}(z_{i,t-1}), -\sum\nolimits_{k=3}^{p} \rho_{ik}(z_{i,t-1}), \ldots, -\rho_{ip}(z_{i,t-1}), \\ &\boldsymbol{\varrho}_{i0}'(z_{i,t-1}), -\sum\nolimits_{k=2}^{q} \boldsymbol{\varrho}_{ik}'(z_{i,t-1}), -\sum\nolimits_{k=3}^{q} \boldsymbol{\varrho}_{ik}'(z_{i,t-1}), \ldots, -\boldsymbol{\varrho}_{iq}'(z_{i,t-1})\Big]',\end{aligned}$$

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

and

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

Given the 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 (8). To this end, we specify the speed of adjustment and the other model short-run dynamics as varying in unrestricted form across countries, but as not varying with $z_{i,t-1}$. Also introducing the weak conditional (or state-dependent) pooling restriction that countries that share the same values of the conditioning state variables also share the same long-run multipliers, $\boldsymbol{\theta}_i(z_{i,t-1}) = \boldsymbol{\theta}(z_{i,t-1})$,[13] we

[12]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 conditioning state variables in sequential form, one state variable at a time. See Binder, Georgiadis and Sharma (2011) for a model featuring the simultaneous presence of multiple state variables.

[13]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 pooling restriction of Barro regressions and fixed-effects panel data models (that involves all slope coefficients), 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

then have the conditional pooled mean group (CPMG) panel data model

$$\begin{aligned}\Delta y_{it} &= \mu_i + \varphi_i \cdot t + \alpha_i \cdot y_{i,t-1} + \boldsymbol{\beta}_i'(z_{i,t-1}) \cdot \boldsymbol{x}_{i,t-1} + \boldsymbol{\psi}_i' \cdot \boldsymbol{h}_{it} + \epsilon_{it} \\ &= \mu_i + \varphi_i \cdot t + \alpha_i \cdot \left[y_{i,t-1} - \boldsymbol{\theta}'(z_{i,t-1}) \cdot \boldsymbol{x}_{i,t-1}\right] + \boldsymbol{\psi}_i' \cdot \boldsymbol{h}_{it} + \epsilon_{it}. \end{aligned} \tag{9}$$

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 states. Note that this framework thus allows the long-run multipliers to differ across countries, but also to differ 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 reliably estimable, the number of variables in $\boldsymbol{x}_{it}$ has to be limited, and the time-series dimension available for each country cannot be too small. Keeping these restrictions in mind, there are numerous advantages of the panel modelling framework of Equation (9) 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:

$$T^{-1} \cdot (y_{iT} - y_{i0}) = \beta_0 + \beta_1 \cdot y_{i0} + \boldsymbol{\gamma}' \cdot \boldsymbol{x}_i + \boldsymbol{\delta}' \cdot \boldsymbol{z}_i + v_{iT}. \tag{10}$$

The advantages of our state-dependent dynamic panel data model in Equation (9) compared to the Barro regression framework in Equation (10) stem from the facts that the model in Equation (9)

(i) is a model with country-specific dynamics, with lag orders chosen on the basis of model selection criteria, unlike for Equation (10), where limited common dynamics across countries are 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 (10) 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 $\boldsymbol{\psi}_i$, as well as long-run coefficients $\boldsymbol{\theta}(z_{i,t-1})$ that in general are identical only for the same realizations of the state variables, $z_{i,t-1}$, whereas

Sharma (2011) 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 based mean group estimates.

the model in Equation (10) 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 under the model in Equation (10) is typically assumed to be cross-sectionally homoskedastic;

(v) allows for non-linear (interaction) terms in $z_{i,t-1}$ and $\boldsymbol{x}_{it-1}$, whereas the model in Equation (10) is fully linear.

In terms of capturing essential aspects of the HDI and GDP development processes, these modelling features result in the following:

(i) We can capture high degrees of cross-country heterogeneity both concerning the short- and long-run parameters, while also capturing common long-run features prevailing under the same state variable values. In our model set-up, unlike in the set-up of the Barro regression, the long-run development effects of changes in economic policies can vary across countries that feature differing institutions. Our model in Equation (9) allows us to investigate this state variable dependence through flexible-form functionals, for example Chebyshev polynomials. As we will document in Section 4, empirically the size of the cross-country variation of these long-run effects can be large, implying that policy recommendations based on Barro regressions for numerous countries will be subject to a "one size fits all" fallacy. As we will also document in Section 4, the speed with which countries' long-run development paths are reached after a change in economic policy can exhibit non-trivial cross-country variation as well. Barro regressions by construction cannot capture this feature of the data, leading to mis-assessment concerning the time horizon required for the development effects of changes in economic policies to reach their long-run levels.

(ii) Our model in Equation (9) can effectively deal with potential endogeneity of the explanatory variables in $\boldsymbol{x}_{it}$, thus allowing us to measure causal effects of changes in our policy variables, as opposed to bi-directional correlations between these policy variables and HDI (GDP). To expand upon this point, consider for illustrative purposes a simplified special case of the model in Equation (7):

$$y_{it} = \mu_i + \varphi_i \cdot t + \rho_i(z_{i,t-1}) \cdot y_{i,t-1} + \varrho_i(z_{i,t-1}) \cdot x_{it} + \epsilon_{it}. \tag{11}$$

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

$$x_{it} = \gamma_i + \delta_i \cdot t + \kappa_i \cdot x_{i,t-1} + u_{it}, \tag{12}$$

with $Cov(\epsilon_{it}, u_{it}) = \sigma_{\epsilon u,i} \neq 0$. Clearly, the least squares estimator of the coefficients in Equation (11) will then be subject to an endogeneity bias. As noted by Pesaran and Shin (1999), a great appeal of the autoregressive distributed lag model structure in Equation (11) 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

$$\epsilon_{it} = \frac{\sigma_{\epsilon u,i}}{\sigma^2_{u_i}} \cdot u_{it} + \xi_{it}, \tag{13}$$

where by construction $Cov(\xi_{it}, u_{it}) = 0$. Substituting from Equation (12) into Equation (13), we obtain

$$\epsilon_{it} = \frac{\sigma_{\epsilon u,i}}{\sigma^2_{u_i}} \cdot (x_{it} - \kappa_i \cdot x_{i,t-1} - \gamma_i - \delta_i \cdot t) + \xi_{it}. \tag{14}$$

Substituting from Equation (14) into Equation (11), we obtain a model with an augmented lag structure, involving the additional regressor $x_{i,t-1}$, but in which neither x_{it} nor $x_{i,t-1}$ can cause an endogeneity bias and would thus require instrumentation, as $Cov(\xi_{it}, u_{it}) = Cov(\xi_{it}, u_{i,t-1}) = 0$.

Before turning to the discussion of our empirical results, let us conclude this section by discussing our choices for the model variables, y, $\boldsymbol{x}$, and z. For y, we choose *hdi* or *lgdp*;[14] 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 (stimulating output), namely the logarithm of per capita government consumption (*lgov*, reflecting aspects of fiscal policy), the logarithm of per capita (private plus public) investment in physical capital (*linv*, reflecting both aspects of fiscal policy and various policy incentives for private sector saving and investment), as well as the logarithm of per capita imports plus exports (*lopen*, reflecting various policy measures to stimulate international trade).[15] See, for example, Binder, Georgiadis and Sharma (2011) for a review of some of the theoretical growth lit-

[14]See Section 2.

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

erature 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 contains a notably smaller number of regressors. We allow for additional variables that often get consideration as further regressors in Barro regression based analyses 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 in government consumption, in investment in physical capital as well as trade openness. As variables entering the set of conditioning state variables, we consider an index of the quality of (public sector) governance (*govqual*), and, as reflecting portions of the equality provided by a country's institutions, of gender inequality (*geninq*).[16] [17] To measure the quality of (public) sector governance, 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 on this index. As an illustration, Figure 6 provides the 2005 quality of governance ranking sorted from highest (Finland) to lowest (Democratic Republic of Congo) levels of quality of governance (the higher the index value, the higher the quality and the lower the risk associated with a country's public sector governance). Motivating our second index, gender inequality, considerable concern has been 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 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 a country's 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

[16]We abandoned attempts to also consider an index of the development conduciveness of the religious environment (due to issues of lack of robustness of results and concerns as to whether such conduciveness might not poorly proxy for a measure of societal trust), and 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).

[17]See, for example, Acemoglu, Robinson and Johnson (2005) and Rodrik, Subramanian and Trebbi (2004) for contributions stressing the role of institutions for a country's economic development.

compared to males is an indicator for gender bias, as it is critically influenced by gender bias in health care and nutrition.[18] 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 of its institutions). 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 (9) 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.3. For the conditioning functional, we work with first-order Chebyshev polynomials, so that

$$\theta_\ell(z_{i,t-1}) = \theta_{\ell 0} + \theta_{\ell 1} \cdot z_{i,t-1}, \tag{15}$$

with $\ell = 1, 2$.[19] For us to incorporate a country in our sample,we require that there are at least 30 consecutive time-series observations available for the dependent, all explanatory and all conditioning state variables. Table 1 provides a list of the $N = 87$ countries that we can thus include in our sample. See Appendix A for further details concerning the measurement of our y and $\boldsymbol{x}$ variables.

4 Empirical Findings

As motivated in detail in Section 3, we present estimation results and their substantive economic implications for two models:
For the set of Barro regression models[20]

$$\begin{aligned} T^{-1} \cdot (y_{iT} - y_{i0}) &= \beta_0 + \beta_1 \cdot y_{i0} + \gamma_1 \cdot govgdp_i + \gamma_2 \cdot invgdp_i + \gamma_3 \cdot opengdp_i \\ &\quad + \delta_1 \cdot govqual_i + \delta_2 \cdot geninq_i + v_{iT}, \end{aligned} \tag{16}$$

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

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

[20]The regressors in Equation (16) except for y_{i0} are intertemporal averages over the sample period.

where y_{it} is hdi_{it} or $lgdp_{it}$,[21] $govqual_{it}$ reflects quality of governance, and $geninq_{it}$ gender inequality, and for the set of CPMG state-dependent panel models

$$\begin{aligned}\Delta y_{it} &= \mu_i + \varphi_i \cdot t + \alpha_i \cdot \big[y_{i,t-1} - \theta_1(z_{i,t-1}) \cdot lgov_{i,t-1} - \theta_2(z_{i,t-1}) \cdot linv_{i,t-1} \\ &\quad -\theta_3(z_{i,t-1}) \cdot lopen_{i,t-1}\big] + \boldsymbol{\psi}_i' \cdot \boldsymbol{h}_{it} + \epsilon_{it}, \end{aligned} \tag{17}$$

where y_{it} is again hdi_{it} or $lgdp_{it}$, and z_{it} is one of $govqual_{it}$, or $geninq_{it}$.[22] See Section 3 for a description of all the variables, and a definition of the short-run dynamics, which for ease of notation in Equation (17) again are captured through elements of $\boldsymbol{h}_{it}$.

Tables 2 and 3 provide the coefficient estimates as well as implied speed of convergence coefficients for the Barro regression model.[23] 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).[24] The half-lifes 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 50% shorter than that for HDI. With respect to the development determinants, for the regressors capturing or reflecting macroeconomic policies, investment in physical capital enters all Barro regressions with a positive sign. Government consumption has both economically and statistically about zero effect on HDI, but affects GDP negatively (as also in Barro and Sala-i-Martin, 2004), though not in a statistically significant manner. Trade openness is economically and statistically insignificant (with a negative sign) in all regressions where HDI is the dependent variable, but enters (though not statistically significant) with a positive sign whenever GDP is the dependent variable. The variables reflecting institutional characteristics - qual-

[21]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 (16) as ratios relative to GDP, that is, $govgdp_i = T^{-1}\sum_{t=1}^{T} exp(lgov_{it} - lgdp_{it})$, $invgdp_i = T^{-1}\sum_{t=1}^{T} exp(linv_{it} - lgdp_{it})$, and $opengdp_i = T^{-1}\sum_{t=1}^{T} exp(lopen_{it} - lgdp_{it})$.

[22]Note the distinctions between the definitions of the regressors in the Barro regression model in Equation (16) and the CPMG state-dependent panel data model in Equation (17).

[23]See Appendix C for a derivation of the length of the half-lifes implied by Equations (16) and (17).

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

ity of governance and gender inequality[25] - have significant effects only in the GDP model. Generally, according to the Barro regressions, investment in physical capital is the most robust determinant of both human development and output growth. Quality of governance, the initial condition and possibly gender inequality matter in statistically significant form for long-run GDP development, but not for that of HDI. Stronger governance and more equal gender opportunities spur output growth, and there is conditional convergence in terms of GDP of poorer countries towards richer ones.

Let us turn to the estimation results for our CPMG state-dependent panel model. As for the Barro regressions, we begin with commenting on the speeds of convergence to steady state. In Tables 4 and 5 we provide the means and medians of the country-specific speed of adjustment parameter estimates for our two dependent and two conditioning state variables. For example, when choosing governance quality as the conditioning state variable and HDI as the dependent variable (left results column of Table 4), the average speed of adjustment of the 24 OECD countries in our sample is -0.25. The half-lifes obtained from the CPMG state-dependent panel model across the board are much shorter than those obtained from the Barro regressions. To give just a couple of examples: For HDI, under the Barro regression the half-life, though depending on the details of the model specification, is at least 86 years, but under the CPMG state-dependent panel model falls to two to three years. For the logarithm of GDP per capita, under the Barro regression, the half-life is at least 47 years, but is down to no more than 15 months under the CPMG state-dependent panel model. As our panel model 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-run cross-country heterogeneities, and is capturing the adjustment dynamics to the conditional, country-specific, long-run equilibrium. The adjustment dynamics are rather similar across our two indices capturing state dependence, quality of governance and gender inequality. The GDP adjustment processes for both state variables tend to be fastest for Sub-Saharan Africa and the LDCs, and (relatively) slowest for the Asian and OECD countries. For HDI, the half-lifes tend to be shortest for Latin America and the Caribbean, and relatively longest for Sub-Saharan Africa and the LDCs. Overall, however, there is limited variation of the half-lifes across conditioning states and/or country groups. As is clear from the strikingly different

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

half-lifes implied by the Barro regression model, this does not imply that cross-country heterogeneities would not be an important consideration for development questions. Rather, the CPMG state-dependent panel model effectively filters out cross-country heterogeneities, and the half-life results indicate that for our sample the speeds of convergence to country-specific long-run equilibria are fast, rendering the heterogeneity in half-lifes a matter of several months only, which in a growth context is relatively negligible.

Concerning the estimated long-run multiplier functionals for the CPMG state-dependent panel model, displayed in Figures 8 and 9, several observations stand out.[26] The figures, most pronouncedly so 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 variables. 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. Turning to specific policy variables and conditioning state variables, let us consider first the results when conditioning the long-run multiplier on quality of governance. The sign of the long-run effect of a government consumption stimulus for both HDI and GDP changes as the quality of governance increases sufficiently. 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.[27] The scope of fiscal policy in the form of government consumption is much more limited for countries in which the quality of governance is high. On the other hand, strong scores on quality of governance strengthen the long-run development effects both of investment in physical capital and of trade, both for HDI and GDP. Taken together, the government consumption and physical capital investment effects suggest that while government consumption expenditure in countries with strong quality of governance is not a suitable vehicle for long-run growth, a different assessment may hold for government investment expenditure. Moving to our estimation results when the conditioning state index is gender inequality, the variations of the long-run multiplier functionals for GDP occur on an overall more compact scale when compared with the corresponding functionals under quality of

[26]For space reasons, we omit tables with the complete sets of coefficient estimates for the CPMG state-dependent panel model. The tables are available from the authors upon request.

[27]Such negative effects could be due to interest rate effects or distortionary tax schemes, for example.

governance conditioning. The slopes of the long-run multiplier functionals still suggest that as a country improves upon its gender equal opportunity score, stimuli to investment in physical capital and to trade openness bring about stronger output growth. The magnitude of state variation of the HDI development effects implied by economic policy changes is of about the same magnitude when conditioning on gender inequality as when conditioning on the quality of governance. The strongest variation is observed for the long-run HDI effects of changes in investment in physical capital. Strong scores on gender equal opportunity strengthen the long-run development effects of investment in physical capital.

Exploiting the rich dynamic structure of our CPMG 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 CPMG state-dependent panel model with the time path of the effect of the corresponding economic policy variable change in period $t = 0$ obtained from the Barro regression model.[28] See Appendix D.1 (D.2) for the calculation of the dynamic multiplier in the Barro regression (in the CPMG state-dependent panel) model. The dynamic multipliers in Figure 11 display for all 87 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 assigned countries to one of three clusters, based on the average values of the conditioning state variables governance quality and gender inequality, and with the clusters constructed to create relatively homogenous country groupings. We assign each country to one of the three clusters: Cluster 1 containing all countries scoring well below average on gender inequality and at most average on governance quality; Cluster 2 containing all countries scoring in the extended medium range of values for governance quality and close to average or better on gender inequality; and Cluster 3 finally containing all countries scoring at least in the 80% percentile on governance quality (all these countries happen to have an average or higher score on gender inequality). See Figure 10 for a graphical illustration that these three clusters naturally emerge when considering our two state variables governance quality and gender inequality, and Table 6 for a listing

[28] It is certainly sensible to argue that changes in, say, government consumption expenditure will in general also induce changes in, say, trade openness. Nevertheless, as here we wish to emphasize the comparison between dynamic adjustments as can be computed for the Barro regression model and those implied by the CPMG state-dependent panel model, we compute orthogonal dynamic multipliers based on changes in a single policy variable only.

of the countries within these three clusters. Each dynamic multiplier trajectory in Figure 11 corresponds to the average trajectory across the two conditioning state variables governance quality and gender inequality: For each of these two conditioning states, we trace the in-sample effects of a period $t = 0$ (ten percent) increase of the $\boldsymbol{x}$ variable in question if the two conditioning state variables had evolved as they actually did in sample.[29] The Barro regression based multipliers are, of course, state invariant. The left column in Figures 11 and 12 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 CPMG state-dependent panel model in Equation (17), and the starred lines depict the dynamic multipliers implied by the Barro regression model in Equation (16). Figure 11 depicts for the CPMG state-dependent panel model the dynamic multipliers separately for each country within a given cluster, whereas Figure 12 displays the averages of these dynamic multipliers across all countries in a given cluster. Finally in Figure 12, the dash-dot line depicts the long-run effects as implied by the CPMG state-dependent panel model. Several observations stand out upon inspection of Figures 11 and 12. First, there is considerable heterogeneity across clusters in both the short- and the long-run effects of the policy changes implied by the CPMG state-dependent panel model, specifically of the GDP effects, but within a diminished scale also of the HDI effects. As just one example, for countries in Cluster 3, the logarithm of GDP per capita after an increase in investment in physical capital in both the short and long run grows about twice as much as for countries in Cluster 1. The 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 that all coefficients driving the short-run dynamics in the CPMG state-dependent panel model are allowed to be country-specific. Cross-country heterogeneity is also prominently present in the dynamic multipliers reflecting the GDP effects of a government consumption stimulus: While the average long-run effects are negative for Cluster 3, they are positive for Clusters 1 and 2. At the same time, for a number of countries in Clusters 1 and 2 the short-run government consumption stimulus effects are larger in magnitude than the long-run effects. Even in countries with limited

[29] As the dynamic multipliers for our CPMG panel model are state dependent, there are other possibilities also 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.

governance quality, therefore, the development scope of government consumption stimuli is limited. Second, the policy effects on HDI implied by the CPMG state-dependent panel model generally tend to be quantitatively, but in some instances also qualitatively, different from those on GDP. For example, while an increase in investment in physical capital leads to a significant gain in the logarithm of GDP per capita across all clusters, the same stimulus across all clusters at best has a small positive long-run effect on HDI. Third, both the short- and the long-run development effects in the CPMG state-dependent panel model are generally different from the corresponding effects in the Barro regression model, not least because the Barro model features homogenous effects across all countries and linear adjustment processes. Only for specific cases are the multiplier effects implied by the Barro regression model similar to the average multiplier effects implied by the CPMG state-dependent panel model. In general, even if one is interested in average effects across certain institutional characteristics, these cannot be well measured by a model neglecting heterogeneities. This is perhaps most strikingly observed for the development effects of policies aimed at increasing trade openness: The CPMG state-dependent panel model predicts that an increase in trade openness on average across our three clusters spurs the long-run value of HDI rather strongly (at least among the macroeconomic policies we consider), and also spurs the long-run value of GDP. According to the Barro model, on the other hand, increasing trade openness is not beneficial for HDI and of small value for GDP.

Tables 7 and 8 focus on the effects of the various economic policy changes depicted in Figures 11 and 12, with Table 7 providing the development effects after 20 years, and Table 8 providing these effects in the steady state.[30] The two tables highlight some commonalities in the development effects of changes in our three economic policy variables. Stimuli in investment in physical capital and in trade openness across all three country clusters have positive long-horizon effects on GDP. Also, increased trade openness across all three clusters also has positive long-horizon effects on HDI. For government consumption stimuli, as noted earlier, state conditioning plays a pronounced role, in that the long-horizon HDI and GDP effects of such stimuli diminish and turn negative with advances in governance quality and/or gender equality, as underlying the construction of our three clusters. The Barro regression model seems to overstate the extent to which government consumption stimuli may have detrimental long-term GDP development effects.

[30] Table 8 also lists the steady state effects implied by the Barro regression models that were not plotted in Figures 11 and 12.

Let us finally discuss the relation between our findings in this section and those in Section 2. In Section 2, we had presented (see in particular Figures 1, 3 and 5) what appeared to be evidence that HDI would exhibit unconditional convergence features not present in GDP. In this section, however, 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. Tables 9 and 10 indicate a likely source for this apparent discrepancy of findings: HDI and GDP appear to be unit root processes. Both country-specific unit root testing and panel unit root testing (at least when cross-sectional dependence is captured) does suggest so. The (popular) moment analysis and regression methods we employed in Section 2 are not valid in the presence of a unit root: Bounded second moments then do not exist, and a regression of the level of a variable on (only) its growth rate is unbalanced and yields inconsistent parameter estimates. Our CPMG state-dependent panel model, in contrast, is applicable even in the presence of unit roots. Thus our findings in this section that both HDI and GDP converge conditionally to state-dependent development paths, with HDI adjustment significantly more drawn-out than GDP adjustment, should be taken at face value. In Section 2, we had also appeared to have 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 unit root testing results as well: Two unit root processes may spuriously appear to be correlated. A regression in first differences may then yield seemingly different insights. Our CPMG state-dependent panel model points to some of the sources of the differences in the HDI and GDP growth processes: Core macroeconomic policies have notably different effects on HDI vs. GDP growth even at extended horizons.

5 Conclusion

In this paper, we have applied a novel dynamic panel 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. In contrast to the Barro regression model framework, the CPMG state-dependent panel model we have taken to the data 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 governance quality and gender inequality. 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 cross-country convergence properties, the HDI adjustment process is slower than that for GDP. Realizing gains in HDI development requires more patience than is the case for GDP. Some macroeconomic policies, in particular stimulation of investment in physical capital and government consumption stimuli, spur GDP development (notably) more strongly than development of HDI. While we also find that policies aimed at increasing trade openness spur HDI development actually more strongly than that of GDP, HDI development policies should nevertheless 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 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 promising development strategies. One key example of this is that fiscal stimuli in the form of government consumption positively affect GDP in countries with low governance quality, but negatively affect long-run GDP in countries with high governance quality. The range of economic policies and of societal characteristics (that render the development effects of changes in economic policies state dependent) we have considered in this paper has been rather limited. This is primarily due to data limitations that can hinder estimation of the CPMG 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 is in the direction of overcoming such limitations.

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

Data for the shares of government consumption, investment in physical capital, and imports as well as exports are taken from the Penn World Tables Mark 6.3. Data for GDP per capita and HDI were provided to us by UNDP from their hybrid HDI database.

B Construction of the Conditioning State Variables

B.1 Quality of Governance

The quality of governance 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 enrolment 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 (2008).

B.3 Extracting the Trend Component

To extract the trend component from each of the series for $\{z_{i,t-1}\}_{i=1,2,\dots,N;\,t=1,2,\dots,T}$, while ensuring that the trend component remains pre-determined and thus not complicating estimation of our CPMG 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 $z_{i,t-1}^{TR}$;

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

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

The conditioning state variable we use for estimation of our CPMG state-dependent panel model is given by the vector $(z_{i0}, z_{i1}, z_{i2}, z_{i3}, z_{i4}^{TR}, z_{i5}^{TR}, \ldots, z_{i,T-1}^{TR})'$. To keep notation simple, while always 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 $\{z_{i,t-1}\}$.

C Half-Lifes in the Barro Regression and CPMG State-Dependent 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, $\widetilde{y}_{it}^E = Y_{it}/(A_{it}L_{it})$ (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 $\partial(\dot{\widetilde{y}}^E/\widetilde{y}^E)/\partial\widetilde{y}^E = \partial[\dot{\widetilde{y}}^E(i,t,\widetilde{y}^E)/\widetilde{y}^E]/\partial\widetilde{y}^E < 0$, and at the steady-state the change is zero so that $\dot{\widetilde{y}}^E(i,t,\widetilde{y}_i^{E*})/\widetilde{y}^E = 0$. Defining $y^E = log(\widetilde{y}^E)$ and noting that $\dot{\widetilde{y}}^E/\widetilde{y}^E = \dot{y}^E$, a first-order Taylor approximation of the rate of change of output in per capita efficiency units around the steady-state level $\widetilde{y}_i^{E*}$ is given by

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

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

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

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

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

where $\beta_1 = -T^{-1} \cdot \left(1 - e^{-\lambda T}\right)$. Tacking on a stochastic disturbance term v_i,[31] assuming $log(A_{i0}) = \boldsymbol{\pi}' \cdot \boldsymbol{z}_i + log(A_0) + e_i$, where $\boldsymbol{z}_i$ 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

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

where $\epsilon_i = v_i - \beta_1 \cdot e_i$.[32] The coefficient β_1 in the Barro regression model in Equation (10) 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, t^{HL}, as from Equation (C.2) we have that

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

and

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

C.2 CPMG State-Dependent Panel Model

To derive the half-life in our CPMG state-dependent panel model, consider an autoregressive representation of y_{it}, assuming for simplicity of exposition a determin-

[31] 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).

[32] See Rodríguez (2006) for how the effects of the variables capturing predictable heterogeneity in initial technology could enter the Barro regression model in a non-linear form.

istic model with a first-order lag structure,

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

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

$$\frac{y_{it}^{HL} - y_i^*}{y_{i0} - y_i^*} = \frac{1}{2} \quad \Longrightarrow \quad t^{HL} = \frac{log(0.5)}{log(\rho_i)}. \tag{C.9}$$

In the CPMG state-dependent panel model considered in Equation (9), $y_i^* = \boldsymbol{\theta}(z_i^*)' \cdot \boldsymbol{x}_i^*$ and $\rho_i = 1 + \alpha_i$.

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

D.1 Barro Regression Model

Consider first the Barro regression model in Equation (10),

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

Neglecting any transitional dynamics, a policy change in the ℓ-th element of the $\boldsymbol{x}$ regressor vector implies a change in the long-run level of the dependent variable given by

$$\widetilde{y}_{iT}^{\ell} - y_{iT} = T \cdot \gamma_\ell \cdot (\widetilde{x}_{i\ell} - x_{i\ell}), \tag{D.1}$$

where $\widetilde{x}_{i\ell}$ denotes the value of the ℓ-th regressor after the policy change, and $\widetilde{y}_{iT}^{\ell}$ the new long-run level of y_i after the policy change. In case the dependent variable is HDI, $\widetilde{y}_{iT}^{\ell} - y_{iT}$ reflects the long-run level change of HDI relative to its baseline level. In case the dependent variable is the logarithm of GDP per capita, $\widetilde{y}_{iT}^{\ell} - y_{iT}$ reflects the long-run percentage change of GDP per capita relative to its baseline level. Recall that in the Barro regression model the variables in $\boldsymbol{x}$ are measured as shares of GDP, while the variables in $\boldsymbol{x}$ in the CPMG state-dependent panel data model are measured as per capita quantities. In order to work with comparable policy changes across the two models, for each country we calculate the long-run increase in the share of x_ℓ in GDP implied by a ten percent increase in x_ℓ in the CPMG state-dependent panel model, and use the implied change in the share of x_ℓ in GDP as the policy change for the Barro regression model. Turning now to transitional dynamics, as follows from Appendix C.1, Equation (C.3), the transition path leading to the new long-run level of the dependent variable in the Barro regression model is given by

$$y_{it} - y_{i0} = (1 - e^{-\lambda t}) \cdot (\widetilde{y}_{iT}^{\ell} - y_{i0}), \tag{D.2}$$

with $\lambda = -log(1 + t\beta_1)/t$.

D.2 CPMG State-Dependent Panel Model

Let us rewrite the CPMG state-dependent panel model in Equation (9) as

$$\begin{aligned} y_{it} &= \mu_i + \varphi_i \cdot t + (\rho_{i1} + \rho_{i2} + \ldots + \rho_{ip}) \cdot y_{i,t-1} + (\boldsymbol{\varrho}_{i0} + \boldsymbol{\varrho}_{i1} + \ldots + \boldsymbol{\varrho}_{iq})' \cdot \boldsymbol{x}_{it} \\ &\quad + \sum_{\ell=1}^{p-1} \left(- \sum_{s=\ell+1}^{p} \rho_{is} \right) \cdot \Delta y_{i,t-\ell} + \sum_{\ell=0}^{q-1} \left(- \sum_{s=\ell+1}^{q} \boldsymbol{\varrho}_{is} \right)' \cdot \Delta \boldsymbol{x}_{i,t-\ell} + \epsilon_{it} \qquad \text{(D.3)} \\ &= \mu_i + \varphi_i \cdot t + (\alpha_i + 1) \cdot y_{i,t-1} - \alpha_i \cdot \boldsymbol{\theta}'(z_{i,t-1}) \cdot \boldsymbol{x}_{it} \\ &\quad + \sum_{\ell=1}^{p-1} \delta_{i\ell} \cdot \Delta y_{i,t-\ell} + \sum_{j=0}^{q-1} \boldsymbol{\gamma}_{i\ell}' \cdot \Delta \boldsymbol{x}_{i,t-\ell} + \epsilon_{it}. \qquad \text{(D.4)} \end{aligned}$$

Estimates of the slope coefficients in Equation (D.4) can be used to compute estimates of $\rho_{ik},\ k = 1, 2, \ldots, p,\ \boldsymbol{\varrho}_{ik},\ k = 0, 1, \ldots, q$, from Equation (D.3) as

$$\begin{bmatrix} \rho_{i1} \\ \rho_{i2} \\ \vdots \\ \rho_{ip} \end{bmatrix} = \begin{bmatrix} \alpha_i + 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 & 0 \\ -1 & 1 & 0 & \cdots & 0 & 0 \\ 0 & -1 & 1 & \cdots & 0 & 0 \\ \vdots & & \ddots & & \vdots & \vdots \\ \vdots & & & \ddots & 1 & 0 \\ \vdots & & & & -1 & 1 \\ 0 & 0 & 0 & \cdots & 0 & -1 \end{bmatrix} \cdot \begin{bmatrix} \delta_{i1} \\ \delta_{i2} \\ \vdots \\ \delta_{i,p-1} \end{bmatrix}, \tag{D.5}$$

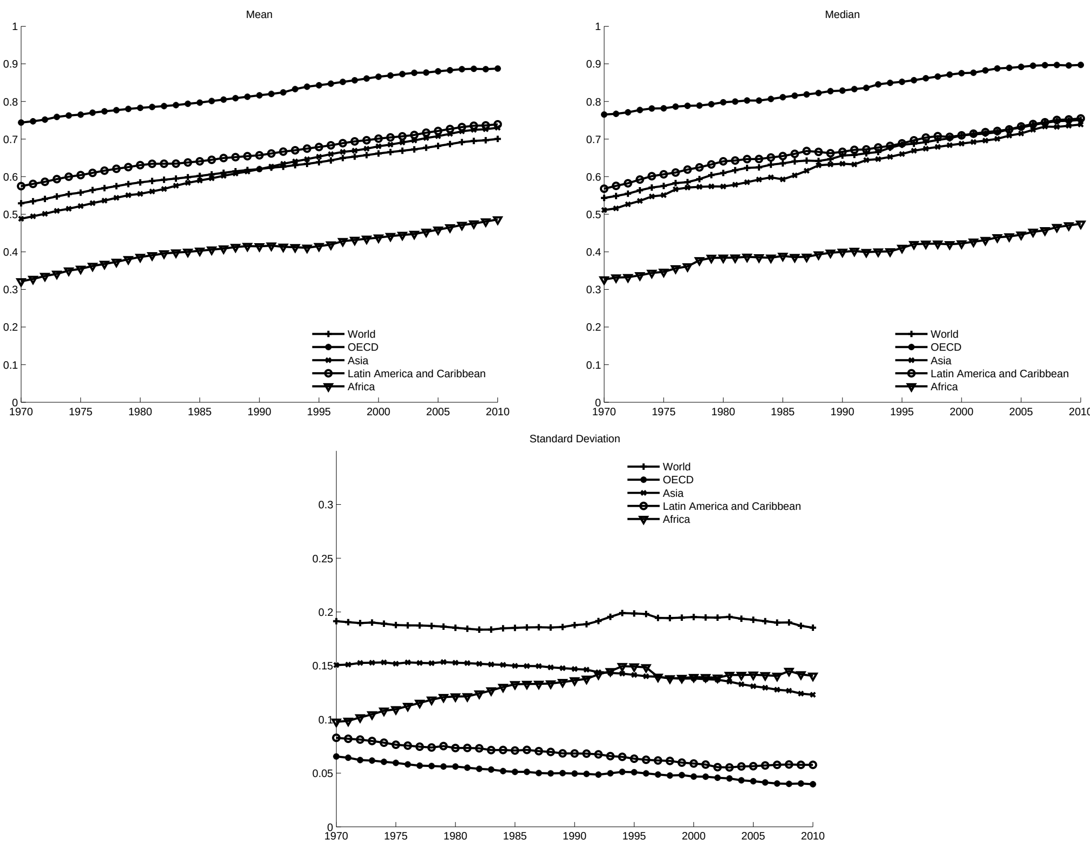
and

$$\begin{bmatrix} \varrho_{i\ell 1} \\ \varrho_{i\ell 2} \\ \vdots \\ \varrho_{i\ell p} \end{bmatrix} = \begin{bmatrix} -\alpha_i \cdot \theta_\ell(z_{i,t-1}) \\ 0 \\ \vdots \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 & 0 \\ -1 & 1 & 0 & \cdots & 0 & 0 \\ 0 & -1 & 1 & \cdots & 0 & 0 \\ \vdots & & \ddots & & 1 & 0 \\ \vdots & & & \ddots & \vdots & \vdots \\ \vdots & & & & -1 & 1 \\ 0 & 0 & 0 & \cdots & 0 & -1 \end{bmatrix} \cdot \begin{bmatrix} \gamma_{i\ell 0} \\ \gamma_{i\ell 1} \\ \vdots \\ \gamma_{i,\ell,q-1} \end{bmatrix}, \quad \text{(D.6)}$$

for $\ell = 1, 2, \ldots, m$. Using $\rho_{ik},\ k = 1, 2, \ldots, p$, $\boldsymbol{\varrho}_{ik},\ k = 0, 1, \ldots, q$, a simulated series $\{\widehat{y}_{it}\}$ for which $\widehat{x}_{\ell ir} = x_{\ell ir} + \mathit{policychange}$, $t \geq r$, 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 $\{\widehat{y}_{it}\}$. We set $\mathit{policychange} = 0.1$ and for $\{x_{\ell ir}\}$ we use country i's actual values of *lgov*, *linv*, and *lopen*.

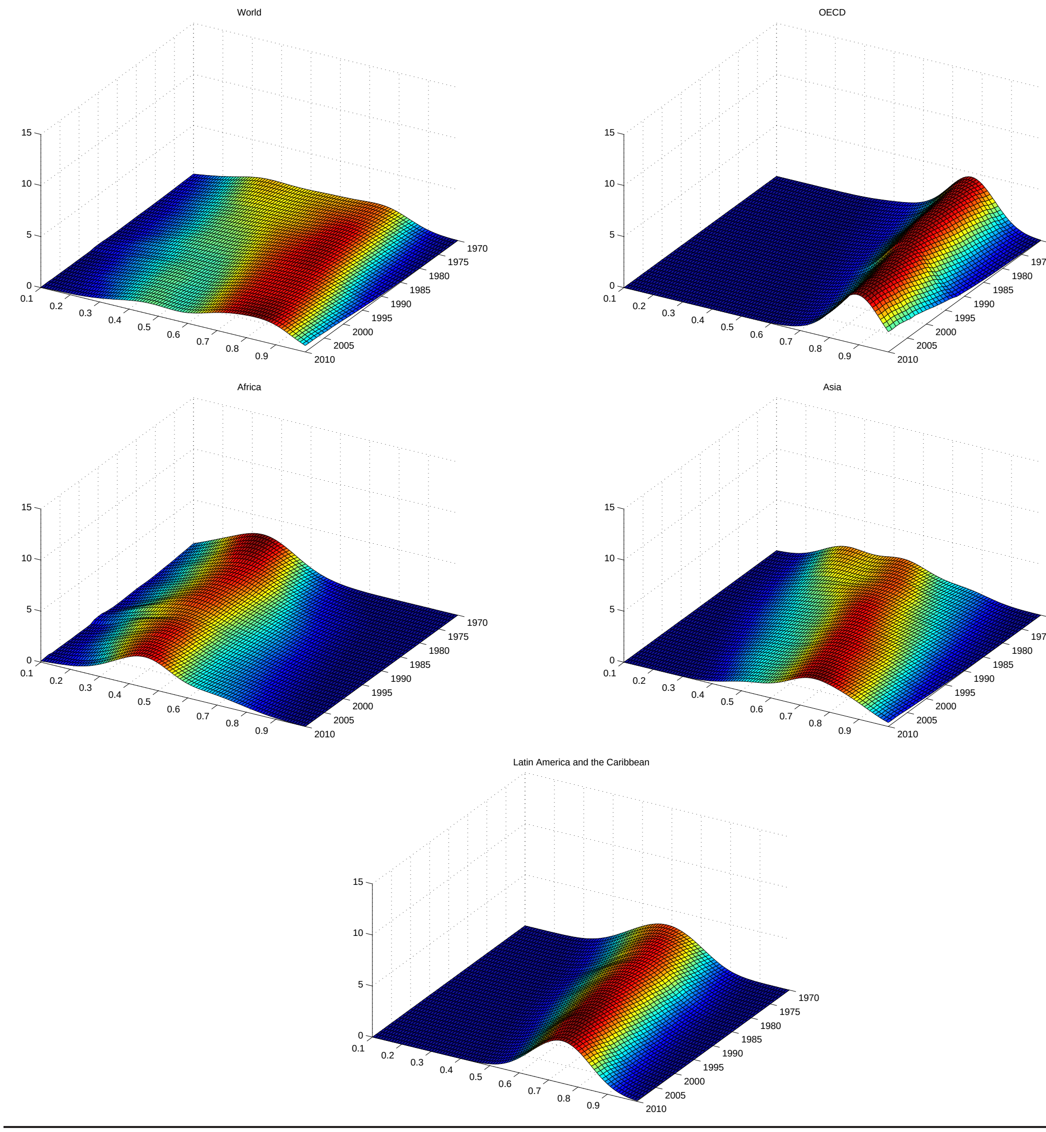
E Figures

Figure 1: Evolution of the Moments of HDI



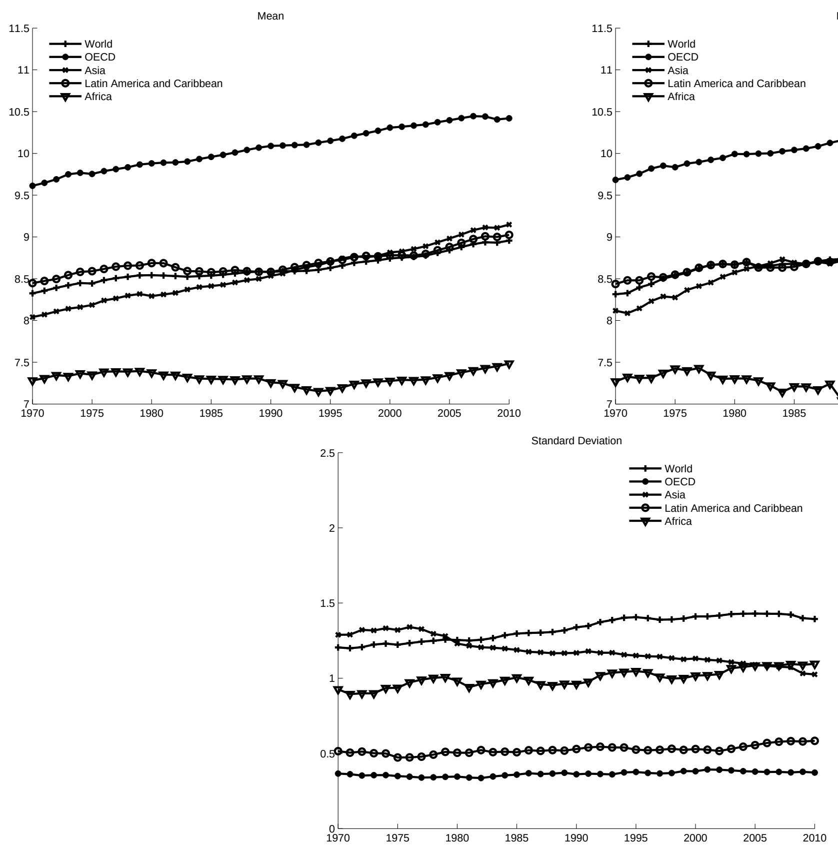
Note: The graphs depict the evolution of the cross-country mean, median and standard deviation of HDI for $N = 87$ countries for the time period from 1970 to 2010. The upper left-hand panel plots the evolution of the mean, the upper right-hand panel plots the evolution of the median, and the lower panel 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



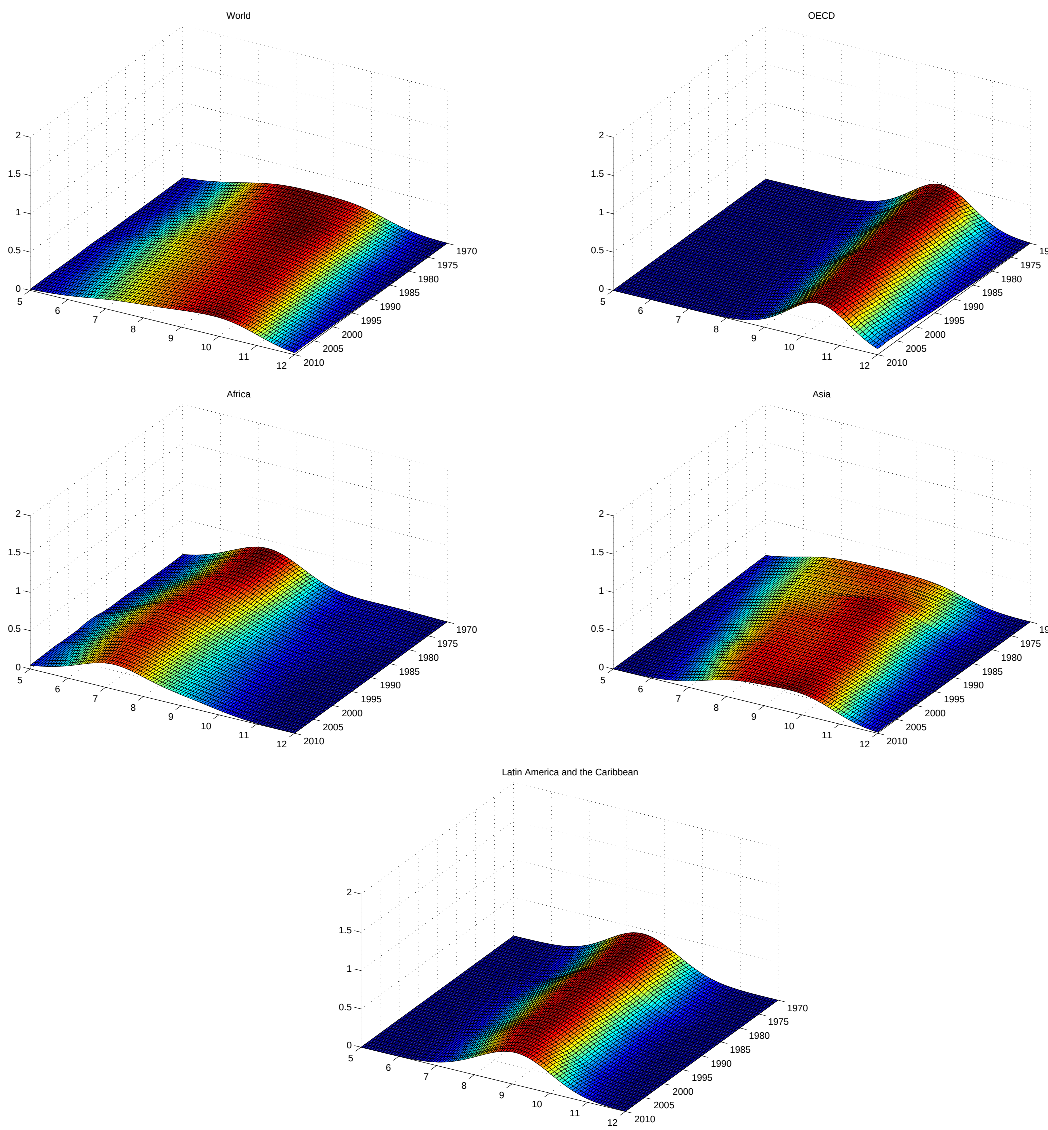
Note: The graphs depict the evolution of the cross-sectional distribution of HDI for $N = 87$ countries for the time period from 1970 to 2010. The upper left-hand panel plots the evolution of the cross-sectional distribution of HDI for the full sample ("world"), the upper right-hand panel plots this 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



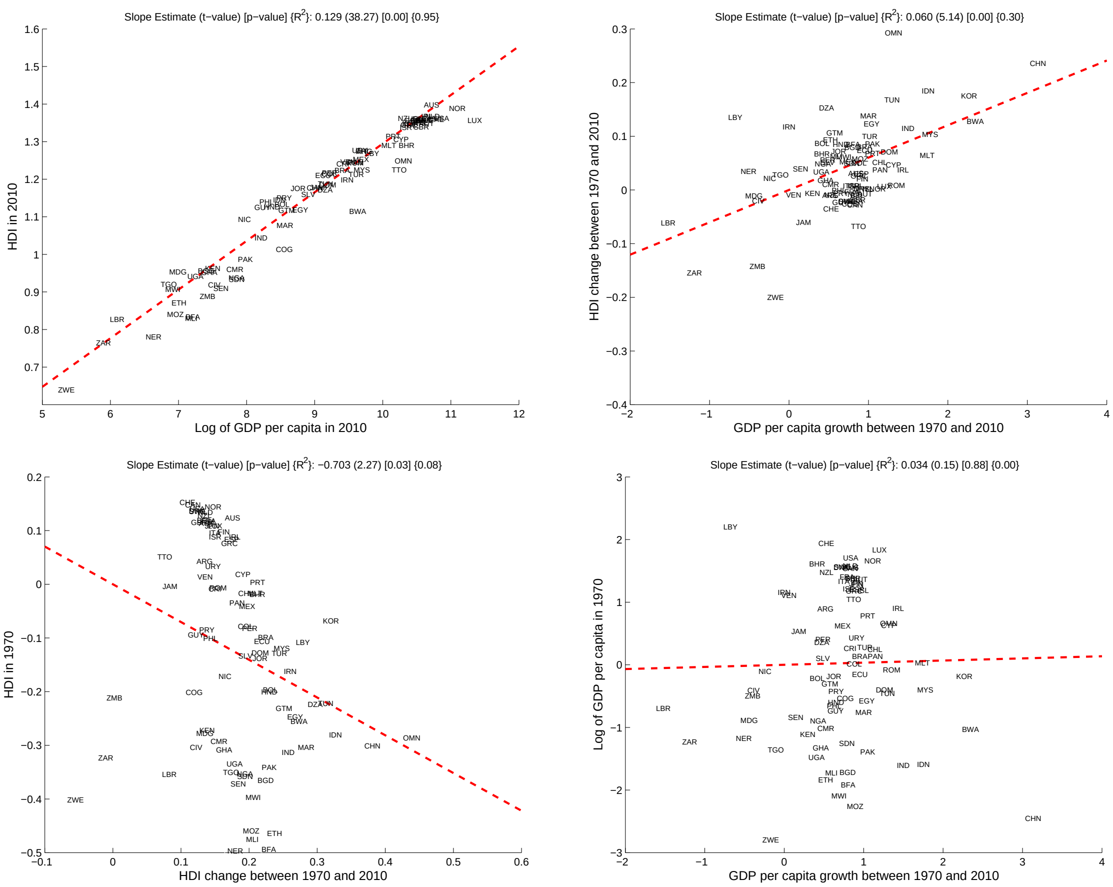
Note: The graphs depict the evolution of the cross-country mean, median, and standard deviation of the logarithm of GDP per capita for $N = 87$ countries for the time period from 1970 to 2010. See the note to Figure 1.

Figure 4: Evolution of the Cross-Sectional Distribution of the Logarithm of GDP per Capita



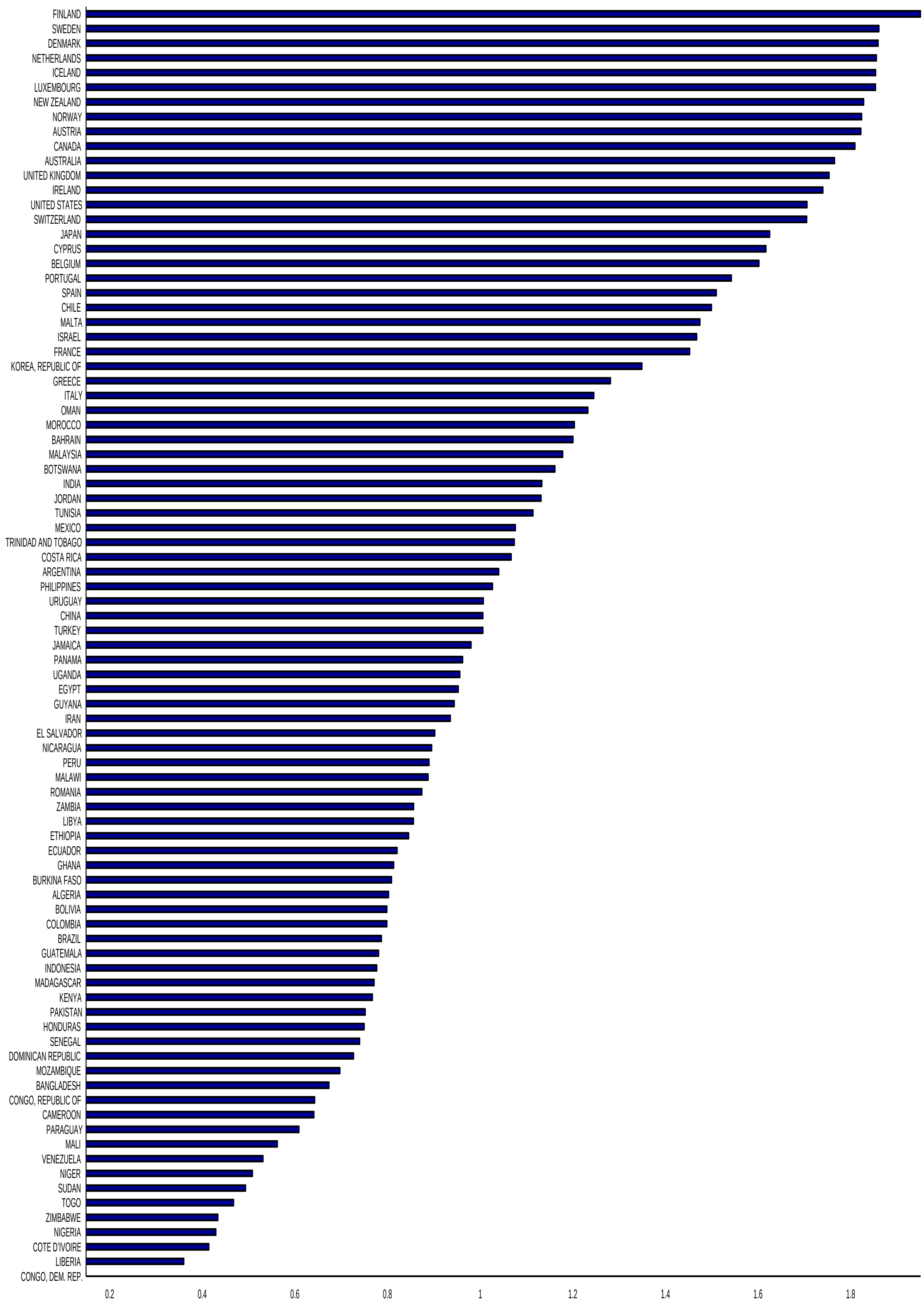
Note: The graphs depict the evolution of the cross-sectional distribution of the logarithm of GDP per capita for $N = 87$ countries for the time period from 1970 to 2010. See the note to Figure 2.

Figure 5: Correlation Between Trends in HDI and GDP per Capita Between 1970 and 2010



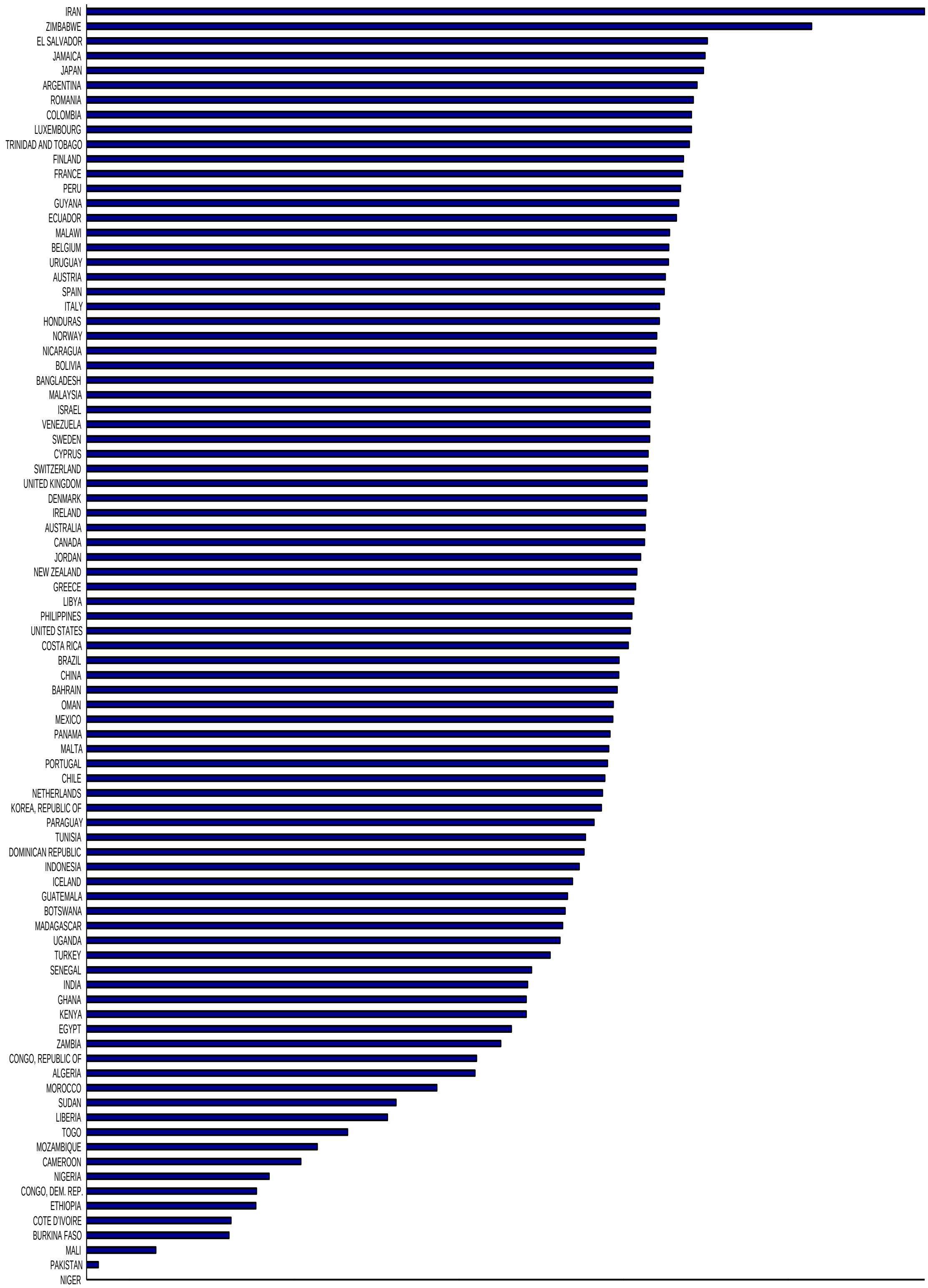
Note: The graphs depict correlations between HDI in 2010 and the logarithm of GDP per capita in 2010 (upper left-hand panel), the change in HDI and GDP per capita growth between 1970 and 2010 (upper right-hand panel), HDI in 1970 and the change in HDI between 1970 and 2010 (lower left-hand panel), and the logarithm of GDP per capita in 1970 and GDP per capita growth between 1970 and 2010 (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 against the variable displayed on the horizontal axis, after controlling only for an intercept in both variables.

Figure 6: Country Rankings for the Quality of Governance Index in 2005



Note: The graph depicts the cross-country ranking of the quality of (public sector) governance for 2005. The countries are sorted from highest to lowest ranks of quality of governance. The length of each bar reflects the value of the quality of governance index in 2005.

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

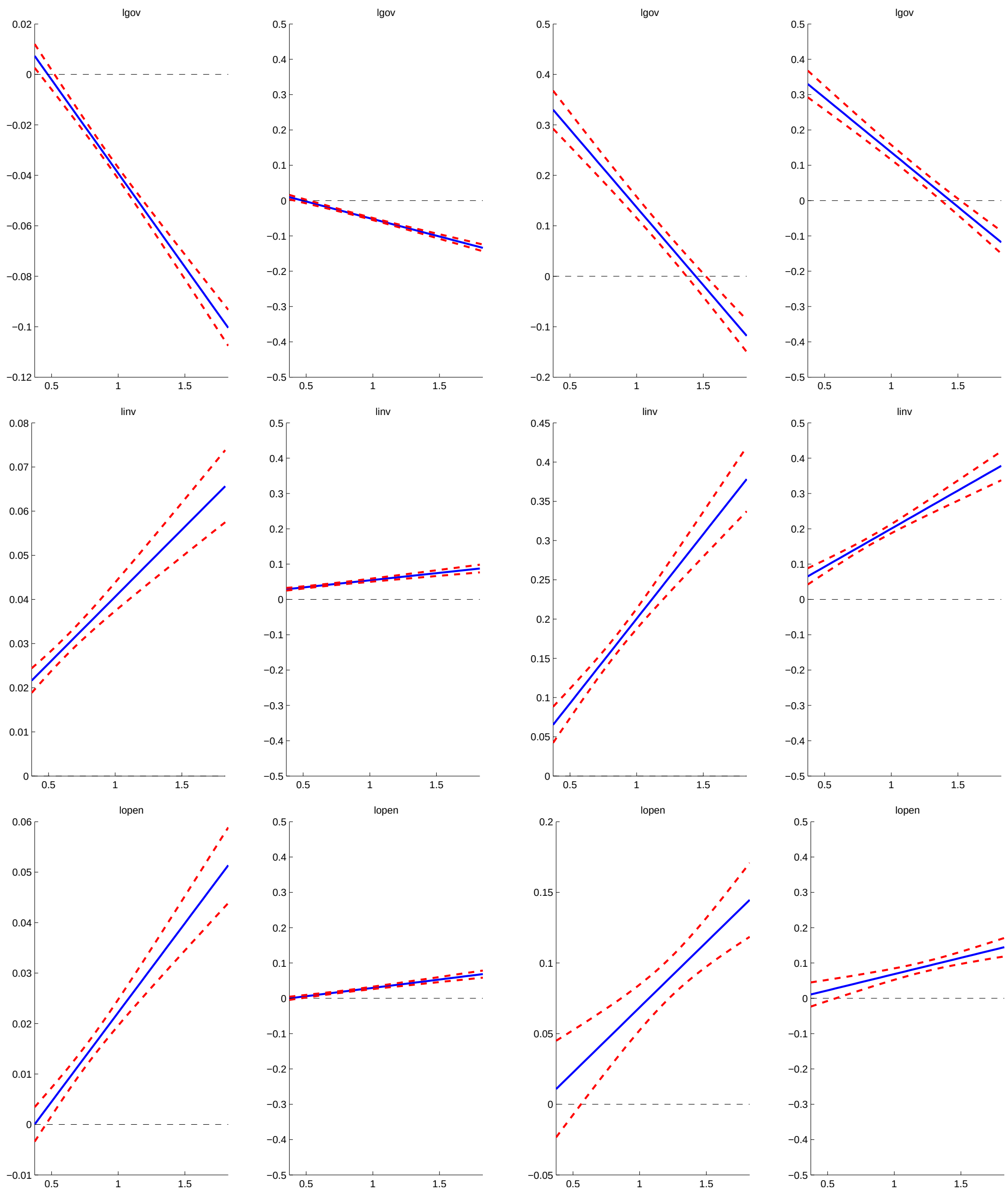


Note: The graph depicts the cross-country ranking of gender inequality for 2005. The countries are sorted from lowest to highest degrees of gender inequality. The length of each bar reflects the degree to which a country has achieved gender equality.

Figure 8: Quality of Governance Index

HDI

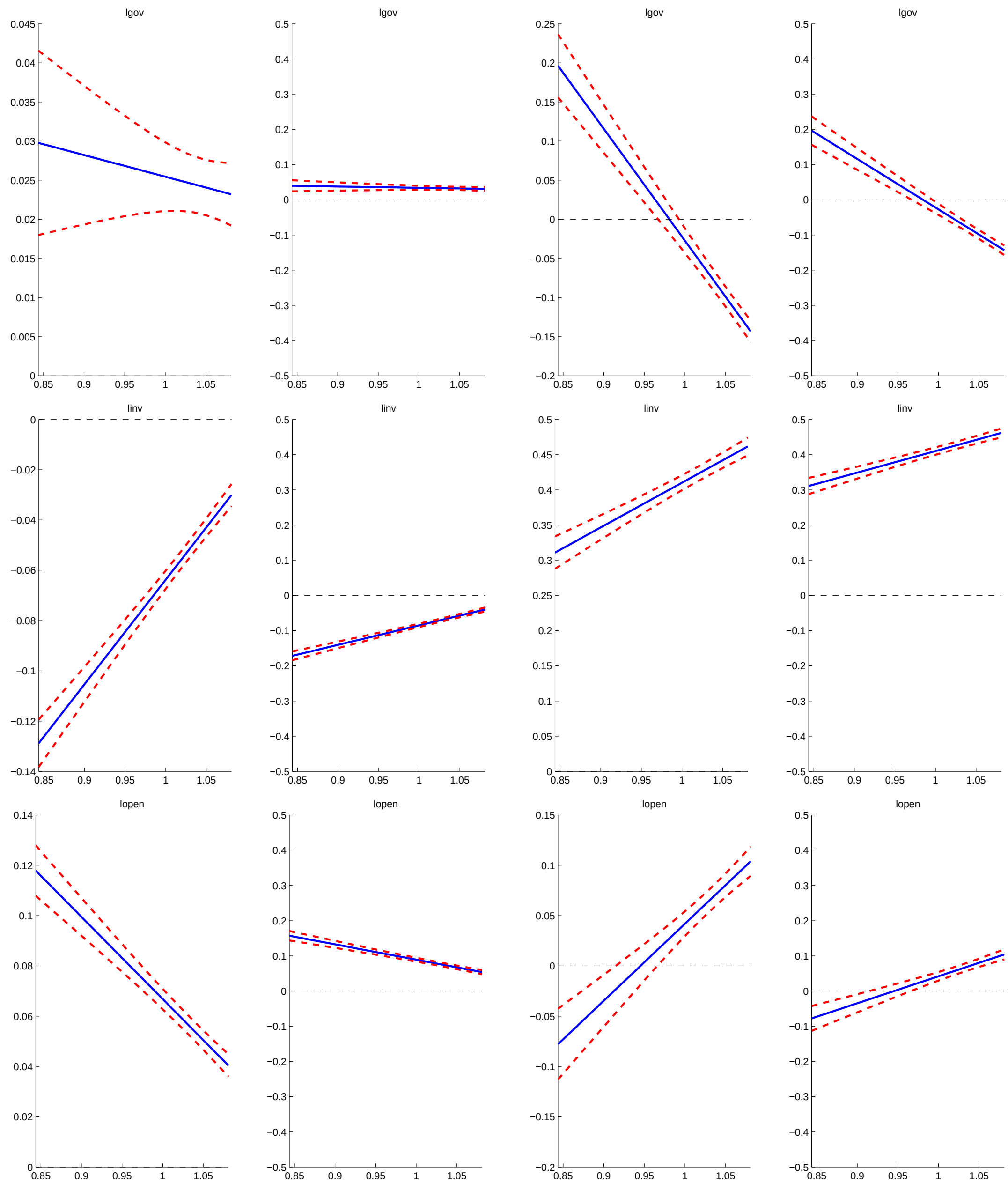
Logarithm of GDP per Capita



Note: The graphs depict the estimated long-run multiplier functionals $\widehat{\theta}_k(z_{i,t-1})$ from Equation (17) with the conditioning index $z_{i,t-1}$ being quality of governance. For each choice of the dependent variable, the graphs present two sets of results. First, in the left column for HDI the long-run coefficient functional estimates are depicted. Second, in the right 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 period value of HDI). For the logarithm of GDP per capita, the left column depicts the long-run coefficient functional estimates, and the right column the long-run percentage change of GDP per capita in response to a one percentage change in the corresponding explanatory variable. In each panel, the solid line depicts the point estimates, and the dashed lines depict 95% confidence bands. The scales in the second and fourth columns are adjusted to be the same for the HDI and logarithm of GDP per capita graphs.

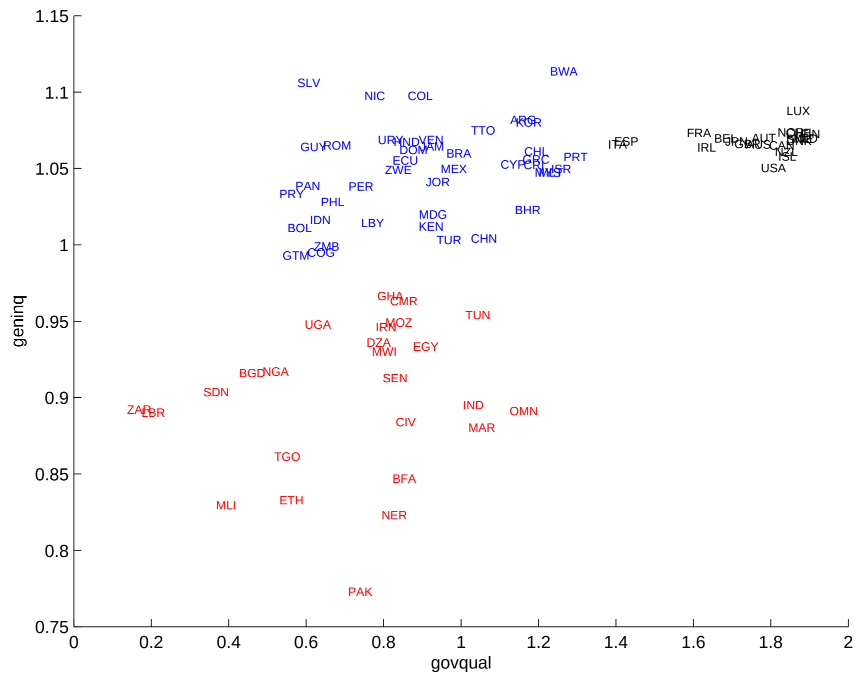
Figure 9: Gender Inequality

HDI | Logarithm of GDP per Capita



Note: The graphs depict the estimated long-run multiplier functional $\widehat{\theta}_k(z_{i,t-1})$ from Equation (17) 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 8.

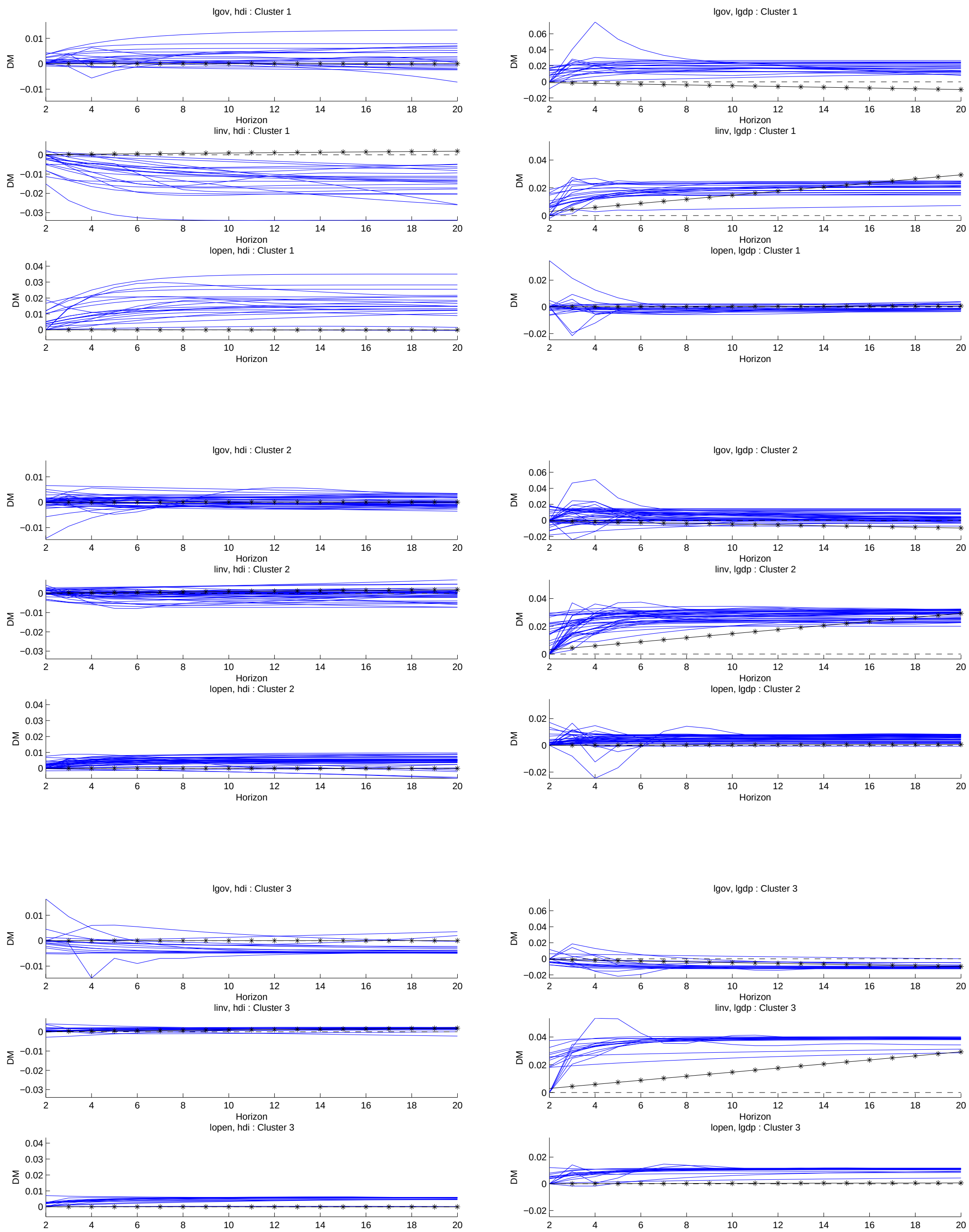
Figure 10: The Country Clusters



Note: The graph depicts a scatter plot of countries' average quality of governance scores against countries' average gender inequality scores. The brightness of the country codes indicates the adherence of the countries to our three country clusters.

Figure 11: Dynamic Multipliers Across Clusters

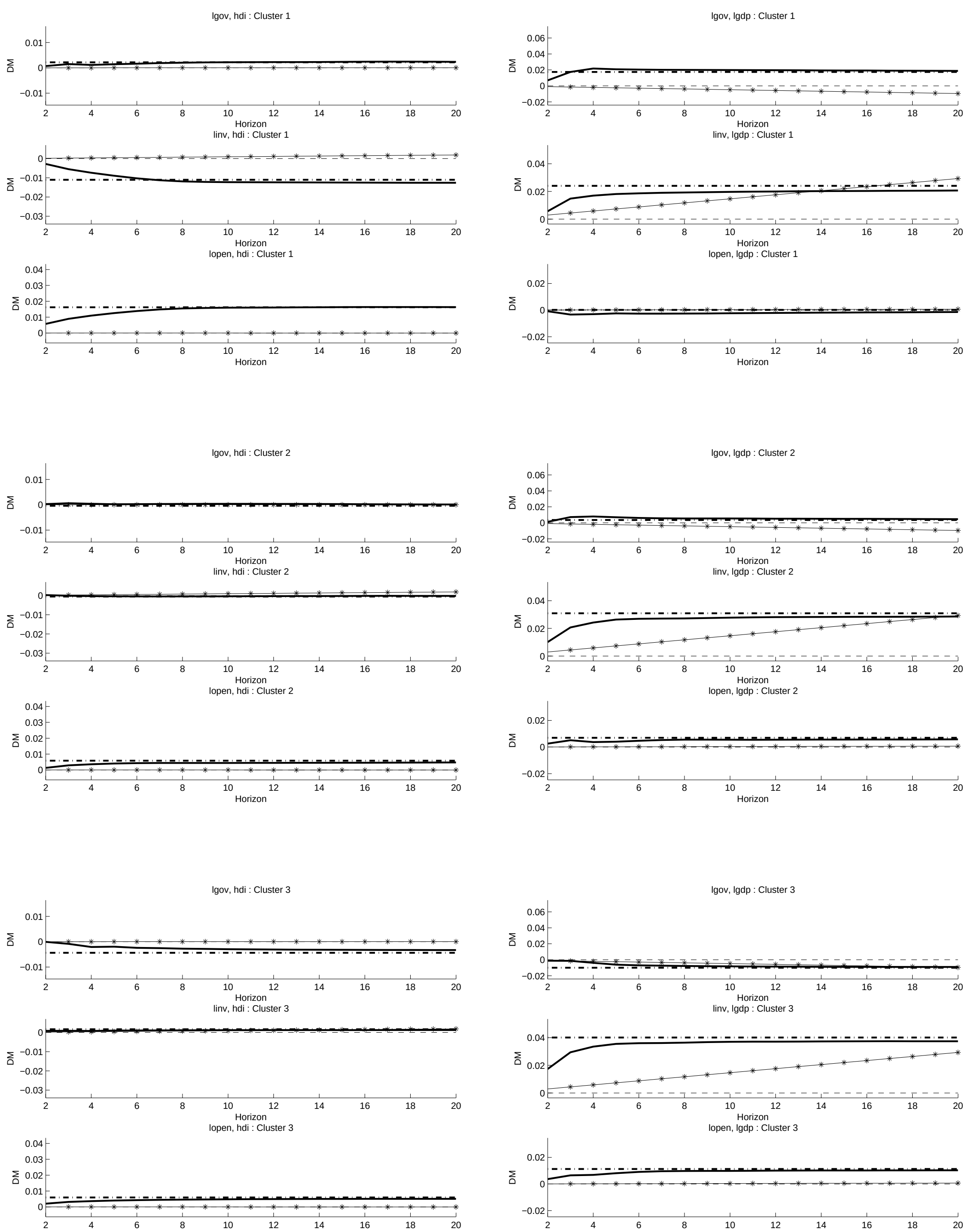
HDI | Logarithm of GDP per Capita



Note: Each sub-panel displays the dynamic multipliers (solid lines) for a permanent ten basis points increase for a given policy 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 CPMG state-dependent panel model and the Barro regression model.

Figure 12: Cluster-Average Dynamic Multipliers

HDI | Logarithm of GDP per Capita



Note: Each sub-panel depicts the cluster average of the dynamic multipliers for the CPMG state-dependent panel model as plotted in Figure 11. Also depicted in each sub-panel is the corresponding multiplier (transition path) implied by the Barro regression model (starred line). For example, in the upper left-hand panel the average dynamic response 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 multiplier implied by the Barro regression model (starred line) as well as the long-run effect implied by the CPMG state-dependent panel model (dash-dot line).

F Tables

Table 1: Countries Included

Algeria	Kenya
Argentina	Korea, Republic of
Australia	Liberia
Austria	Libya
Bahrain	Luxembourg
Bangladesh	Madagascar
Belgium	Malawi
Bolivia	Malaysia
Botswana	Mali
Brazil	Malta
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	Oman
Cyprus	Pakistan
Denmark	Panama
Dominican Republic	Paraguay
Ecuador	Peru
Egypt	Philippines
El Salvador	Portugal
Ethiopia	Romania
Finland	Senegal
France	Spain
Ghana	Sudan
Greece	Sweden
Guatemala	Switzerland
Guyana	Togo
Honduras	Trinidad and Tobago
Iceland	Tunisia
India	Turkey
Indonesia	Uganda
Iran	United Kingdom
Ireland	United States
Israel	Uruguay
Italy	Venezuela
Jamaica	Zambia
Japan	Zimbabwe
Jordan	

Note: The table lists the countries included in our sample.

Table 2: Barro Regression with Δhdi as Dependent Variable

Variable	Model 1	Model 2	Model 3
Const	0.0052^{***} (5.96)	0.0072 (1.52)	0.0059 (1.14)
$hdi0$	-0.0069^{***} (3.00)	-0.0036 (1.29)	-0.0064 (1.53)
$govgdp$	0.0001 (0.05)	-0.0000 (0.01)	0.0002 (0.09)
$invgdp$	0.0080^{***} (2.66)	0.0081^{**} (2.43)	0.0084^{***} (2.70)
$opengdp$	-0.0003 (0.54)	-0.0002 (0.39)	-0.0002 (0.39)
$govqual$	0.0012 (1.58)	-	0.0012 (1.39)
$geninq$	-	-0.0026 (0.45)	-0.0012 (0.18)
R-Squared	0.16	0.11	0.14
Implied λ	0.008	0.004	0.007
Half-Life	86	> 100	96
N	87	87	87

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

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

Variable	Model 1	Model 2	Model 3
Const	0.0560^{***} (3.10)	-0.0227 (0.76)	0.0203 (0.86)
$lgdp0$	-0.0098^{***} (3.40)	-0.0054^{*} (1.70)	-0.0113^{***} (3.20)
$govgdp$	-0.0228 (1.27)	-0.0336 (1.56)	-0.0236 (1.37)
$invgdp$	0.0805^{***} (3.15)	0.0819^{**} (2.47)	0.0723^{***} (2.82)
$opengdp$	0.0026 (0.68)	0.0005 (0.10)	0.0019 (0.49)
$govqual$	0.0255^{***} (4.39)	-	0.0261^{***} (4.73)
$geninq$	-	0.0692^{*} (1.77)	0.0485 (1.43)
R-Squared	0.43	0.27	0.46
Implied λ	0.012	0.006	0.014
Half-Life	57	> 100	48
N	87	87	87

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

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

	y_{it}: *hdi*					y_{it}: *lgdp*				
Country Group	Mean	Median	H-L	H-L (Months)	N	Mean	Median	H-L	H-L (Months)	N
All Countries	-0.27	-0.24	2	26	87	-0.5	-0.48	1	12	87
OECD	-0.25	-0.24	2	28	24	-0.46	-0.45	1	14	24
Sub-Saharan Africa	-0.24	-0.21	3	30	24	-0.57	-0.54	1	10	24
Latin America and Caribbean	-0.37	-0.3	2	18	21	-0.53	-0.5	1	11	21
Asia	-0.23	-0.2	3	32	16	-0.42	-0.4	1	15	16
LDCs	-0.24	-0.21	2	30	15	-0.56	-0.55	1	10	15

Note: The table reports the speed of adjustment parameter estimates, $\widehat{\alpha}_i$, from Equation (17) for the full sample, as well as 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 both choices of the dependent variable, the table reports the mean and the median across countries within the country group in question, the country group's implied half-life (in years and months) as well as the number of countries in the group.

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

	y_{it}: *hdi*					y_{it}: *lgdp*				
Country Group	Mean	Median	H-L	H-L (Months)	N	Mean	Median	H-L	H-L (Months)	N
All Countries	-0.28	-0.25	2	25	87	-0.51	-0.49	1	12	87
OECD	-0.24	-0.2	3	30	24	-0.42	-0.4	1	15	24
Sub-Saharan Africa	-0.2	-0.22	3	37	24	-0.58	-0.51	1	9	24
Latin America and Caribbean	-0.37	-0.27	2	18	21	-0.53	-0.47	1	11	21
Asia	-0.36	-0.38	2	18	16	-0.49	-0.43	1	12	16
LDCs	-0.22	-0.25	3	33	15	-0.6	-0.53	1	9	15

Note: See the note to Table 4.

Table 6: 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	Ecuador	Netherlands
	Mali	El Salvador	New Zealand
	Morocco	Greece	Norway
	Mozambique	Guatemala	Spain
	Niger	Guyana	Sweden
	Nigeria	Honduras	Switzerland
	Oman	Indonesia	United Kingdom
	Pakistan	Israel	United States
	Senegal	Jamaica	
	Sudan	Jordan	
	Togo	Kenya	
	Tunisia	Korea, Republic of	
	Uganda	Libya	
		Madagascar	
		Malaysia	
		Malta	
		Mexico	
		Nicaragua	
		Panama	
		Paraguay	
		Peru	
		Philippines	
		Portugal	
		Romania	
		Trinidad and Tobago	
		Turkey	
		Uruguay	
		Venezuela	
		Zambia	
		Zimbabwe	
Mean			
govqual	0.69	0.88	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 governance quality and gender inequality scores. See also Figure 10.

Table 7: Development Effects of Policy Changes for Our Three Clusters of Countries: 20 Year Time Horizon

	hdi			lgdp		
	lgov	linv	lopen	lgov	linv	lopen
Cluster 1	0.23	-1.26	1.63	1.88	2.06	-0.14
Cluster 2	0.01	-0.02	0.47	0.46	2.86	0.58
Cluster 3	-0.33	0.13	0.51	-0.90	3.74	1.03
Barro	0.00	0.19	-0.01	-0.95	2.93	0.07

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

Table 8: Long-Run Development Effects of Policy Changes for Our Three Clusters of Countries

	hdi			lgdp		
	lgov	linv	lopen	lgov	linv	lopen
Cluster 1	0.22	-1.10	1.62	1.75	2.40	0.02
Cluster 2	-0.04	-0.05	0.58	0.36	3.09	0.69
Cluster 3	-0.44	0.17	0.60	-0.99	4.01	1.12
Barro	0.01	1.61	-0.05	-5.50	17.56	0.31

Note: See the note to Table 7. Rather than reporting development effects for a time horizon of 20 years as Table 7 does, this table reports the long-run (steady state) development effects.

Table 9: Unit Root Tests for HDI

Significance Level:	1%	5%	10%
hdi			
Augmented Dickey-Fuller	0	10	11
Maddala and Wu (1999)	No	No	No
Im, Pesaran and Shin (2003)	Yes	Yes	Yes
Pesaran (2007)	No	No	No

Note: The table reports results for the traditional augmented Dickey-Fuller unit root test and the panel unit root tests of Maddala and Wu (1999), Im, Pesaran and Shin (2003) and Pesaran (2007). The augmented Dickey-Fuller test is based on

$$\Delta y_{it} = \alpha_i + \delta_i \cdot t + \rho_i \cdot y_{i,t-1} + \sum_{k=1}^{p_i} \phi_{ik} \cdot \Delta y_{i,t-k} + u_{it}, \qquad \text{(F.1)}$$

which is estimated for each country separately. For the augmented Dickey-Fuller test, the table reports the number of countries in the sample for which the null of a unit root, $H_0 : \rho_i = 0$, is rejected at the 1%, 5%, and 10% significance levels. The three panel unit root tests are based on

$$\Delta y_{it} = \alpha_i + \delta_i \cdot t + \rho_i \cdot y_{i,t-1} + \sum_{k=1}^{p_i} \phi_{ik} \cdot \Delta y_{i,t-k} + \beta_i \cdot f_t + u_{it}, \qquad \text{(F.2)}$$

where f_t is an unobserved common factor capturing cross-sectional dependence; $\beta_i =$ for the Maddala and Wu (1999) and Im, Pesaran and Shin (2003) panel unit root tests, with this restriction being relaxed for the Pesaran (2007) panel unit root test. Pesaran (2007) in effect approximates f_t by cross-sectional averages of the observables. For the panel unit root tests, the table reports whether the null of a unit root in all countries, $H_0 : \rho_i = 0$ for all i, is rejected in favor of the alternative hypothesis, $H_1 : \rho_i < 0$ for a non-zero fraction of countries, at the 1%, 5%, and 10% significance levels.

Table 10: Unit Root Tests for the Logarithm of GDP per Capita

	Significance Level:	1%	5%	10%
lgdp				
	Augmented Dickey-Fuller	0	13	18
	Maddala and Wu (1999)	Yes	Yes	Yes
	Im, Pesaran and Shin (2003)	Yes	Yes	Yes
	Pesaran (2007)	No	No	No

Note: See the note to Table 9.