Deep and Proximate Determinants of the World Income Distribution

Davide Fiaschi, Andrea Mario Lavezzi and Angela Parenti*

Abstract

This paper studies the deep and proximate determinants of the evolution of the cross-country distribution of GDP per worker in the period 1960-2008 by a novel methodology based on information criterion. We find that countries of our sample follow three distinctive growth regimes identified by two deep determinants, the life expectancy at birth in 1960 and the share of Catholics in 1965, and that each regime is characterized by nonlinearities. Growth regimes appear as the major cause of the increased inequality and polarization, while technological catching-up, proxied by the initial level of GDP per worker, acts in the opposite direction. Finally, human capital marginally reduces polarization, while investment rates and employment growth has not any distributional effect.

Keywords: polarization, growth regimes, parameter heterogeneity, nonlinearities, model uncertainty.

JEL: *C14; O47*

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1 Introduction

The literature on growth empirics has not reached a consensus on the determinants of world income inequality (Johnson and Papageorgious, 2017). We believe that this failure is mainly due to the lack of consideration of a hierarchy among the set of candidate determinants which was, on the contrary, a key characteristic of the seminal paper by Durlauf and Johnson (1995). Therefore, in this paper we propose a new methodology based on information criterion which allows to identify deep and proximate determinants in the spirit of Rodrik (2003), and to deal with other critical issues discussed in the literature such as model uncertainty, nonlinearities and endogeneity. We then apply this methodology to the investigation of the determinants of inequality and polarization in the world distribution of income, measured by GDP per worker, in the period 1960-2008.

The most significant stylized fact on the evolution of the cross-country income distribution is the shift from unimodality in the 1960s to bimodality in the 1990s (see Durlauf et al., 2005, for exhaustive discussion and references). Several, and potentially complementary, explanations have been advanced. A first explanation relies on the assumption that different countries obey different growth processes, i.e. they belong to different *growth regimes* according to their initial conditions proxied, for example, by GDP per capita, human capital, or life expectancy (see, e.g., Durlauf and Johnson, 1995, Durlauf et al., 2001, and Kourtellos, 2011). Another explanation is based on the effect of nonlinearities in the growth process (see, e.g., Liu and Stengos, 1999), while a third one distinguishes *deep* (or fundamental) from *proximate* growth determinants, assuming that the former determine the latter and, ultimately, long-run outcomes (see Rodrik, 2003).[1] The deep determinants proposed in the literature include: institutions (Acemoglu et al., 2005); culture, in particular in the form of social capital (Knack and Keefer, 1997, Temple and Johnson, 1998) and religion (Durlauf et al., 2012); geography (Bloom et al., 2003); and ethnolinguistic fractionalization (Easterly and Levine, 1997, Tan, 2009). The proximate determinants are those typically appearing in the production function, i.e. factors of production and technology (see, e.g., Rodrik, 2003 and Weil, 2012). Embracing one or the other explanation implies profoundly different growth-enhancing policies (Rodrik, 2003).

Our empirical strategy integrates the insights of these different lines of research. Specifically, our methodology identifies growth regimes by a set of candidate deep determinants (we label "deep" determinant any variable used to identify growth regimes), and *simultaneously* estimates a nonlinear growth model within each growth regime, which includes the proximate determinants suggested by Mankiw et al. (1992): initial income per worker (as a proxy for technological catching-up), investment rate, employment growth and human capital.[2] Applying this methodology to a sample of 84 coun-

[1] Weil (2012, p. 53) classifies growth determinants into "proximate" and "ultimate".

[2] Brock (2001) proposes a taxonomy of growth determinants based on their time scales, where "deep" determinants are moving on a slower time scale than "proximate" determinants, while Tan (2009) distinguishes between "development clubs", identified on the basis of the sole deep determinants, and "growth regimes",

tries over the period 1960-2008, we identify as relevant deep determinants initial health conditions, proxied by life expectancy at birth in 1960 and culture, proxied by the share of Catholics in 1965. In particular, we identify three regimes: "high life expectancy regime", "low life expectancy/high share of Catholics regime", and "low life expectancy/low share of Catholics regime". Furthermore, we show that nonlinearities within the regimes are a pervasive phenomenon. By a counterfactual analysis we demonstrate that growth regimes are the main source of polarization and inequality. Among the proximate determinants, initial income has the opposite distributional effect, human capital marginally reduces polarization, while the investment rate and the employment growth rate have no significant effects.

Our results contrast with several existing findings, and contain some novelties. Contributions on the relative importance of competing deep determinants of growth such as institutions and geography conclude that institutions prevail (Rodrik et al., 2004, Tan, 2009, Owen et al., 2009 and Flachaire et al., 2014). In the identification of growth regimes we consider the largest set of candidates with respect to the existing literature, among which institutions and geography: the latter are however both dominated by life expectancy at birth in 1960 and the share of Catholics in 1965. Our results therefore confirm the importance of culture, as proxied by the share of Catholics in 1965, in development, as thoroughly discussed in Guiso et al. (2006), but as regime identifier and not as a covariate in a growth regression.[3] Finally, with the partial exception of Kourtellos (2011), no previous work found life expectancy as an identifier of growth regimes.[4]

We find significant nonlinearities within regimes, suggesting that previous works based on linear specifications may suffer from misspecification bias. Moreover, proximate determinants are generally significant in all regimes with an important difference: human capital has a positive effect on growth only in the "low life expectancy/low share of Catholics" regime. This evidence can help to explain why Durlauf et al. (2012) do not find any effect of human capital, given their choice to consider our deep determinants as additional covariates in a regression, and to estimate linear models. We do not find any significant distributional effect of cross-country heterogeneity in investment and employment growth rates but, differently from Beaudry et al. (2005), a significant effect of the initial level of GDP per worker.

Lastly, we contribute to the debate on whether: "the transition to the long-run steady-state [can be] associated with non-monotonic evolution of the distribution of income across countries. Thus, convergence may be preceded by polarization and clustering, and club convergence will be generated by these models in the medium run" (Galor, 1996, p. 96). In particular, Lucas (2000) and Galor (2007) claim that polarization is a transitory phenomenon caused by the different timing of countries'

identified by both the deep and proximate determinants.

[3]The role of religion as a covariate has been convincingly challenged by Durlauf et al. (2012).

[4]However, Kourtellos (2011) does not deal with the issue of model uncertainty.

take-off. Lucas (2000) argues that countries randomly start their growth process and, subsequently, adopt the technology of the leading countries. Differently, Galor and Weil (2000) and Galor (2007) propose the Unified Growth Theory (UGT), according to which a country transits from a Malthusian Regime to a Post-Malthusian Regime, and finally reaches the Modern Growth Regime. Although our "high-life expectancy" regime has the characteristics of the Modern Growth Regime (but the other two regimes differ from those hypothesized by the UGT), our counterfactual analysis suggests that in the period 1960-2008 the predicted regime transitions did not take place for a relevant number of countries. Thus our analysis suggests that "club convergence" is a persistent phenomenon. An important (and obvious) caveat to this claim is that while Lucas (2000) and Galor (2007) consider a very long-run horizon, our analysis is limited to 48 years (which is however a long period compared to other studies on distribution dynamics).

The paper is organized as follows: Section 2 discusses the related literature; Section 3 describes the methodology; Section 4 presents the empirical analysis; Section 5 concludes. The appendices contain some technical details on the methodology and on data.

2 Related Literature

The importance of classifying growth determinants into deep and proximate is discussed, among others, by Rodrik (2003) and Weil (2012). An investigation of the impact of deep determinants for long-term development is proposed by Spolaore and Wacziarg (2013), who also offer an exhaustive review of the existing literature. The main thrust of the argument is that, while the proximate determinants *directly* affect growth, they are themselves determined by other, *deeper*, determinants such as geography, institutions and culture.[5] Weil (2012) highlights the several links between deep and proximate determinants. For example, geographic location can favor trade and technological spillovers; institutions can encourage savings and the accumulation of factors; culture can imply openness or closure to new ideas and technologies, a positive attitude towards hard work, favoring efficiency, or to thriftiness favoring accumulation.[6] Understanding economic growth and comparative development, therefore, requires to identify the relevant deep determinants. The novelty of our approach is the *joint* identification of the relevant deep determinants and of the growth models within each of the identified growth regimes.

In the literature, different methods have been utilized to identify growth regimes. Durlauf and Johnson (1995) and Tan (2009) use clustering algorithms (denoted by CART and GUIDE respectively)

[5]Among the deep determinants, Weil (2012) also considers inequality, while Rodrik (2003) includes trade openness.

[6]For a detailed account see Weil (2012). Rodrik (2003) contains some remarks on the exogeneity, or (partial) endogeneity, of the deep determinants and on their interrelations.

that sequentially partition the countries into regimes on the basis of some deep determinants; Desdoigts (1999) utilizes a projection pursuit approach based on proximate determinants, and indirectly identifies the relevant deep determinants; Owen et al. (2009), Flachaire et al. (2014) and Anderson et al. (2016) use finite mixture models, while Bos et al. (2010) split a sample of countries by a multinomial logit model, and then estimate a stochastic frontier model within each growth regime. The main difference with respect to these works is that we allow for nonlinearities within each regime and study the effect of growth regimes on the evolution of the income distribution.[7] Moreover, our procedure allows for model selection under uncertainty that if "ignored, [would imply that] precision is often overestimated, achieved confidence interval coverage is below the nominal level, and predictions are less accurate than expected" (Burnham and Anderson, 2003).

Our work is also related to the studies on the determinants of distribution dynamics. Specifically, Quah (1996) introduces the concept of *conditioned* stochastic kernel,[8] based on residuals from a regression of GDP per worker on proximate determinants, while Quah (1997) proposes a conditioned stochastic kernel based on GDP per capita normalized with respect to a weighted sample average, where weights are defined by geographical proximity or intensity of trade with other countries. By considering the residuals of a regression, however, Quah (1996) can only obtain an estimate of the *joint* distributional effect of the determinants included in the regression, while we are able to identify the effect of individual variables. Quah (1997), instead, considers one variable at the time, but does not control for the effect of other determinants. Johnson (2005) and Feyrer (2008), differently, explain the income distribution dynamics by a comparison with the distributions of proximate growth determinants, such as human capital, physical capital and total factor productivity, assuming a common worldwide Cobb-Douglas production function. By allowing for the presence of growth regimes, we do not assume the existence of a common production function.

Finally, the use of counterfactual analysis to study the determinants of distribution dynamics was previously proposed by Beaudry et al. (2005), Cheshire and Magrini (2005) and Henderson and Russell (2005). In particular, Beaudry et al. (2005) analyse the distributional effect of proximate determinants comparing the periods 1960-1978 and 1978-1998, characterized by the emergence of polarization. Their strategy consists in estimating counterfactual distributions for the second period assuming that a factor of interest (e.g. the estimated coefficient of a growth regression or the distribution of a growth determinant) maintains in the second period the same value of the first. Differently, Cheshire

[7]Partial exceptions are Desdoigts (1999), who does not specify any growth model, and Bos et al. (2010), who estimate a stochastic frontier model assuming a translog production function. In addition, Maasoumi et al. (2007) consider a nonlinear growth model *assuming* the existence of two regimes, i.e. OECD and non-OECD countries, but focus is on growth rates' distribution.

[8]The stochastic kernel is an operator mapping the current distribution into the future distribution. See Appendix H for details.

and Magrini (2005) estimate a growth regression, and then compute counterfactual distributions by comparing a "predicted" stochastic kernel (computed on the basis of fitted values of growth regression) with a "simulated" stochastic kernel (computed on the basis of alternative values of the determinants in the growth regression), while Henderson and Russell (2005) propose a counterfactual analysis based on the production-frontier approach. None of these works, however, allow for growth regimes and nonlinearities.

3 The Methodology for the Empirical Investigation

To introduce our methodology consider Figure 1, which reports the estimated distributions of relative (with respect to sample mean) GDP per worker in 1960 and 2008, along with the estimated long-run equilibrium distribution, denoted as *ergodic* distribution for a sample of 84 countries.[9] In the following we will denote these three types of distribution as *actual* distributions.

[Figure 1 about here.]

Figure 1 confirms the stylized fact emerging from the literature: the distribution is initially unimodal, but subsequently becomes twin-peaked (see, e. g., Quah, 1997). Moreover, the shape of the ergodic distribution suggests that the tendency of polarization is doomed to persist in the long run.[10] In terms of the BIPOL bipolarization index proposed by Anderson et al. (2012), polarization increases from 0.75 in 2008 to 1.26 in the ergodic distribution. Inequality, measured by the Theil index, also increases over the period: the index rose from 0.54 in 1960 to 0.68 in 2008.

Our aim is to identify the determinants of these changes in inequality and polarization through a novel methodology. In particular, in Section 4 we will investigate the role of deep and proximate determinants of growth by a methodology including six steps: i) the identification of growth regimes in presence of nonlinearities (Section 3.1); ii) the specification and estimation of a nonlinear, regime-specific growth regression (Section 3.2); iii) the decomposition of a country's GDP per worker (Section 3.3); iv) the computation of counterfactual final (i.e. end-of-period) distributions (Section 3.4); v) the estimation of counterfactual ergodic distributions (Section 3.5); vi) the evaluation of the distributional effect of proximate determinants by their *marginal growth effect* (Section 3.6).

[9]See Appendix A for data sources, and Appendix 3.1.1 for the country list. Technical details on the estimation can be found in the online Appendix. Dataset and codes are available at authors' website.

[10]Silverman's bootstrap tests for multimodality show that the null hypothesis of unimodality cannot be rejected at the usual significance levels for the 1960 distribution, while it can be rejected at 1% of significance for the 2008 distribution and for the ergodic distribution (Silverman, 1986). Henderson et al. (2008) find the same results with a larger sample of countries (see their Table III).

3.1 Identification of Growth Regimes

In this section we describe the procedure to identify growth regimes based on information theory which has fundamental advantages with respect to existing methods (CART, GUIDE, threshold regressions, finite mixture approach, etc.). The use of the Akaike information criterion (AIC) allows for model selection with *non-nested*, *non-linear* models in presence of endogeneity and, at the same time, for tackling *model selection uncertainty* by ranking the candidate models in terms of their probability of being the *best approximating model* of the true model.[11]

The approach based on AIC has also advantages with respect to Bayesian methods: it does not depend on the choice of prior probabilities and it is computationally less demanding when the number of models under consideration is high. Even though model selection based on AIC implicitly assumes that the "true" model is in the set of candidate models, which is likely to be false, Takeuchi (1976) derives a generalized AIC robust to the absence of the "true" model in the candidate set, and concludes that AIC represents a "parsimonious approach to bias correction" for the absence of "true" model in the candidate set (see Anderson, 2007, p. 70). Finally, the use of Bayesian methods does not allow to use information theory, which is at the basis of our approach to account for model selection uncertainty (see Section 3.1.2 below). In particular, the Bayesian information criterion (BIC), the most known alternative in Bayesian literature to AIC, which appears very similar to AIC to the casual eye, "has [unfortunately] nothing linking it to information theory, [it is] a misnomer" (see Anderson, 2007, p. 160).

3.1.1 The Procedure to Explore all Potential Growth Regimes

The procedure to explore all potential growth regimes is articulated into five steps:

1. Define the set of deep determinants $\mathbf{Z}$ and consider a subset $\mathbf{Z}_q$. For each deep determinant, a threshold value will be used to partition the sample.

2. On the basis of $\mathbf{Z}_q$ identify all possible P_q partitions of countries by sequentially splitting the sample.

   For each subset q and partition p a maximum number of regimes $M_{q,p}$ can be identified. Assign each country to a growth regime and gather them in the set $\mathbf{GR}_{q,p} = \left\{R_{q,p,1}, ..., R_{q,p,M_{q,p}}\right\}$, where $R_{q,p}$ are the possible regimes. Collect all these partitions of countries in the set $\mathbf{GR}_q = \left\{\mathbf{GR}_{q,1}, ..., \mathbf{GR}_{q,P_q}\right\}$.

3. For each growth regime estimate a semiparametric growth regression controlling for endogeneity

[11] See Anderson (2007) for a general introduction to this approach and Claeskens and Hjort (2008) for a technical exposition of model selection based on AIC.

using the Control Function Method, and obtain the residuals:

$$\hat{\upsilon}_{q,p,i} = g_i - \hat{\alpha}_t\left(m_{q,p}\right) - \sum_{j=1}^{K} \hat{\mu}_j\left(X_{i,j}, m_{q,p}\right),$$

where $m_{q,p}$ is the growth regime of country i, given Z_q and P_p.

4. Compute the total log-likelihood (up to a constant) of the model:

$$\log\left(\mathcal{L}\right)_{q,p} = -\left(\frac{N}{2}\right)\log\left(\frac{\sum_{m=1}^{M_{q,p}}\sum_{i\in R_{q,p,m}}\hat{\upsilon}^2_{q,p,i}}{N}\right),$$

and the related $AICc$:

$$AICc_{q,p} = -2\log\left(\mathcal{L}\right)_{q,p} + 2F\left(\frac{N}{N-F-1}\right), \tag{1}$$

where F is the total number of estimated parameters in the model.[12]

5. The minimum $AICc_{q,p}$ in q and p, $AICc_{\min}$, *jointly* identifies i) the best partition of countries into different growth regimes and ii) the best estimation of the semiparametric growth model for each growth regime: this represents the *best model* for our sample.

The number of deep determinants that can be used in the identification of growth regimes is limited by the number of countries N and sub-periods S, given that in each partition a minimum number of observations is needed for the semiparametric estimation of the growth model. For example, using two deep determinants, $\mathbf{Z}_q = (\mathbf{Z}_{q,1}, \mathbf{Z}_{q,2})$, and one threshold for each of them ($Z^{TRESH}_{q,1}$ and $Z^{TRESH}_{q,2}$) implies searching for the existence of four growth regimes in the $(\mathbf{Z}_{q,1}, \mathbf{Z}_{q,2})$-space. On average, $(N \times S)/4$ observations will be available for the estimation of the growth model within each regime. In particular, in Figure 2 it is assumed that $\mathbf{Z}_{q,1}$ is the first partitioning variable, and each partition cannot be populated by less than N^{MIN} countries. The resulting partition can include at least one, and at most four growth regimes (see Figure 3). Moreover, the total number of possible partitions P_q depends on the number of deep determinants considered in the analysis, and on the different values they display. For example, considering the same two deep determinants $\mathbf{Z}_q = (\mathbf{Z}_{q,1}, \mathbf{Z}_{q,2})$, each one taking on N different values (i.e. the maximum, equal to the number of countries in the sample), implies that $P_q = N \times N = N^2$. This means that the maximum number of partitions is equal to $N^2\left(|\mathbf{Z}|^2 - |\mathbf{Z}|\right)$.

[Figure 2 about here.]

[12]The use of semiparametric techniques increases the number of estimated parameters proportionally to the identified nonlinearities (see Section 4.2).

3.1.2 Model selection uncertainty

To account for the *model selection uncertainty*, we compute for each model the *loss of information* as in Anderson (2007, pp. 84-86):

$$\Delta AICc_{q,p} = AICc_{q,p} - AICc_{\min}, \tag{2}$$

where $AICc_{q,p}$ is the AIC of Model (q,p) (corresponding to a partition p of countries and a subset q of deep determinants, see Appendix 3.1.1) corrected for the degrees of freedom (see Anderson, 2007), and $AICc_{\min}$ is the model with the minimum AIC among all the models considered in the procedure. Thus, $\Delta AICc_{q,p}$ ranks the candidate models: the larger $\Delta AICc_{q,p}$, the less likely Model (q,p) is the best approximating model in the candidate set. The simple transformation:

$$\exp\left(-\frac{\Delta AICc_{q,p}}{2}\right) \tag{3}$$

provides the likelihood of Model (q,p), and the following normalisation:

$$w_{q,p} = \frac{\exp\left(-\Delta AICc_{q,p}/2\right)}{\sum_q \sum_p \exp\left(-\Delta AICc_{q,p}/2\right)} \tag{4}$$

gives the probability of Model (q,p) to be the best model in the candidate set. It is worth remarking that $w_{q,p}$ can be interpreted as the: "Bayesian posterior model probabilit[y] under the assumption of savvy model priors" (see Anderson, 2007, p. 88), or as the probability to be the *least false* model under the plausible assumption that the true model is unknown or too complex to be modelled (Claeskens and Hjort, 2008). Our choice of the *best* model will be therefore based on the probabilities given by Eq. (4). These probabilities provide an information similar to the tests on thresholds proposed by Hansen (2000), but with the advantage, in presence of multiple thresholds, to be a joint test and not a sequential test on each threshold.

3.2 Modelling Growth of Output Per Worker

Consider a set of countries indexed by i, $i = 1, ..., N$, partitioned into growth regimes indexed by m, $m = 1, ..., M$. Denote the set of countries in regime m as R_m. Growth is observed over a period of T years, indexed by t. Output per worker of country i at time t, y_{it}, can be expressed as:

$$y_{it} = y_{i0} e^{g_i t}, \tag{5}$$

where y_{i0} is the initial level of output per worker and g_i is the *annual* rate of growth.

The growth rate of country i is modelled by a semiparametric specification to account for nonlinearities, that is:

$$g_i = \alpha(m) + \sum_{j=1}^{K} \mu_j \left(X_{i,j}, m\right) + \upsilon_i, \tag{6}$$

where $\mathbf{X}_i = (X_{i,1}, ..., X_{i,K})$ is a collection of K proximate determinants, $\alpha(m)$ is a constant term for countries in R_m, $\mu_j(\cdot, m)$ are one-dimensional nonparametric functions operating on each of the K elements of $\mathbf{X}_i$ for countries in R_m, and υ_i is an error term with the properties: $E(\upsilon_i|\mathbf{X}_i) = 0$, $\mathrm{var}(\upsilon_i|\mathbf{X}_i) = \sigma^2(\mathbf{X}_i, m)$ (i.e. the model allows for heteroskedasticity). The semiparametric specification allows for a varying marginal effect of proximate determinants on growth. As we will show in Section 3.3 the semiparametric specification is crucial for the correct identification of the proximate determinants' distributional effect, i.e. their effect on inequality and polarization in the distribution dynamics..

3.3 Decomposition of the Growth Rate

The starting point for the identification of the distributional effect of the *k-th* proximate determinant is the decomposition of the growth rate. In particular Eq. (6) can be rewritten as:

$$g_i = \alpha(m) + \sum_{j=1, j\neq k}^{K} \mu_j(X_{i,j}, m) + \mu_k(X_{i,k}, m) + \upsilon_i. \tag{7}$$

i.e.:

$$g_i = g_i^{-k} + g_i^k + g_i^r, \tag{8}$$

where g_i^{-k} is growth rate of output per worker obtained by "factoring out" the effect of $X_{i,k}$, i.e. $g_i^{-k} = \alpha(m) + \sum_{j=1,j\neq k}^{K} \mu_j(X_{i,j}, m)$; $g_i^k = \mu_k(X_{i,k}, m)$ is the part of the annual growth rate explained by $X_{i,k}$, capturing the "marginal" effect of $X_{i,k}$ on g_i, that we denote as *marginal growth effect*; $g_i^r = \upsilon_i$ is the annual "residual growth", not explained by the determinants in $\mathbf{X}_i$.

3.4 The Counterfactual Distribution

We will compute two types of counterfactual distribution to identify the distributional effect of, respectively, the proximate determinants and the growth regimes. In particular, we model the distributional effect of a proximate determinant as determined by its sample distribution.

Let $\tilde{y}_{iT}^k$ denote the counterfactual output per worker for the *k-th* proximate determinant, i.e. the output per worker that country i would attain at T if there were no differences within the sample in the level of the *k-th* determinant. To identify this effect, we impose upon each country the *sample mean* of that determinant.[13]

[13] If the determinant of interest is characterized by the presence of outliers, the median of the distribution could be preferable as a more robust measure. The use of the sample mean of the determinant aims at approximating its average effect on countries' growth. Other counterfactuals could be built using quantiles of the distribution. For example, Sirimaneetham and Temple (2009) compute counterfactual growth rates by imposing on each country of their sample the value of the determinant of interest (an index of macroeconomic stability) measured at the 95th percentile of the sample.

Hence, the counterfactual growth rate of country i for the k-th proximate determinant, $\tilde{g}_i^k$, is defined as:

$$\tilde{g}_i^k \equiv \hat{\alpha}(m) + \sum_{j \neq k} \hat{\mu}_j (X_{i,j}, m) + \hat{\mu}_k (\bar{X}_k, m), \tag{9}$$

where $\bar{X}_k = N^{-1} \sum_{i=1}^{N} X_{i,k}$, and $\hat{\mu}_k(\cdot)$ is the estimated smooth function relative to the *k-th* determinant, obtained from the estimation of Eq. (6). Therefore, the counterfactual output per worker of country i at T is given by:

$$\tilde{y}_{iT}^k = y_{i0} e^{\tilde{g}_i^k T}. \tag{10}$$

The distribution of $\tilde{y}_{iT}^k$ is the counterfactual distribution with respect to the *k-th* determinant. Given the assumption on the existence of growth regimes, the effect of the *k-th* proximate determinant on the distribution dynamics is evaluated *within each regime*.

The estimation of the counterfactual distribution for growth regimes is based instead on the idea of a random assignment of each country to one of the M regimes. Let $\tilde{y}_i^R$ denote the counterfactual output per worker for the growth regimes, i.e. the *expected value* of output per worker that country i would attain at T if, instead of belonging to a specific regime, it had a probability $1/M$ of belonging to one of the existing regimes.[14] In particular, we compute the counterfactual growth rate of country i for growth regimes as:

$$\tilde{g}_i^R \equiv \frac{\sum_{m=1}^{M} \left[\hat{\alpha}(m) + \sum_j \hat{\mu}_j (X_{i,j}, m) \right]}{M}, \tag{11}$$

from which we obtain the counterfactual output per worker of country i:

$$\tilde{y}_{iT}^R = y_{i0} e^{\tilde{g}_i^R T}. \tag{12}$$

The distribution of $\tilde{y}_{iT}^R$ is the counterfactual distribution with respect to the growth regimes. In a pooled cross-section analysis, like the one we perform in Section 4, random assignment to regimes amounts to assuming random transitions across regimes in each sub-period considered.

3.5 The Actual and Counterfactual Ergodic Distributions

The actual and counterfactual output per worker allow estimating the actual and counterfactual ergodic distributions, based on the actual and counterfactual stochastic kernels for each determinant and for growth regimes. In particular, the ergodic distribution highlights whether the estimated distribution dynamics over the period of interest has completely exhausted its effects or, otherwise, significant distributional changes are expected in the future.[15]

[14]An alternative counterfactual analysis corresponds to the case where regimes do not exist. When regimes exist, as we show below, its computation is however not feasible because such a case cannot be observed.

[15]For details on the estimations see the online Appendix H.

3.6 The Distributional Effect of Proximate Determinants

The distributional effect of a proximate determinant is evaluated by the *conditional* marginal growth effect, and by the differences between the actual and counterfactual distributions at time T and in the long run.

3.6.1 The Conditional Marginal Growth Effect

The effect of the *k-th* proximate determinant on the distribution dynamics is well captured by the relation between the *marginal growth effect* (MGE) of the *k-th* determinant in Eq. (8), g_i^k, and the initial level of output per worker y_{i0}, i.e. $g_i^k|y_{i0}$, that we denote as *conditional marginal growth effect* (CMGE) of the *k-th* determinant. It may be observed that the estimation of Eq. (6) must include all the explanatory variables in order to avoid omitted-variable problems and obtain an unbiased estimate of the marginal growth effect.

If $E[g_i^k|y_{i0}]$ is not statistically different from the expected value of the marginal growth effect, $E[g_i^k]$, i.e. if $E[g_i^k|y_{i0}] = E[g_i^k]\ \forall y_{i0}$, then the *k-th* determinant has no distributional effects. On the contrary, if $E[g_i^k|y_{i0}]$ is statistically different from $E[g_i^k]$ and, in particular, has everywhere an increasing (decreasing) relation with y_{i0}, then the *k-th* determinant is a source of divergence (convergence) within a regime. Figure 4 shows the case of $E[g_i^k|y_{i0}]$ decreasing in y_{i0}, which implies a more dispersed counterfactual distribution.

[Figure 3 about here.]

Clearly, other types of CMGE can be observed. For example, if $E[g_i^k|y_{i0}]$ displays a "$\backsim$"-shaped form, the determinant is a potential source of polarization within the regime.

3.6.2 Nonlinearities and Differences between Actual and Counterfactual Distributions

In presence of nonlinearities in the growth model, the *k-th* determinant can have an effect on the distribution dynamics even if the expected value of the CMGE is not statistically different from the expected value of the MGE, i.e. if $E[g_i^k|y_{i0}] = E[g_i^k]\ \forall y_{i0}$. In particular:

$$E\left[\log\left(y_{iT}\right)|y_{i0}\right] = E\left[\log\left(\tilde{y}_{iT}^k\right)|y_{i0}\right], \tag{13}$$

if:[16]

$$\sum_{m=1}^{M} E\left[\mu_k(X_{i,k}, m)|y_{i0}\right] = \sum_{m=1}^{M} \mu_k(\bar{X}_k, m). \tag{14}$$

The condition in Eq. (14) holds under the following two (sufficient) conditions:

[16]See Appendix B for the derivation of the condition in Eq. (14).

1. $E[\mu_k(X_{i,k}, m)|y_{i0}] = E[\mu_k(X_{i,k}, m)]$, i.e. $\mu_k(X_{i,k}, m)$ and $y_{i,0}$ are mean-independent, i.e. the effect of the *k-th* determinant on output per worker in country i has to be independent of the initial output per worker in each regime m.

2. $E[\mu_k(X_{i,k}, m)] = \mu_k[E(X_{i,k}, m)] = \mu_k(\bar{X}_k, m)$, i.e. $\mu_k(\cdot, m) = \beta_k^m X_{i,k}^m$; the *marginal* effect of the *k-th* determinant has to be constant in each regime m, i.e. the term $X_{i,k}$ in growth regime m has a linear effect on growth.

Therefore, even if the CMGE of *k-th* determinant is not statistically different from the MGE (i.e. Condition 1 holds),[17] such a determinant can have a distributional effect if it has a nonlinear effect on growth (i.e. Condition 2 fails). In growth empirics violations of Conditions 1 and 2 are common. For example Durlauf et al. (2001) find violations of Condition 1, while Liu and Stengos (1999) find violations of Condition 2. In Section 4 we show that also in our sample violations of these two conditions generally occur.

4 Explaining the Evolution of the World Income Distribution

In this section we apply the methodology described in Section 3. In particular, in Section 4.1 we describe the dataset, in Section 4.2 we report the estimate of the best model, in Section 4.3 we investigate the distributional effect of proximate determinants and of growth regimes by a counterfactual analysis and, finally, in Section 4.4 we provide a summary and a general discussion of our findings.

4.1 Data

Our sample consists of 84 countries for the period 1960-2008 (see Table 9 in Appendix C for the country list). The dependent variable in the growth regressions is the average annual growth rate of GDP per worker.

Drawing on the vast literature discussed in the introduction we consider as candidate determinants of growth regimes five main types of "deep" determinants: *initial conditions*, i.e. the values in 1960 of GDP per worker, human capital (in particular the share of workforce with primary or secondary education), and life expectancy at birth;[18] *geography*, proxied by the absolute value of latitude, the malaria ecological index, the percentage of tropical area, the land area within 100 km of distance to sea-coast or navigable rivers, the average number of frost-days, and the proportion of land with five

[17] Note that by definition $g_i^k \equiv \mu_k(X_{i,k})$.

[18] Life expectancy at birth is a typical proxy for the health conditions of a country. A large literature considers education and health within a broader concept of human capital (see, e.g. Mushkin, 1962, Sachs and Warner, 1997 and Weil, 2007).

or more frost-days per month (see, e.g., Tan, 2009, Rodrik, 2002); the *quality of institutions*, proxied by the initial level of democracy or of constraints on the executive; a measure of *ethnolinguistic fractionalization* (see, e.g., Easterly and Levine, 1997); and *culture*, proxied by different shares of population in 1965 belonging to the following religious denominations: Protestant, Catholics, Muslims, Animists (see, e.g., Rodrik, 2002, Guiso et al., 2006, Durlauf et al., 2008). Following Mankiw et al. (1992) we consider as proximate determinants the initial level of GDP per worker, the investment rate, the growth rate of employment, and human capital, in the form of average years of schooling.[19]

Three remarks are in order on the sources of data. First, we choose PWT 7.1 instead of the more recent PWT 9.0 to maximize the number of countries available in the sample.[20] Second, we use the most recent version (2.0) of Barro and Lee (2013)'s dataset on human capital, in which many shortcomings of the previous versions have been eliminated (see Cohen and Leker, 2014, for details).[21] Finally, the number of countries in the sample is reduced with respect to its potential largest value based solely on data from PWT for the inclusion of institutions (with a reduction from a potential sample size of 109 to 90 countries) and, secondly, of human capital (with a reduction to 97 countries). Overall, the inclusion of both variables restricts the sample to 85 countries. Finally, the inclusion of life expectancy implies a further reduction to 84 countries.

4.2 The Best Model

In the estimation of the semiparametric growth model in Eq. (6), we pool cross-section data on five sub-periods: 1961-1970, 1971-1980, 1981-1990, 1991-2000, and 2001-2008. The dependent variable, g_{it}, is the average annual growth rate of GDP per worker of each sub-period. The proximate determinants are: i) the (log of) the initial level of GDP per worker of the sub-period, whose effect proxies for technological catch-up and/or decreasing marginal productivity of capital (log.y0); ii) the (log of) average annual growth rate of employment augmented by the depreciation rate and the exogenous rate of technological progress (equal to 0.03 and 0.02 respectively, see Mankiw et al., 1992) (log.n); iii) the (log of) the average annual investment rate (log.i/y); and, iv) the (log of) average years of schooling (log.h) as a proxy for the stock of human capital. Averages are computed over each sub-period. The growth model includes time dummies to account for possible changes across sub-periods in the exogenous growth rate of technological progress.

[19] See Appendix A for the definition, source and descriptive statistics of the variables.

[20] The use of PWT 9.0 would limit the number of countries to 61; the reasons of this strong reduction is related to the different use of the several rounds of the International Comparison Program, see: `http://www.rug.nl/research/ggdc/data/pwt/v80/comparing_pwt80_with_pwt71.pdf` for more details.

[21] The use of one of the most important alternative datasets, proposed by Cohen and Soto (2007), provides measures of human capital highly correlated with the ones used in the paper (never below 0.91), but it would reduce the sample to 79 countries.

Proximate determinants in growth regression are likely to be endogenous for several reasons, in particular for: simultaneity (when an explanatory variable is jointly determined with the dependent variable, typically because both variables depend on an omitted explanatory variable) and measurement error. The identification of valid and strong instruments is highly debated in the growth empirics literature. Durlauf et al. (2005, p. 638-639) point out that: "the belief that it is easy to identify valid instrumental variables in the growth context is deeply mistaken. We regard many applications of instrumental variable procedures in the empirical growth literature to be undermined by the failure to address properly the question of whether these instruments are valid [...] Since growth theories are mutually compatible, the validity of an instrument requires a positive argument that it cannot be a direct growth determinant or correlated with an omitted growth determinant". Bazzi and Clemens (2013) provide evidence on ways instruments that are valid in some studies can be invalid in others, and show the ways in which plausibly valid instruments can mask important weak instrument biases.

In the estimation of growth regressions within each regime, we control for the presence of endogeneity in all proximate determinants (except for the initial level of GDP per worker) using as instruments their value in 1960. Although we expect such instruments to be relevant and strong, some concerns about their validity are present. A large literature relates growth to initial conditions and initial stocks of human capital (e.g. Cohen, 1996 and Goetz and Hu, 1996). Moreover, the initial levels of investment rate and employment growth could easily be correlated with omitted growth determinants and, therefore, our instrumental variables could be correlated with omitted growth determinants. However, in our analysis some of these potentially omitted determinants are likely included in the candidate set of deep determinants and the use of a semiparametric specification reduces the possibility that model misspecification would lead to endogeneity. Moreover, we provide a test of omitted-variable bias due to initial conditions proxied by the initial level of GDP per worker (see Appendix G for details). Given the presence of semiparametric additive components, we used the Control Function Method (CFM) instead of two-stage least squares (see Appendix F).

4.2.1 Growth Regimes

The best (approximating) model among all the ones that were fitted, identified following the procedure described in Section 3.1, contains three growth regimes based on life expectancy at birth in 1960 and the share of Catholic population in 1965: a "high life expectancy regime" (*Regime H*) comprising 20 countries; a "low life expectancy/high share of Catholics" regime (*Regime LH*) comprising 47 countries, and, "low life expectancy/low share of Catholics" regime (*Regime LL*), comprising 17 countries (see Figure 5). In particular, the threshold for life expectancy is equal to 68.35 years, while the threshold for the share of Catholics is equal to 0.03 for the "low life expectancy" countries. Table 9 in Appendix C contains the list of countries in the three regimes. The best model has a 99% probability to be the best (approximating) model among all those that were fitted, as showed in Table 8 in Appendix C.

Moreover, taken life expectancy and the share of Catholics as partitioning variables, in order to check the robustness of the thresholds we calculate the (*conditioned*) probabilities of the models estimated for all possible partitions of countries to be the least false. Our best model has a probability of about 30% to be the least false, and only six alternative partitions have more than 5% of probability but involve only marginal changes in the thresholds (see Figure 9 in Appendix C).

The importance of taking into account the possible existence of growth regimes can be appreciated by comparing the value of AICc of our best model, equal to 2230.49, with that of the pooled regression without regimes equal to 2081.81 (the implied probability that the pooled regression to be the least false model is about zero).[22] Moreover, if we consider the deep determinants as proximate determinants (i.e. they are included as covariates), as is commonly done in the literature, AICc surges to 2100.59 when only life expectancy and the share of Catholics are considered, and to 2102.62 with the additional inclusion of one variable for each type of deep determinants, i.e. latitude, democracy, and ethnolinguistic fractionalization (their implied probabilities to be the least false model are both about zero). Overall, this evidence suggests that growth regimes are strongly informative on the countries' dynamics, and our identifying deep determinants, life expectancy and share of Catholics, contain (almost) all the information of the set of candidate deep determinants.

[Figure 4 about here.]

Regime H mainly includes Western countries and countries from the Western offshoots; Regime LH comprises two European countries (Portugal and Romania), some Arabic countries, all Central and South American countries, many Sub-Saharan countries and South Africa, and Sri Lanka, the only Asian country; Regime LL mainly contains Asian countries, in particular from Middle-East and South-East Asia, two Sub-Saharan countries, and Greece. The three growth regimes can be ordered in terms of their average relative GDP per worker in 1960: 2.35 (H), 0.63 (LH), and 0.44 (LL). Their average growth rate of GDP per worker over the period was respectively 2.1%, 1.1%, and 2.6%, suggesting that convergence only occurred between Regimes LL and H. Indeed, in 2008 their average relative GDP per worker becomes, with respect to the sample mean, 2.42 (H), 0.51 (LH), and 0.70 (LL), showing that, on average, countries in LL surpassed countries in LH.

The identified regimes are not strictly related to long-run outcomes, but they correspond to different growth models, e.g. having or not a high life expectancy at birth in 1960 or a certain share of Catholics in 1965 is not unambiguously related to experiencing a high or low growth rate or converge to a certain GDP level. Only in the case of high-life expectancy at birth we have a clear-cut identification of highly-developed countries. In this case culture does not partition countries.[23] Life expectancy,

[22] Results are available upon request.

[23] This result is in contrast with Desdoigts (1999) who finds a cluster of developed countries in which a partition into Protestant and Catholic groups emerges.

in particular, prevails on the quality of institutions for these countries, perhaps not surprisingly in the light of the evidence discussed in Weil (2014) on the primacy of health for the development of countries. Regime LH highlights the emergence of a similarity based on the share of Catholics for countries from Africa and South America, suggesting that the widespread use of continental dummies in growth empirics might not be fully appropriate.

Our results are in contrast with Owen et al. (2009), Tan (2009), and Flachaire et al. (2014) who, adopting different methodologies, find a primacy of institutions on initial level of human capital and geography in the identification of (only two) growth regimes. Moreover, differently from Tan (2009), we do not find that ethnic fractionalization identifies growth regimes. However, none of these works included religion among the possible regime identifiers. In this respect, in their seminal work on growth regimes Durlauf and Johnson (1995, p. 378), remark that some anomalies of their partition in four growth regimes may be explained by omitted initial conditions, such as social capital, that should proxy for: "cultural norms and values ... which may range from attitudes towards work to respect of property rights". Surprisingly, subsequent work on growth regimes mainly ignored this remark and no study, to the best of our knowledge, assessed the importance of culture as a possible deep growth determinant.

[Figure 5 about here.]

Figure 6 presents a re-examination of the tendency of polarization reported in Figure 1 as the result of the distribution dynamics between and within the three growth regimes. Table 1 shows that inequality, measured by the Theil index, increased by 5 percentage points between 1960 and 2008. In particular, both the between- and within-group components show a moderate increase, while the between-group component accounts for the largest share of inequality in both years. Polarization is a phenomenon emerging only at the end of the period: the BIPOL index is in fact not computable for the distribution in 1960 which is clearly unimodal.

Figure 6 highlights that the emergent polarization is the result of a strong tendency for convergence within Regime H, and a substantial immobility of the distribution of countries in Regime LH, characterized only by a slight tendency to within-group convergence. Countries in Regime LL, although starting from an average initial per worker GDP lower than those of Regime LH, display a tendency to spread out on a larger GDP range, in particular for the presence of some fast-growing economies such as China and South Korea. We interpret this evidence as supporting the presence of *club convergence*, where club membership is determined by the share of Catholics in 1965 and life expectancy at birth in 1960. Anderson et al. (2016) find a similar dynamics among three income groups identified by a finite mixture model. In particular, their analysis of transitions in 1970-2010 reveals that convergence only occurred between the low-income and middle-income groups.

To further characterize the regimes, Table 2 reports the mean and standard deviation of the distribution of proximate determinants for the whole sample and within each regime (see also Figure 10 in Appendix D).[24] Initial income is on average higher and less dispersed in Regime H, while no significant differences exist in the average levels of Regimes LH and LL, but the distribution is different as two peaks characterize Regime LH. The main aspect of the distributions of the employment growth rate is that it is on average lower in Regime H. No remarkable differences appear in the investment rate across Regimes, while human capital appears clearly higher on average and less dispersed in Regime H.

[Table 1 about here.]

Among the identified regimes, Regime H has the characteristics predicted by UGT of Galor and Weil (2000): high income, low employment growth (which may proxy for low population growth), and, overall, high human capital levels.[25] The striking feature of our results is that the variable that better identifies this regime is life expectancy at birth in 1960, supporting the idea that a sufficiently high level of health is a necessary condition for the accumulation of human capital. However, the characteristics of the other two regimes do not support the prediction of UGT, in particular we do not find any difference in their demographic patterns.

4.2.2 Semiparametric Growth Regressions

Table 3 reports the estimation results of the semiparametric growth model in Eq. (6) within each regimes. In each estimation exogeneity cannot be rejected at 5% significance level.[26] As expected, results of the first-stage regressions show that almost all the instruments are significant (Tables 10-12 in Appendix F). However, as discussed in Section 4.2, our instruments could be invalid. Although this hypothesis cannot be formally tested, we find some evidence in favour of its validity. Ashley and Parmeter (2015) quantify the minimum degree of correlation between the possibly-endogenous variables and the model errors which is sufficient to overturn the inference on the regression parameters. By applying their methodology to the Mankiw et al. (1992)'s model (as in our case), they find that quite substantial correlations are necessary to reverse the inference on the estimated parameters, concluding that in such case the need for valid instruments is mitigated. Moreover, in a recent paper Guo et al. (2016) study the properties of the endogeneity test under invalid instruments and find that if some instruments (even a single) are moderately (or strongly) invalid, then the endogeneity test will always reject the null hypothesis of exogeneity even if there is truly no endogeneity present. Accordingly, if

[24]Feyrer (2008) and Johnson (2005) proposed to explain the income distribution dynamics by the distribution of growth determinants. We will see that, without accounting for nonlinearities, this approach can be misleading.

[25]See also Kuznets and Murphy (1966) on the concept of *modern growth*.

[26]See Appendix F and online Appendix I for the details on the estimations.

our instruments were invalid we would have always rejected the null hypothesis of exogeneity. Finally, no omitted-variable bias seems to be present in the best model at 5% significance level (See Appendix G).

[Table 2 about here.]

The goodness of fit, measured by generalized R^2, is fairly high in all the regimes, ranging from 0.43 in Regime LH to 0.74 in Regime H.[27] A comparison of the estimation of a growth model without regimes, reported in the first column of Table 3, and the models estimated within each regime, shows that not accounting for growth regimes represent a serious miss-specification of the model. The estimation of the regime-specific growth models reported in columns 2-4 of Table 3 highlights substantial parameter heterogeneity across regimes, both in terms of magnitude of non-explained growth (see the estimated values of the intercept and of the time dummy coefficients), and nonlinearities. In particular, the time average of non-explained growth, which reflects total factor productivity (TFP) growth, is equal to 2.1% in Regimes H, to 1.1% in Regime LH and to 2.6% in Regime LL.[28] The values of the time dummies also show that countries in Regimes LH and LL seem to be more sensitive to shocks than countries in Regime H. All proximate determinants are statistically significant at usual significance levels, with the exception of the investment rate in Regime LL and human capital in Regimes H and LH.

[Figure 6 about here.]

Figure 7 reports the effects of each proximate determinant on growth of GDP per worker, along with the estimated effect of each determinant in the model with no regimes (labelled as *pooled*). The relation between initial per worker GDP and the growth rate highlights the tendency to within-regime convergence. This tendency is clear in Regimes H and LH, although the estimated function is steeper in Regime H, indicating a higher speed of convergence. The estimated function is instead concave in Regime LL, indicating that a moderate but not-uniform tendency to within-regime catching-up characterizes this regime. Employment growth has the expected negative marginal effect on growth in all regimes, with nonlinearities in Regimes LL and LH. The effect of the investment rate on growth is non-significant in Regime LL, while it is nonlinear in Regimes LH and H. Given the large confidence

[27]The better fit of the augmented Solow model in the group of the most developed countries is found in other studies (see, e.g., Durlauf and Johnson, 1995, p. 375, Tan, 2009, p. 1119, Owen et al., 2009, p. 276) which, however, do not allow for nonlinearities within the regimes.

[28]The time-averaged non-explained growth in regime H is calculated as the weighted average of the following values: 2.8%, 1.5%(=2.8%-1.3%), 1.8%(=2.8%-1.0%), 2.8%(=2.8%-0%) and 1.7%(=2.8%-1.1%), with weights 10/48, 10/48, 10/48, 10/48 and 8/48 respectively. Non-explained growth in the other regimes is computed in the same way.

bands, however, in the latter two regimes the effect is likely to be non-increasing in relevant ranges of the variable. Finally, human capital has a clear, positive marginal effect on growth in Regime LL only.[29]

4.3 Distributional Effects

In this section we present the estimated distributional effect of each proximate determinant and of growth regimes, while we refer to Section 4.4 for a general discussion of our findings.

Table 4a shows that the counterfactual distribution of initial GDP per worker is characterized by a much higher value of the Theil index, implying that initial GDP per worker remarkably reduces inequality: if all countries had had the same value of initial GDP per worker, inequality would have been much higher. This effect is mainly due to the between-group component, which would have been three times higher. Figure 13a highlights that, in the counterfactual distribution for their regime, countries in Regime H would have had a much higher level of GDP per worker. In particular, given that the conditional marginal growth effect in Regime H has a steep negative slope (see Figure 11a), "assigning" the sample average value of log.y0 to all countries in that regime would amount to assign to these countries a much higher growth rate than the one that most of them actually experienced. The counterfactual distribution of Regime LH is not very different from the actual one, while for Regime HH the counterfactual distribution shows that some countries would have been even further away from the others with very high income levels. Moreover, initial GDP per worker strongly reduces polarization: Table 4a shows that in 2008 the polarization index is much higher in the counterfactual distribution. The same tendency is confirmed for the long run, as illustrated by a comparison of the BIPOL index for the actual ergodic distribution (AED) and the one computed for the counterfactual ergodic distribution (CED), as well as their graphical representation in Figure 13d.

[Table 3 about here.]

[Table 4 about here.]

[Figure 7 about here.]

The growth rate of employment moderately increases inequality as the Theil index and its between-group component are slightly higher in the actual than in the counterfactual distribution (see Table 4b). The effect is overall small, as shown by the negligible differences between actual and counterfactual distributions in Figure 13b and the almost flat conditional marginal growth effects reported in Figure 11b. Also, employment growth moderately acts in favour of polarization, as shown by the values of the

[29] For Regime H this may reflect the sorting of the countries, which have reduced the cross-country variation in human capital within this regime.

BIPOL index. The effect on polarization is more pronounced in the comparison between the actual and counterfactual ergodic distributions (see Figure 13e).

The investment rate appears to slightly increase inequality, as the Theil index is higher in the actual than in the counterfactual distribution. This mainly appears to depend on within-group inequality (see Table 4c). However, the investment rate reduces polarization, as the BIPOL index is lower in the actual distributions (both in 2008 and in the long run, see also Figure 13f). Overall, the effect is modest (see Figures 13c and 11c).

Human capital tends to marginally decrease inequality and polarization (see Table 4d). Examination of the Theil index reveals that human capital reduces between-group inequality, but increases within-group inequality. In fact, due in particular to the strong positive effect in Regime LL (Figure 11d), human capital contributed to the growth and catching-up of these countries, which would have been otherwise more dispersed (see Figure 8a). In the long run, human capital generated a less-polarized distribution than the one that would have obtained if all countries shared the same human capital value (Figure 8c).

Growth regimes are a major source of inequality and, especially, of polarization. Table 4e shows that both components of the Theil index are lower in the counterfactual than in the actual distribution. In other words, if countries were allowed to randomly switch among regimes in each sub-period, the distribution of the expected value of their counterfactual GDP per worker would have displayed less inequality. Figure 8b highlights that countries in Regime LH would have displayed a much higher mobility onwards, while countries in Regime LL would have been much less dispersed. The most striking result, however, is that the counterfactual distribution of 2008 and the counterfactual ergodic distribution do not show evidence of polarization, as shown by the dynamics displayed in Figure 8d.

4.4 Discussion of Results

Our findings contribute to the debate on the evolution of the cross-country income distribution in many respects. First, the roots of the observed increase inequality and polarization do not seem ascribable to the traditional Solovian growth determinants, i.e. the accumulation of physical capital and employment growth, but to the existence of growth regimes, i.e. of different growth processes followed by countries. This result is in contrast with, among others, Beaudry et al. (2005) and Feyrer (2008).

Three main differences among regimes emerged: i) the levels of TFP growth are remarkably heterogeneous. In particular, TFP growth is very similar in Regime H and Regime LL (equal to 2.1% and 2.6% respectively), while in regime LH it takes on a value approximately half of the value of the other regimes equal to 1.1%; ii) the conditional marginal growth effect of initial GDP, a proxy for technological catching-up, is decreasing in Regimes H and LH and nonlinear in Regime LL; iii) the marginal growth effect of human capital is significant and strongly increasing in GDP per worker in Regime LL only.

The result at point i) offers a novel view on religion, viewed by economists as one of the primary determinants of culture (see, e.g., Weil, 2012, p. 436 and Guiso et al., 2006), although its impact on growth is a controversial issue (Guiso et al., 2006): the influential study of Barro and McCleary (2003) for example finds that some measures of religious behaviour significantly affect growth, while, e.g., Durlauf et al. (2012) subsequently played down the role of religion.

We find that religion is associated to remarkably different levels of TFP growth only for countries with low life expectancy in 1960. This result is consistent with the claim of Guiso et al. (2006) according to which: "[the] dependence of [growth] on cultural variables weakens for more educated people, consistent with the idea that more educated individuals rely less on their inherited culture when they form their priors." In our case, the significant dimension of human capital is not education but health. Among the countries with low life expectancy, i.e. countries where inherited culture could crucially affect individual decisions, we find that Catholic religion appears associated to lower TFP, suggesting in our view a lower capacity of adopting foreign technology and/or develop new ones. These countries therefore appear endowed with low levels of *social capability*, a concept introduced by Abramovitz (1986), referring to the capacity of a country to introduce new ideas and to exploit existing ones, to capture economic opportunities, etc.. This evidence complements the findings of Guiso et al. (2006) on the importance of culture, as proxied by trust, for economic development.

Our finding of a negative correlation between Catholic religion and TFP levels, in particular in Regimes LH and LL, seems at odds with the historically high Catholic propensity in establishing education institutions (see, e.g., Bader and Maussen, 2012 for Europe) as education, by increasing human capital accumulation, should favor technology development and/or adoption.[30] Becker and Woessmann (2009) make a similar point with respect to the diffusion of Protestantism. They argue that the spread of Protestantism implied the diffusion of education to promote literacy development, and that this, and not the spread of the "Protestant ethic", fostered economic growth. However, our results do not support the "human capital view" on the role of religion on growth. In fact, in our sample PRI.60 has a positive correlation both with PROT.65 and CAT.65, but only for the former it is high and significant (in the same respect see Figure II of Becker and Woessmann (2009)),[31] while SEC.60 has a positive correlation only with PROT.65.[32] However, PROT.65 is not found as a significant regime identifier.

The result at point ii) highlights that technological catching-up occurs within all regimes, but at

[30]We thank an anonymous referee for pointing this out.

[31]Bivariate regressions of PRI.60 on PROT.65 and CAT.65 return coefficients of, respectively, 0.57 (s.e. 0.14) and 0.21 (s.e. 0.08).

[32]Bivariate regressions of SEC.60 on PROT.65 and CAT.65 return coefficients of, respectively, 0.27 (s.e. 0.08) and 0 (s.e. 0.05).

different speed. In Regime H the speed of convergence is high and uniform for all countries (the slope of the estimated relationship is almost constant); in Regime LH the speed of convergence is uniform but almost nil; finally, in Regime LL, the speed of convergence is nil for very poor countries and very high for the richest. This evidence is consistent with the observed differences in TFP growth among regimes.

The result at point iii) instead supports the insight of Nelson and Phelps (1966) that the key role of human capital is to facilitate the adoption of technology and not to be a productive factor *per se*. In particular, we find a positive and significant marginal effect of human capital on growth in Regime LL only (see Figure 7), the only regime which seems to have enjoined significant technological spillovers from Regime H, with a very similar level of TFP growth. Human capital in the form of education, therefore, appears an important growth determinant for countries with low life expectancy at birth. In addition, if the major determinant of long-run growth is TFP (as argued, for example, by Hall and Jones, 1999), the presence of remarkable differences in TFP across regimes casts doubt on the primacy of institutions as a fundamental driver of long-term development (Acemoglu et al., 2005), as we did not find institutions as a primary regime identifier. The higher relevance of culture and health with respect to geography and institutions is consistent with Spolaore and Wacziarg (2013, p. 341)'s claim that: "human traits are important to account for comparative development patterns, quite apart from the effects of geographic and institutional factors". An important caveat is that they refer to long-term development, while we focus on a more recent and shorter period.

Finally, we document that in the period 1960-2008 inequality and polarization across countries increased, and such a tendency is expected to continue in the long run. Specifically, the counterfactual analysis suggests that the persistent nature of the twin-peaked distribution is to be attributed to the existence of regimes and to the persistence of countries within each regime: if transitions across regimes were allowed, the long-run distribution would have been single-peaked. In other words, the estimate of a long-run polarized distribution suggests that no significant transitions across regimes have been taking place in the period of analysis. This evidence challenges the idea that polarization is a transitory phenomenon, as pointed out by Lucas (2000) and Galor (2007). Our evidence of a persistent twin-peaked distribution, on the contrary, is in line with the much-discussed "middle-income trap", according to which many episodes of growth spurts by initially poor countries suddenly stop before the complete catching-up with the richest countries has been achieved (see, e.g., Eichengreen et al., 2012, World Bank, 2013, and Pritchett and Summers, 2014). With a different methodology Anderson et al. (2016) arrive at a similar conclusion: in the period 1970-2010 they find catching-up from the low- to the middle-income class, but not from the middle-income to the high-income class.

5 Concluding Remarks

In this paper we contributed to the literature on growth empirics by proposing a new methodology based on information theory which jointly identifies growth regimes and estimates a semiparametric growth model within each regime. We applied our method to a sample of countries in 1960-2008, a period characterized by an increase in inequality and polarization in the distribution of GDP per worker. We found three growth regimes, identified by life expectancy in 1960 and the share of Catholics in 1965. Countries in each regime follow specific nonlinear "augmented" Solow models. Our findings point to heterogeneity in TFP across regimes, technological catching-up, and, marginally, human capital, as the main determinants of the observed increase in inequality and polarization.

A general policy implication of our analysis is to adopt any action favouring transitions across regimes. In particular, we do not find evidence of poverty trap determined by thresholds in the level of GDP per worker in 1960, raising doubts on the utility of foreign aid (Easterly, 2006); on the contrary, a qualified foreign aid pointing to guarantee an adequate level of health could be very effective supporting regime transitions (see, in the same vein, Sachs and Warner, 1997 and Easterly, 2001). Stimulus to the accumulation of human capital, advocated by a large literature, instead, seems to be effective only in specific cultural environments (Benhabib and Spiegel, 2005).

Our findings also suggest some directions for further research. The first consists in integrating the studies on the evolution of income distribution and technological catching-up (see, e.g., Phillips and Sul, 2009 and Battisti et al., 2013) with those on the identification of growth regimes by spatial econometric techniques, where proximity among countries is explicitly taken into account. In this respect, a promising line of research is to consider growth models with technological spillovers modelled as spatial externalities (see, e.g., Ertur and Koch, 2007). The second direction is to develop a more sophisticated framework of model selection based on "multimodel inference" proposed by Anderson (2007), which represents an alternative approach to Bayesian Model Averaging. The third direction is to analyse transitions across regimes and, in this respect, to understand the reasons why countries do not make such transitions. Jerzmanowski (2006), Bos et al. (2010) and Anderson et al. (2016) represent interesting recent contributions in this line of research. Finally, it remains the key open question of why culture (religion) appears to be so important for TFP growth, i.e. why international technological spillovers can be mainly driven by culture.

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Appendix

A Sources and Descriptive Statistics of Determinants

The dependent variables used in our analysis is:

- **g** is the annualized average growth rate of the real GDP chain per worker.

The deep growth determinants used in our analysis are:

- **GDPpw.60** is the (log) of the real GDP chain per worker in the first year of the sample (*rgdpwok* in Heston et al. (2012) PWT 7.1)

- **PRI.1960** is the percentage of population aged 15 or above with at least primary education and corresponds to the sum of *lp*, *ls*, and *lh* in Barro and Lee (2013) ("percentage of primary (lp), secondary (ls), and tertiary (lh) attained in population"), in 1960.

- **SEC.60** is the percentage of population aged 15 or above with at least secondary education and corresponds to the sum of *ls* and *lh* in Barro and Lee (2013) ("percentage of secondary (ls) and tertiary (lh) attained in population"), in 1960.

- **LE.60** is the life expectancy at birth (years) in 1960 from World Bank (2015).

- **DEM.60.65** corresponds to the average of the *POLITY2* scores of the Polity IV dataset over the period 1960-1965.[33] In particular, the score is computed by subtracting the *AUTOC* score from the *DEMOC* score; the resulting unified polity scale ranges from +10 (strongly democratic) to -10 (strongly autocratic).[34]

- **CON.60-65** corresponds to the average of the *XCONST* score of the Polity IV dataset over the period 1960-1965. In particular, this variable refers to the extent of institutionalized constraints on the decision making powers of chief executives, whether individuals or collectivities. A seven-category scale is used: Unlimited Authority, Intermediate Category, Slight to Moderate Limitation on Executive Authority, Intermediate Category, Substantial Limitations on Executive Authority, Intermediate Category, Executive Parity or Subordination.[35]

[33] Due to the high number of missing values in 1960, we consider the average level of the variable over the period 1960-1965.

[34] In particular, *DEMOC* is derived from codings of the competitiveness of political participation (*XRCOMP*), the openness of political participation (*XROPEN*), the competitiveness of executive recruitment (*PARCOMP*), and constraints on the chief executive (*XCONST*).

[35] Notice that the *XCONST* also enters in the definition of the *POLITY2* indicators.

- **ELF.61** is the ethnolinguistic fractionalization index of Roeder (2001) in 1961. In particular, we use the index constructed using the Taylor and Hudson formula that uses none of the groupings reported in the sources when data on sub-groups are available and treats racial distinctions within ethnolinguistic groups as separate ethnic groups.
- **ABS.LAT** is the absolute value of countries' latitude.
- **ME** is the Malaria Ecology index of Sachs (2003) predictive of malaria risk built upon climatological and vector conditions on a country-by-country basis.
- **TROP.AR** is the percentage of land in the geographical tropics as in Gallup et al. (1999).
- **LND100CR** measures the proportion of a country's total land area within 100 km of the ocean or ocean-navigable river as in Gallup et al. (1999).
- **AR.FR** is the average number of frost-days within the country's borders as in Masters and McMillan (2001).
- **5.FR.DAYS** is the proportion of the country's land that receives five or more frost-days per month as in Masters and McMillan (2001).
- **PROT.65** is the percentage adherents in the country of Protestants in 1965 gather from Maoz and Henderson (2013).
- **CAT.65** is the percentage adherents in the country of Roman Catholics in 1965 gather from Maoz and Henderson (2013).
- **ISLAM.65** is the percentage adherents in the country of Islamics in 1965 gather from Maoz and Henderson (2013).
- **ANI.65** is the percentage adherents in the country of Animists in 1965 gather from Maoz and Henderson (2013).
- **log.y0** is the (log) of initial level of the real GDP chain per worker (*rgdpwok* in PWT 7.1).

The proximate growth determinants used in our analysis are:

- **log.n** is the (log) growth rate of employment, where *workers* are computed as the population from 15 to 64 years obtained from:

$$workers = rgdpch/rgdpwok * pop;$$

  where *rgdpch* is the real GDP chain per capita and *pop* is the population in PWT 7.1.
- **log.i/y** is the (log) investment rate at constant price and corresponds to the variable *ki* in PWT 7.1 divided by 100.

- **log.h** is the (log) average years of schooling attained and corresponds to the *yr_sch* in Barro and Lee (2013).

Tables 5 and 6 contain the descriptive statistics and correlations among the determinants.

[Table 5 about here.]

B Derivation of the Differences between Actual and Counterfactual Distributions

In this appendix we derive an expression to evaluate the difference between the actual and counterfactual distributions. Consider the differences between the actual and the counterfactual distributions at period T, by expressing the value of (log) actual output per worker in period T, y_{iT}, in terms of the estimated counterfactual output per worker, $\tilde{y}_{iT}^k$:

$$\begin{aligned} \log\left(y_{iT}\right) &= \log\left(\tilde{y}_{iT}^k\right) + \sum_{m=1}^{M}\left[\alpha\left(m\right) + \sum_{j=1,j\neq k}^{K}\mu_j(X_{i,j},m) + \mu_k(X_{i,k},m) + \upsilon_i\right. \\ &- \left.\hat{\alpha}\left(m\right) - \sum_{j=1,j\neq k}^{K}\hat{\mu}_j(X_{i,j},m) - \hat{\mu}_k(\bar{X}_k,m)\right], \end{aligned} \tag{15}$$

and taking the expected value of (the log of) actual output per worker of country i in period T conditional upon the actual output per worker in period 0, that is:

$$\begin{aligned} E\left[\log\left(y_{iT}\right)|y_{i0}\right] &= E\left[\log\left(\tilde{y}_{iT}^k\right)|y_{i0}\right] + \sum_{m=1}^{M}E\left[\alpha\left(m\right) - \hat{\alpha}\left(m\right)|y_{i0}\right] + \\ &+ \sum_{m=1}^{M}\sum_{j=1,j\neq k}^{K}E\left[\mu_j(X_{i,j},m) - \hat{\mu}_j(X_{i,j},m)|y_{i0}\right] + \\ &+ \sum_{m=1}^{M}\left(E\left[\mu_k(X_{i,k},m)|y_{i0}\right] - E\left[\hat{\mu}_k(\bar{X}_k,m)|y_{i0}\right]\right) + \\ &+ E\left[\upsilon_i|y_{i0}\right]. \end{aligned} \tag{16}$$

If $\hat{\alpha}$ and $\hat{\mu}_j$ $(j = 1, ..., K)$, are conditional unbiased estimators of α and μ, and $E\left[\upsilon_i|y_{i0}\right] = 0$, Eq. (16) reduces to:[36]

$$E\left[\log\left(y_{iT}\right)|y_{i0}\right] - E\left[\log\left(\tilde{y}_{iT}^k\right)|y_{i0}\right] = \sum_{m=1}^{M}\left\{E\left[\mu_k(X_{i,k},m)|y_{i0}\right] - \mu_k(\bar{X}_k,m)\right\}. \tag{17}$$

From Eq. (17), we can derive a condition for the equality of the expected values of the actual and counterfactual (log of) output per worker at time T conditional on the initial level $\mathbf{y}_0$. In particular, these values are equal, i.e.:

$$E\left[\log\left(y_{iT}\right)|y_{i0}\right] = E\left[\log\left(\tilde{y}_{iT}^k\right)|y_{i0}\right], \tag{18}$$

[36]Note that $E\left[\hat{\mu}_k(\bar{X}_k,m)|y_{i0}\right] = E\left[\hat{\mu}_k(\bar{X}_k,m)\right] = \mu_k(\bar{X}_k,m)$ given that $\bar{X}_k$ is constant with respect to i and $\hat{\mu}_k$ is an unbiased estimator of μ_k.

if:

$$\sum_{m=1}^{M} E\left[\mu_k(X_{i,k}, m)|y_{i0}\right] = \sum_{m=1}^{M} \mu_k(\bar{X}_k, m). \tag{19}$$

C The Identification of Growth Regimes

The search of the best model is based on the exploration of all possible partitions based on the chosen set of deep determinants. Given the number of countries ($N = 84$) and periods ($S = 5$), the search is limited to partitions where each growth regime includes at least 11 countries, the deep determinants jointly considered are no more than 2, and for each determinant we consider at most one threshold (including the case in which the same determinant is used in the two steps). The sequence in which the determinants are used to split the sample could be crucial. Therefore, for each couple of deep determinants $(\mathbf{Z}_{q,1}, \mathbf{Z}_{q,2})$ the procedure is repeated switching the order of $\mathbf{Z}_{q,1}$ and $\mathbf{Z}_{q,2}$ in the splitting. In the implementation of this method the thresholds are defined by the values that the two deep determinants take in the sample. The results in terms of the minimum AICc for all couples of candidate deep determinants is reported in Table 7, together with Bayesian posterior probability of the best model for each couple of deep determinants (see Eq. (4)).

[Table 6 about here.]

The minimum level of AICc is found for the couple: life expectancy in 1960 and the share of Catholic population in the country.

Table 9 contains the country list for the three growth regimes corresponding to the best model.

[Table 7 about here.]

[Figure 8 about here.]

D Distribution of proximate determinants within regimes

[Figure 9 about here.]

E Conditional marginal growth effects

[Figure 10 about here.]

F The Control Function Method and Endogeneity Test

The Control Function Method (CFM) treats endogeneity as an omitted variable problem, where inclusion of estimated first-stage residuals as a covariate corrects the inconsistency of the regression of the dependent variable on the endogenous explanatory variable. This method provides consistent estimation of the underlying regression coefficients (see, e.g. Ng and Pinkse, 1995; Blundell and Powell, 2003). CFM is also used to perform the endogeneity test on the determinants of the growth model.

Following the CFM we use a two-stage procedure: i) first we run a semiparametric regression of each endogenous variable on the exogenous determinants and the instruments; then ii) we insert the first-stage residuals in the original semiparametric regression. To test the null hypothesis that the coefficients of the first-stage residuals are jointly equal to zero, we use a Likelihood Ratio test.

As instruments we use the initial level of each variable (i.e., in 1960) for all the sub-periods of the pooled dataset. In particular we use:

- for **log.n**: the augmented growth rate of employment in 1960 (**log.n.1960**);
- for **log.i/y**: the investment rate in 1960 (**log.i/y.1960**);
- for **log.h**: the number of years of schooling in 1960 (**log.h.1960**).

CFM is used in all estimations, that is for all the models estimated in the procedure to explore all potential growth regimes. Results of the first-stage regressions are reported in Tables 10-12.

[Table 8 about here.]

[Table 9 about here.]

[Table 10 about here.]

G A Test for Omitted-variable Bias in the Growth Model

We propose a test to detect the presence of possible omitted-variable bias in the growth model. In particular, from the estimation of Eq. (8) we obtain $\hat{g}_i^r$, the estimated residual growth of country i defined as $\hat{g}_i^r \equiv \log(y_{iT}/\hat{y}_{iT})$, where $\hat{y}_{iT}$ is the fitted value of the estimated growth model. Collecting the residual growth of all countries in the vector $\hat{\mathbf{g}}^r$ and the initial level of output per worker in the vector $\mathbf{y}_0$, a test of omitted-variable bias in the growth regression is expressed as follows:

$$E[\hat{\mathbf{g}}^r|\mathbf{y}_0] = E[\hat{\mathbf{g}}^r] = 0 \ , \forall \ \mathbf{y}_0. \tag{20}$$

If $\mathbf{y}_0$ is included in the set of proximate determinants, the condition in Eq. (20) ensures that no omitted-variable inconsistency related to $\mathbf{y}_0$ is present in the estimation (see Wooldridge, 2002, pp. 61-63). The violation of Eq. (20) would result in biased and inconsistent estimation of the growth model leading, in turn, to the inconsistency of the estimation of the distributional effect of proximate determinants.

The condition in Eq. (20) can be tested using a global test. In particular, consider two competing nested models for the residual growth:

$$\begin{aligned} \text{Model 1} &: \hat{g}_i^r = \alpha + u_i; \text{ and} \\ \text{Model 2} &: \hat{g}_i^r = \alpha + m\left(y_{i0}\right) + u_i, \end{aligned}$$

from which it is possible to formulate two alternative hypotheses H_0 and H_1:

$$\begin{aligned} H_0 &: E[\hat{\mathbf{g}}^r|\mathbf{y}_0] = \hat{\alpha} = \overline{\hat{\mathbf{g}}}^r = 0; \text{ and} \\ H_1 &: E[\hat{\mathbf{g}}^r|\mathbf{y}_0] = \hat{\alpha} + \hat{m}\left(\mathbf{y}_0\right). \end{aligned}$$

As in linear models we conjecture to compare the residual sum of squares from two competing *nested* models by an F-test, where the *nonparametric F statistic* is given by:

$$F = \frac{(RSS_1 - RSS_2)/(df_2 - df_1)}{RSS_2/df_2}. \tag{21}$$

Although no general expression for the distribution of the nonparametric F statistic is available, Hastie and Tibshirani (1990) suggest that at least some approximate guidance can be given by referring to an F distribution with $(df_1 - df_2)$ and df_2 degrees of freedom (see also Bowman and Azzalini, 1997, pp. 153-154). When the (global) null hypothesis $E[\hat{\mathbf{g}}^r|\mathbf{y}_0] = 0$ for each $\mathbf{y}_0$ is rejected according to the F-test, a local test based on a bootstrap procedure can allow to identify which range of values of $\mathbf{y}_0$ is responsible for the rejection.

For the estimate of the best model, the F-test cannot reject the null hypothesis of mean-independence between the residuals and GDP per worker in 1960 at the usual significance level of 5% ($F = 0.001$ with a *p-value* of 0.98). Moreover, Figure 12 reports the estimated distribution of the residual growth (i.e. $\hat{\mathbf{g}}^r$) conditional on GDP per worker in 1960 (i.e. $\mathbf{y}_0$) for the best model with growth regimes. We also report the estimated conditional mean (i.e. $E[\hat{\mathbf{g}}^r|\mathbf{y}_0]$) (thick line) with the corresponding 95% confidence bands obtained by a bootstrap procedure, and a vertical line representing the estimated unconditional mean (i.e. $E[\hat{\mathbf{g}}^r]$), which is approximately zero as expected. Figure 12 shows that for any level of GDP per worker in 1960 the conditional mean never differs from the unconditional mean at the usual level of significance of 5%. Accordingly, we conclude that the estimate of the best model with growth regimes does not suffer from omitted-variable bias, i.e. the estimated model appears correctly specified, at least conditioning on GDP per worker in 1960.

[Figure 11 about here.]

Online Appendix

H The Estimation of Actual and Ergodic Distributions

In this appendix we describe the estimation of output per worker distributions (actual, counterfactual, and ergodic), and of the stochastic kernel, the operator that maps current distributions into future distributions.

Estimation of the Distribution of Output per Worker

In the estimation of the actual distribution, we use an adaptive kernel, a procedure recommended when observations vary in sparseness over the support of the distribution. Adaptive kernel estimation is a two-stage procedure which mitigates the drawbacks of a fixed bandwidth in density estimation (see Silverman, 1986, p. 101). In general, given a multivariate data set $\boldsymbol{X} = \{\boldsymbol{X}_1, ..., \boldsymbol{X}_N\}$ and a vector of sample weights $\boldsymbol{W} = \{\omega_1, ..., \omega_N\}$, where $\boldsymbol{X}_i$ is a vector of dimension d and $\sum_{i=1}^{N} \omega_i = 1$, we first run the pilot estimate:

$$\tilde{f}(\boldsymbol{x}) = \frac{1}{N \det(\boldsymbol{H})} \sum_{i=1}^{N} \omega_i k \left\{ \boldsymbol{H}^{-1} (\boldsymbol{x} - \boldsymbol{X}_i) \right\}, \tag{22}$$

where $k(\boldsymbol{u}) = (2\pi)^{-1} exp\left(-\frac{1}{2}\boldsymbol{u}^2\right)$ is a Gaussian kernel and the *bandwidth matrix* $\boldsymbol{H}$ is a diagonal matrix $(d \times d)$ with diagonal elements $(h_1, ..., h_d)$ given by the optimal normal bandwidths, i.e. $h_i = [4/(d+2)]^{1/(d+4)} \hat{\sigma_i} N^{-1/(d+4)}$, where $\hat{\sigma_i}$ is the estimated standard error of the distribution of $\boldsymbol{X_i}$. The use of a diagonal bandwidth matrix instead of a full covariance matrix follows the suggestions in Wand and Jones (1993). In the case of $d = 1$ we have $\boldsymbol{H} = \det(\boldsymbol{H}) = (4/3)^{1/5} N^{-1/5} \hat{\sigma}$. We then define local bandwidth factors λ_i by:

$$\lambda_i = \left[\tilde{f}(\boldsymbol{X}_i)/g\right]^{-\alpha}, \tag{23}$$

where $\log(g) = \sum_{i=1}^{N} \omega_i \log\left(\tilde{f}(\boldsymbol{X}_i)\right)$ and $\alpha \in [0, 1]$ is a sensitivity parameter. We set $\alpha = 1/2$ as suggested by Silverman (1986, p. 103). Finally the adaptive kernel estimate $\hat{f}(x)$ is defined as:

$$\hat{f}(\boldsymbol{x}) = \frac{1}{N \det(\boldsymbol{H})} \sum_{i=1}^{N} \lambda_i^{-d} \omega_i k \left\{ \lambda_i^{-1} \boldsymbol{H}^{-1} (\boldsymbol{x} - \boldsymbol{X}_i) \right\}. \tag{24}$$

The Gaussian kernel guarantees that the number of modes is a decreasing function of the bandwidth; this property is at the root of the test of unimodality (see Silverman, 1986, p. 139).

Estimation of the Ergodic Distribution

The ergodic distribution is the long-run distribution of the stochastic process regulating the transitions across the state space, given in our case by relative output per worker levels. Its estimation requires the estimation of the stochastic kernel. A stochastic kernel is an operator mapping the density of a variable at time θ into its density at time $\theta+\tau$, $\tau>0$, and indicates for each level of the variable at time θ its probability distribution at time $\theta+\tau$ over the possible values of the variable. The relation between the densities and the stochastic kernel can be summarized as: $f_{\theta+\tau}(z)=\int_0^\infty \phi_\tau(z|x)\, f_\theta(x)\, dx$, where z and x are values of the variable, and $\phi_\tau(z|x)$ is the stochastic kernel. To estimate the stochastic kernel $\phi_\tau(z|x)\equiv\phi_\tau(z,x)/f_\theta(x)$ we estimate the joint density of z and x, $\phi_\tau(z,x)$, and the marginal density of x, $f_\theta(x)$. In the estimation of $\phi_\tau(z,x)$ we follow Johnson (2005), and use the *adaptive kernel estimator* discussed above.

The ergodic distribution solves:

$$f_\infty(x)=\int_0^\infty g_\tau(x|z)\, f_\infty(z)\, dz, \tag{25}$$

where x and z are two levels of the variable, $g_\tau(x|z)$ is the density of x, given z, τ periods ahead, under the constraint

$$\int_0^\infty f_\infty(x)\, dx=1. \tag{26}$$

Since in our estimates GDP per worker is normalized with respect to its average, the ergodic distribution must satisfy the additional constraint:

$$\int_0^\infty f_\infty(x)\, x dx=1. \tag{27}$$

In all computations we set $\tau=49$. The *counterfactual stochastic kernel*, which is used to estimate the counterfactual ergodic distribution, is estimated considering as final distribution the counterfactual output per worker at T. In presence of growth regimes, an ergodic distribution is computed for each growth regimes and the overall ergodic distribution is the mixture of these regime-specific ergodic distributions.

I The Estimation of a Semiparametric Growth Model

The estimation of Eq. (6) is obtained by penalized likelihood maximization (see Wood, 2011, for details). The model is fitted by minimizing:

$$||\mathbf{y}-\mathbf{X}\beta||^2+\sum_{k=1}^{K}\lambda_k\int_0^1\left[\mu_k''(x)\right]^2 dx, \tag{28}$$

where $\mathbf{y}$ is the vector of response variables (g_i in our case), $\mathbf{X}$ is the matrix of determinants, β is a vector of parameters to be estimated, λ_k, $k=(1,...,K)$, are smoothing parameters, and the penalty, which controls the smoothness of the estimate, is represented by the integrated square of second derivatives of the smooth terms. The vector of parameters β originates from expressing every smooth term in Eq. (6), $\mu_j(.)$, as:

$$\mu_j(X_{i,j})=\sum_{l=1}^{q} b_l(X_{i,j})\,\beta_l \tag{29}$$

where $b_l(x)$ are *basis functions* and q is their number.

Parameters $\beta_{\mathbf{l}}$ are chosen to minimize the function in Eq. (28) for given values of the smoothing parameters λ_k (it is possible to show that the penalty can also be expressed as a function of β). Smoothing parameters are in turn chosen by the minimization of the restricted maximum likelihood (REML) score. Estimation proceeds by penalized iteratively re-weighted least squares (P-IRLS), until convergence in the estimates is reached.

The semiparametric estimation is performed following the approach proposed by Wood (2006) based on penalized regression splines. In particular, we used the *mgcv* package in R Development Core Team (2012), with the restricted maximum likelihood (REML) option (see Wood, 2011).

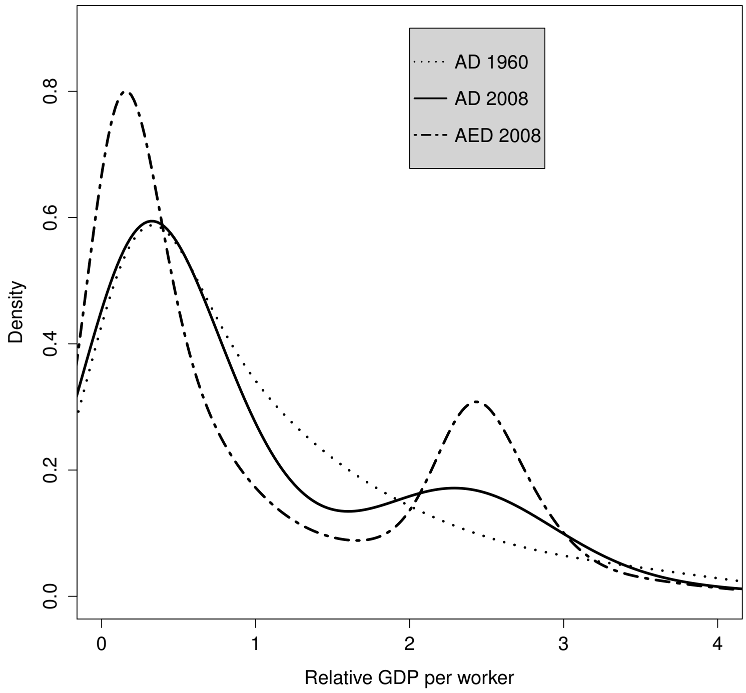


Figure 1: Actual distribution (AD) in 1960 (dotted line), in 2008 (solid line) and actual ergodic distribution (AED) (dashed line) of GDP per worker for a sample of 84 countries.

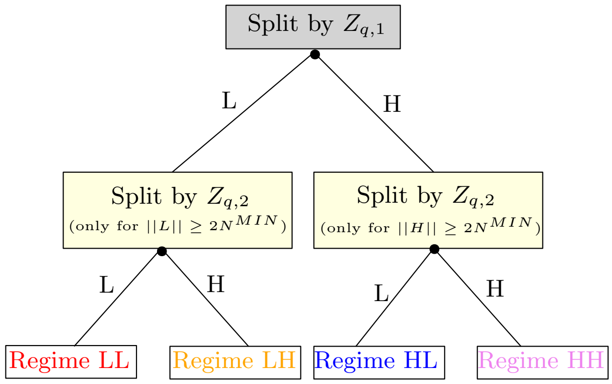


Figure 2: Sequential splitting procedure to identify all possible partitions with two deep determinants $\mathbf{Z}_{q,1}$ and $\mathbf{Z}_{q,2}$.

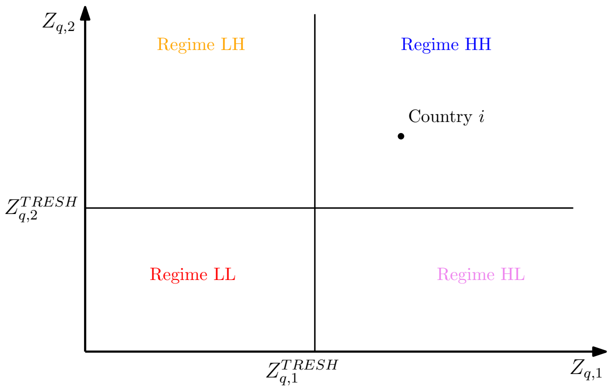


Figure 3: Partition of countries into four growth regimes by two deep determinants $\mathbf{Z}_{q,1}$ and $\mathbf{Z}_{q,2}$ according two thresholds $Z_{q,1}^{TRESH}$ and $Z_{q,2}^{TRESH}$.

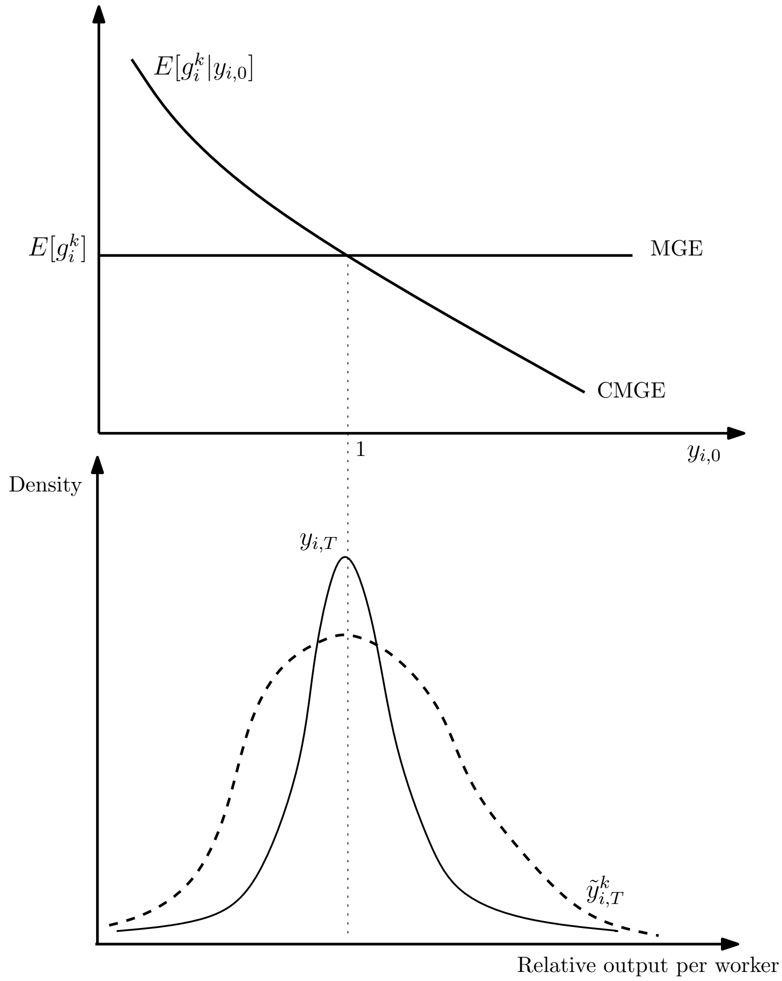


Figure 4: The case of the *k-th* determinant with a distributional effect in favour of a less dispersed distribution: CMGE is a decreasing function of initial level of GDP per worker.

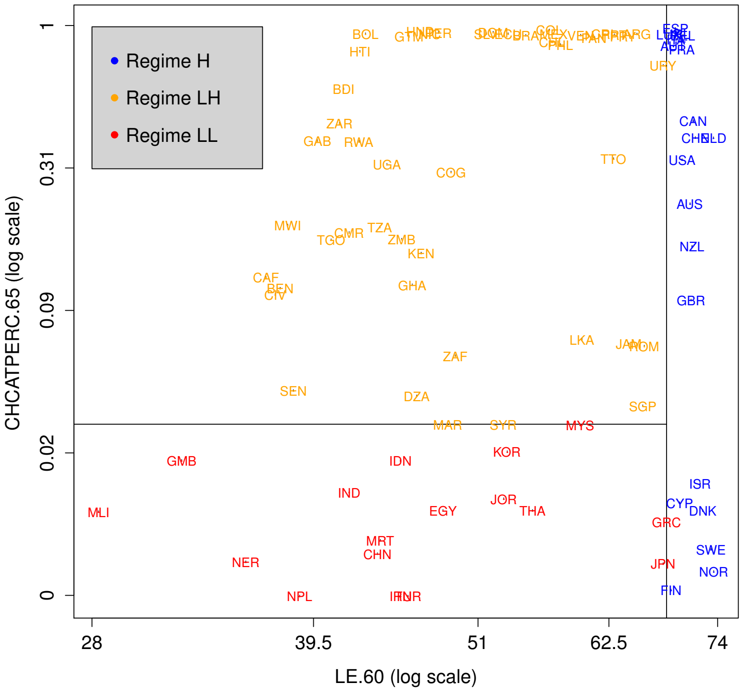


Figure 5: Partition of countries in three growth regimes.

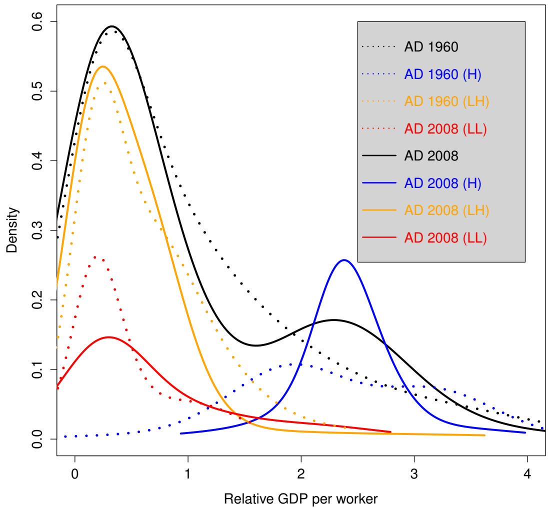


Figure 6: Estimated distributions of GDP in 1960 and 2008 for the whole sample of countries (black), and for each growth regime (blue, orange, and red for Regimes H, LH, and LL respectively).

Theil	Total	Between-group	Within-group
AD 1960	0.42 (0.04)	0.24 (0.05)	0.18 (0.03)
AD 2008	0.47 (0.05)	0.27 (0.05)	0.20 (0.04)
BIPOL			
AD 1960	NA		
AD 2008	0.76 (0.17)		

Table 1: Variable: GDP per worker. Theil index of total, between-group, and within-group inequality and BIPOL index of polarization in 1960 and 2008. Bootstrap standard errors are reported in parenthesis.

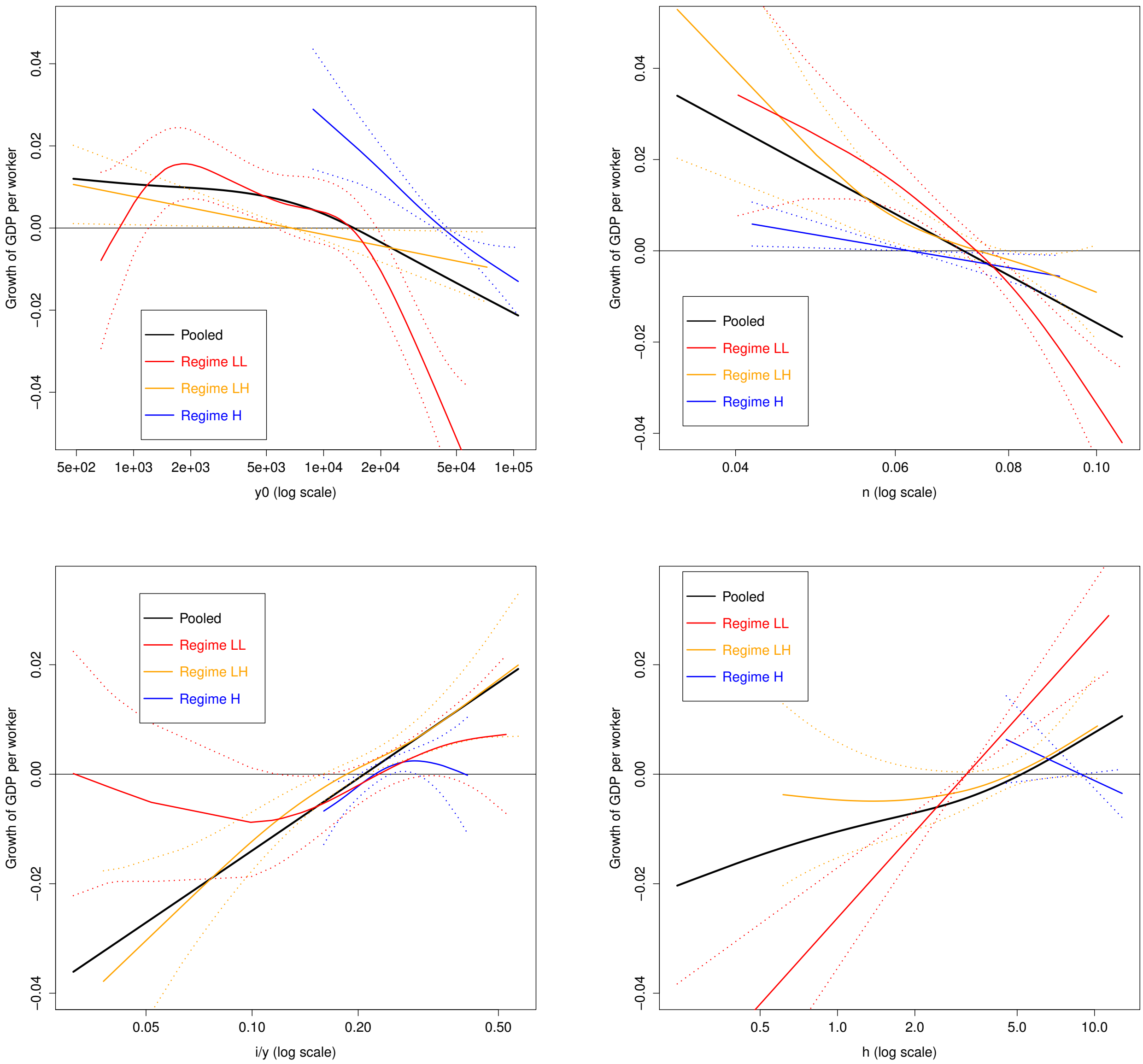
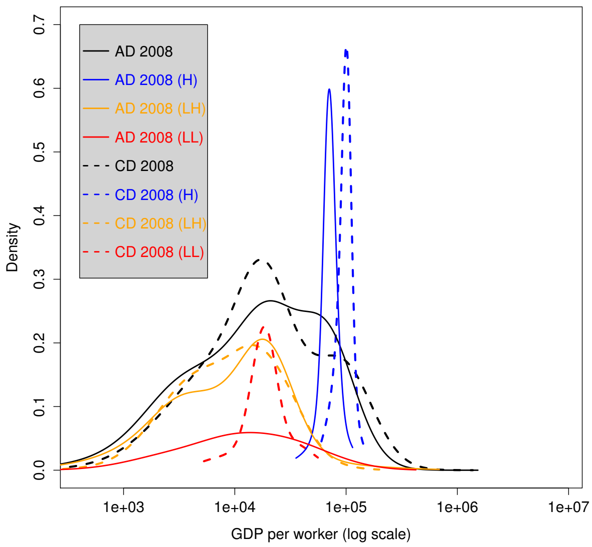
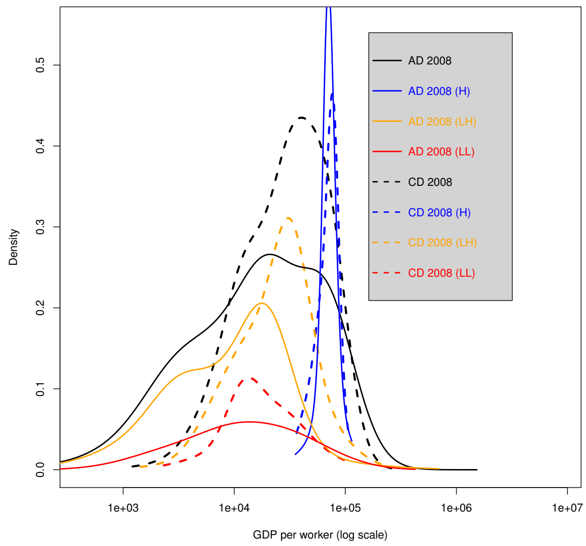


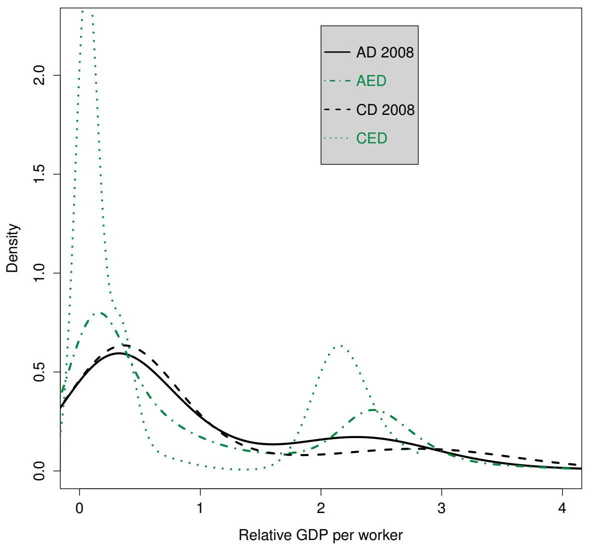
Figure 7: Estimated nonparametric function $\mu_j(\cdot)$ of Equation (6) for model without regimes (light grey line, corresponding to columns 1 in Table 3) and for the best model with three growth regimes (blue, orange and red lines, corresponding to columns 2-4 in Table 3 respectively). 95% confidence bands (dotted lines) are derived from the estimated standard errors based on the Bayesian posterior covariance matrix of the parameters (see Wood, 2011).



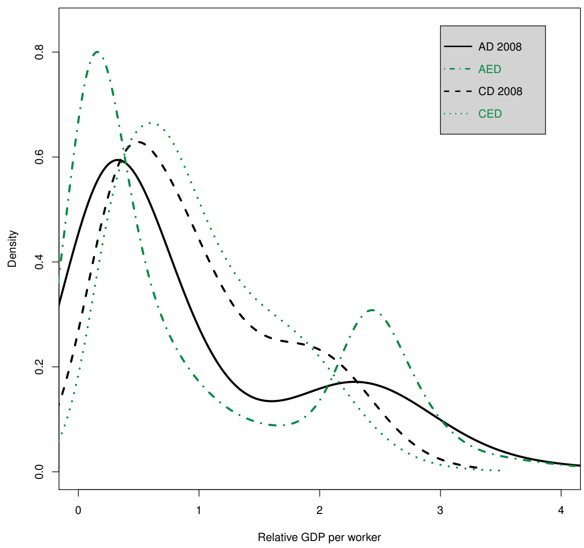
(a) Variable: log.h. Actual and counterfactual distributions in 2008 (whole sample and growth regimes)



(b) Growth regimes. Actual and counterfactual distributions in 2008 (whole sample and growth regimes)



(c) Variable: log.h. Actual and counterfactual final and ergodic distributions.



(d) Growth regimes. Actual and counterfactual final and ergodic distributions.

Figure 8: Actual and counterfactual distributions.

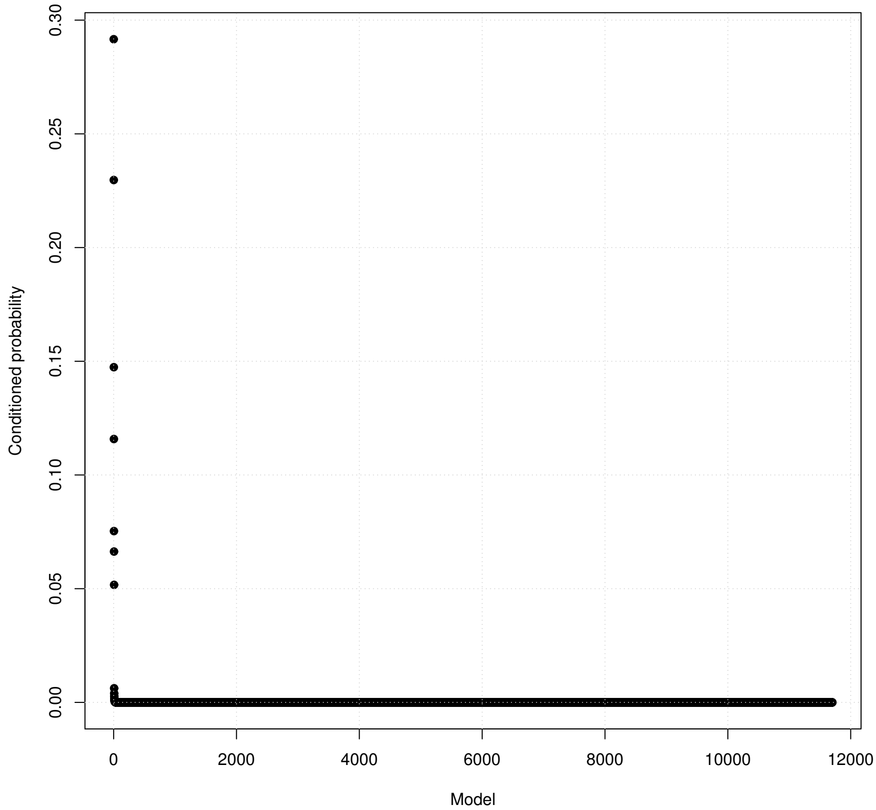
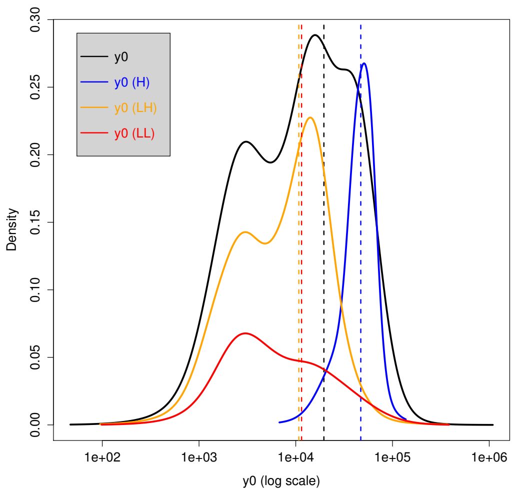
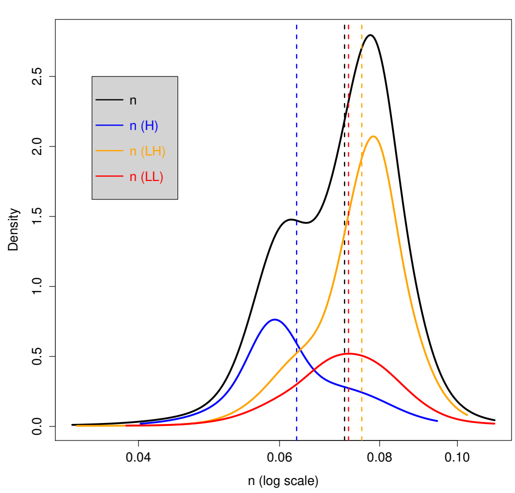


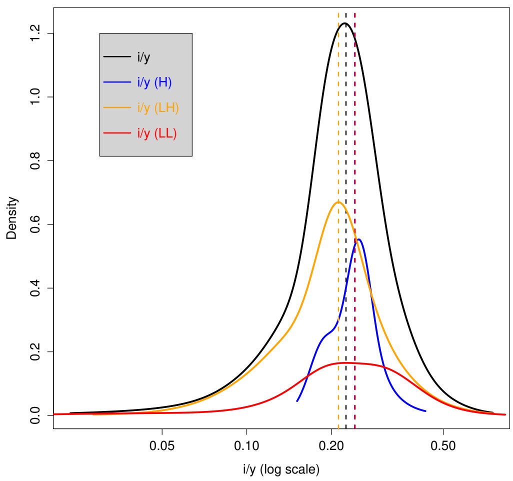
Figure 9: *Conditioned* probability to be the least false model for all possible countries' partition, given life expectancy at birth in 1960 and the % of Catholics in 1965 as partitioning variables.



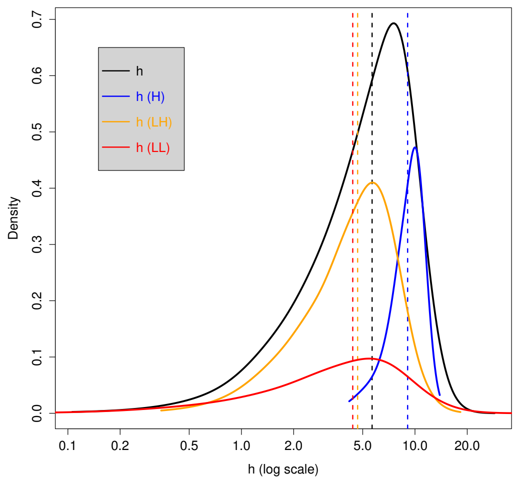
(a) Initial GDP per worker.



(b) (Augmented) Emplomant growth rate.

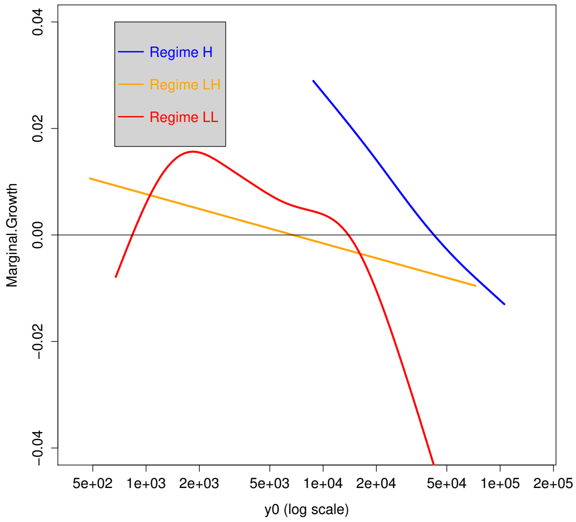


(c) Investment rate.

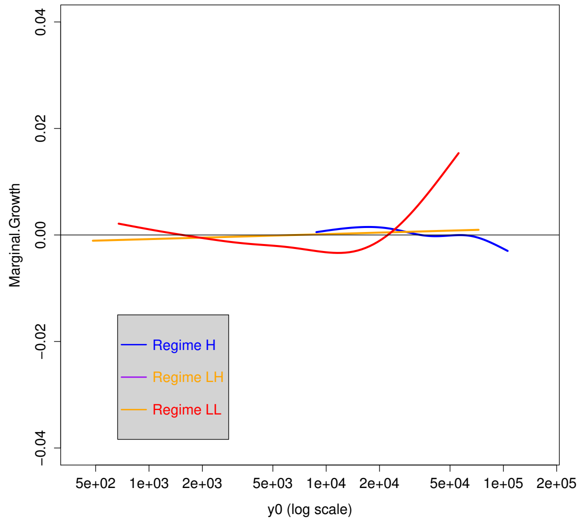


(d) Human capital.

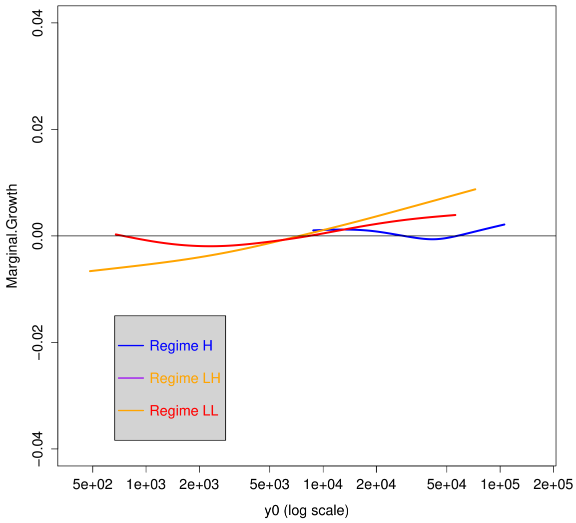
Figure 10: Distribution of proximate determinants for the whole sample and within each growth regime. Dotted vertical lines indicate the average value for the whole sample (black) and in each growth regime (blue, orange and red for Regimes H, LH, and LL respectively). Densities and averages are estimate from pooling observations of all periods for each growth regime.



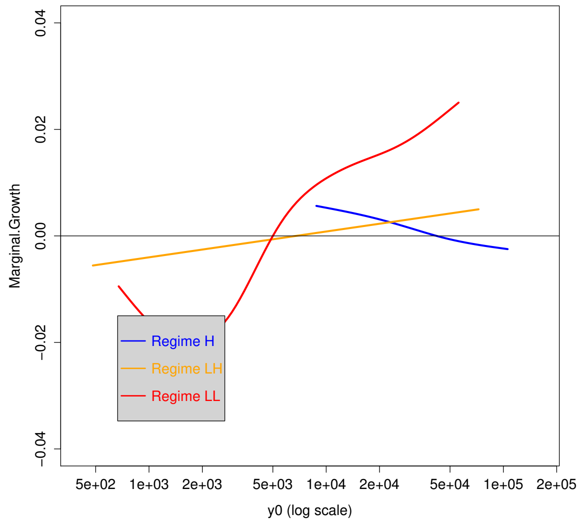
(a) Variable: log.y0.



(b) Variable: log.n.



(c) Variable: log.i/y.



(d) Variable: log.h.

Figure 11: Conditional marginal growth effect in the growth regimes.

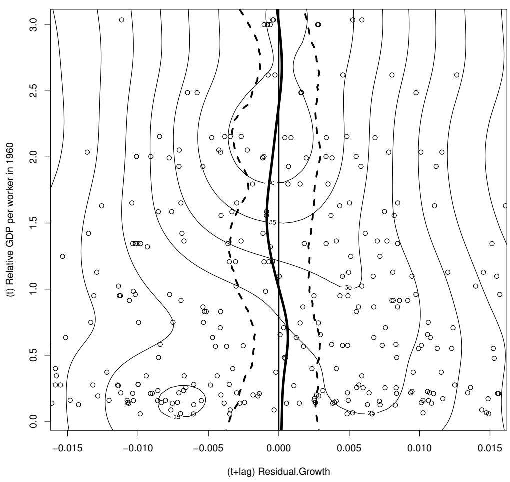


Figure 12: Conditional distribution of residual growth, the conditional mean (thick line), its confidence bands at 95% confidence level (dotted lines) and the unconditional mean (thin vertical line).

		Whole Sample	Regime H	Regime LH	Regime LL
Initial GDP per worker	*Mean*	19535	46997	10760	11484
	SD	19990	17182	10087	13530
(Augmented) Employment growth	*Mean*	0.07	0.06	0.08	0.07
	SD	0.01	0.01	0.01	0.01
Investment rate	*Mean*	0.23	0.24	0.21	0.24
	SD	0.09	0.05	0.09	0.11
Human capital	*Mean*	5.66	9.07	4.67	4.38
	SD	3.07	1.93	2.36	2.98

Table 2: Mean and standard deviation of distribution of proximate determinants for the whole sample and within each regime.

	No Regimes	Regimes		
		Regime H	**Regime LH**	**Regime LL**
Dep. Var: g	Pooled GAM **1960-2008**	Pooled GAM **1960-2008**	Pooled GAM **1960-2008**	Pooled GAM **1960-2008**
Parametric coefficients:	Estimate	Estimate	Estimate	Estimate
Intercept	0.034^{***}	0.028^{***}	0.030^{***}	0.046^{***}
	(0.002)	(0.003)	(0.004)	(0.005)
$D_{1970-1980}$	-0.014^{***}	-0.013^{***}	-0.011^{***}	-0.017^{***}
	(0.003)	(0.003)	(0.004)	(0.006)
$D_{1980-1990}$	-0.029^{***}	-0.010^{***}	-0.038^{***}	-0.023^{***}
	(0.003)	(0.003)	(0.005)	(0.007)
$D_{1990-2000}$	-0.025^{***}	-0.003	-0.028^{***}	-0.031^{***}
	(0.004)	(0.004)	(0.005)	(0.007)
$D_{2000-2008}$	-0.018^{***}	-0.011^{**}	-0.016^{***}	-0.027^{***}
	(0.004)	(0.004)	(0.005)	(0.007)
Semi-parametric coefficients:	EDF	EDF	EDF	EDF
log.y0	2.6^{***}	1.7^{***}	1.0^{**}	4.3^{***}
	(9.88)	(10.67)	(4.96)	(10.6)
log.n	1.0^{***}	1.0^{**}	2.3^{***}	2.2^{***}
	(49.83)	(5.96)	(5.06)	(15.6)
log.i/y	1.0^{***}	2.1^{**}	2.1^{***}	2.3
	(52.34)	(3.49)	(10.95)	(1.39)
log.h	2.1^{**}	1.0	1.9	1.0^{***}
	(2.64)	(2.52)	(1.53)	(0.009)
Endogeneity	NO	NO	NO	NO
Omitted-variable bias	NO	NO	NO	NO
Observations	420	100	235	85
Countries	84	20	47	17
Generalized R^2	0.40	0.74	0.43	0.69
Scale estimate ($*10^{-5}$)	39.7	6.7	42.2	29.6
REML score	-1001.4	-291.0	-535.28	-179.94
AICc	2081.81	2230.49		

Table 3: Estimates of semiparametric growth model in Eq. (6). Significant asymptotic levels: 1%"***" 5%"**" 10%"*". Standard errors and F-values are reported between brackets for parametric and semi-parametric coefficients respectively. **GAM**: Generalized Additive Model. **EDF**: estimated degrees of freedom in the estimate of $\mu_j(\cdot)$. **Endogeneity**: test on the presence of endogeneity and endogeneity-robust estimation via Control Function (see Appendix F). **Omitted-variable bias**: test for omitted-variable bias with distributional effects (see Appendix G). **Generalized $\mathbf{R^2}$**: generalization of R^2 to be used in ML estimates (see Nagelkerke, 1991). **Log.likelihood**: the logarithm of model's likelihood. **Scale estimate**: scale parameter (corresponding to the residual variance of the estimation, see Appendix I). **REML score**: score of the restricted maximum likelihood estimation (it provides the fundamental information on the specification of the model, see Appendix I). **AICc**: Akaike Information Criterion calculated as in Eq.(1) in Appendix 3.1.1.

Theil	Total	Between-group	Within-group
AD 2008	0.47 (0.05)	0.27 (0.05)	0.20 (0.04)
CD 2008	0.90 (0.09)	0.63 (0.10)	0.27 (0.08)
BIPOL			
AD 2008	0.76 (0.17)		
CD 2008	0.93 (0.74)		
AED	1.26 (0.04)		
CED	6.05 (0.40)		

(a) Variable: log.y0.

Theil	Total	Between-group	Within-group
AD 2008	0.47 (0.05)	0.27 (0.05)	0.20 (0.04)
CD 2008	0.41 (0.05)	0.23 (0.04)	0.18 (0.03)
BIPOL			
AD 2008	0.76 (0.17)		
CD 2008	0.65 (0.41)		
ED	1.26 (0.04)		
CED	2.06 (0.03)		

(b) Variable: log.n.

Theil	Total	Between-group	Within-group
AD 2008	0.47 (0.05)	0.27 (0.05)	0.20 (0.04)
CD 2008	0.43 (0.04)	0.28 (0.04)	0.15 (0.03)
BIPOL			
AD 2008	0.76 (0.17)		
CD 2008	0.82 (0.23)		
ED	1.26 (0.04)		
CED	2.02 (0.02)		

(c) Variable: log.i/y.

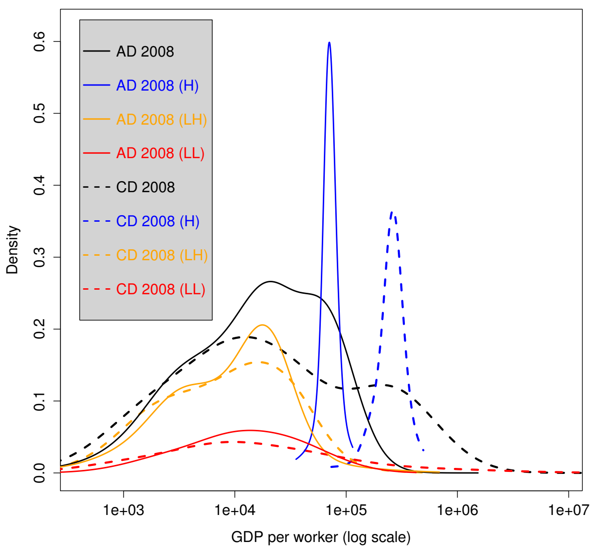
Theil	Total	Between-group	Within-group
AD 2008	0.47 (0.05)	0.27 (0.05)	0.20 (0.04)
CD 2008	0.52 (0.05)	0.42 (0.04)	0.09 (0.02)
BIPOL			
AD 2008	0.76 (0.17)		
CD 2008	0.90 (0.30)		
ED	1.26 (0.04)		
CED	3.31 (0.04)		

(d) Variable: log.h.

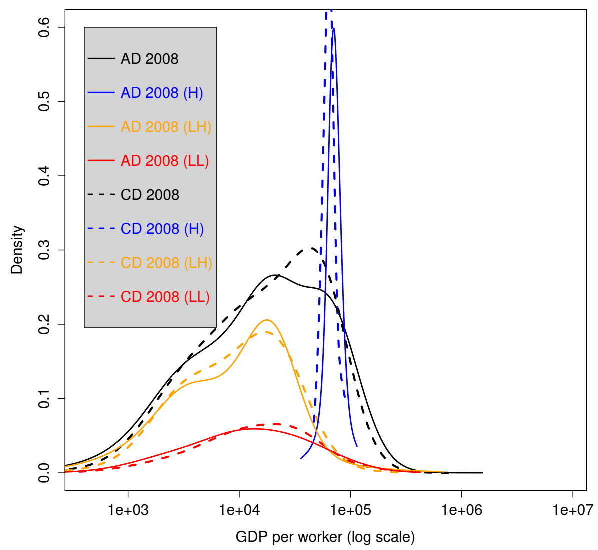
Theil	Total	Between-group	Within-group
AD 2008	0.47 (0.05)	0.27 (0.05)	0.20 (0.04)
CD 2008	0.24 (0.03)	0.10 (0.02)	0.14 (0.02)
BIPOL			
AD 2008	0.76 (0.17)		
CD 2008	NA (NA)		
ED	1.26 (0.04)		
CED	NA (NA)		

(e) Variable: log.h.

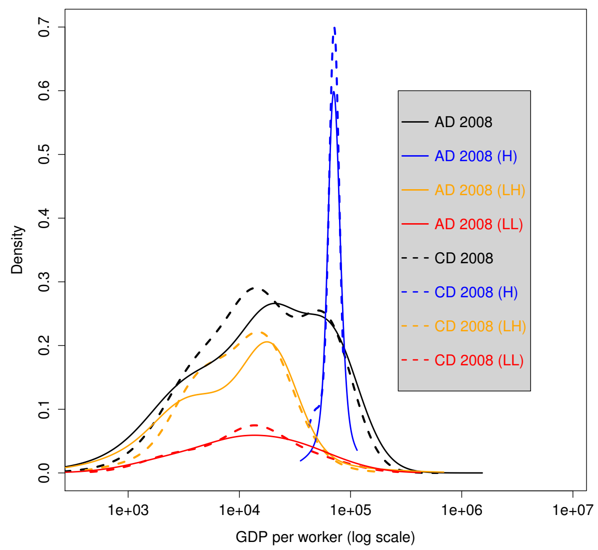
Table 4: Theil index of total, between-group, and within-group inequality and BIPOL polarization index in 1960 and 2008 for the actual, ergodic, and counterfactual distributions. Bootstrap standard errors in parenthesis.



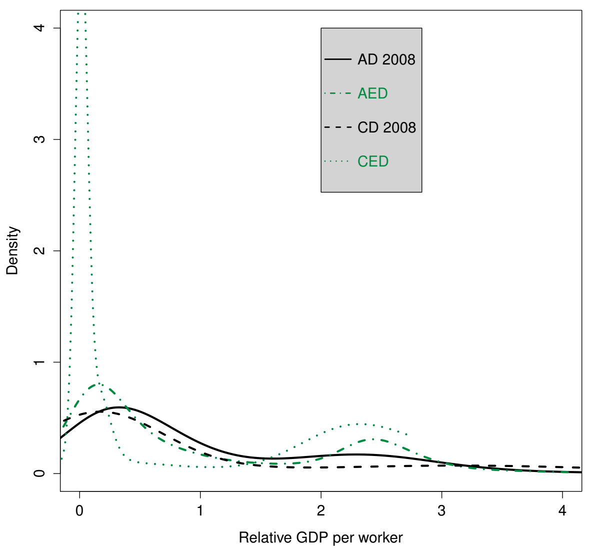
(a) Variable: log.y0. Actual and counterfactual distributions in 2008 (whole sample and growth regimes).



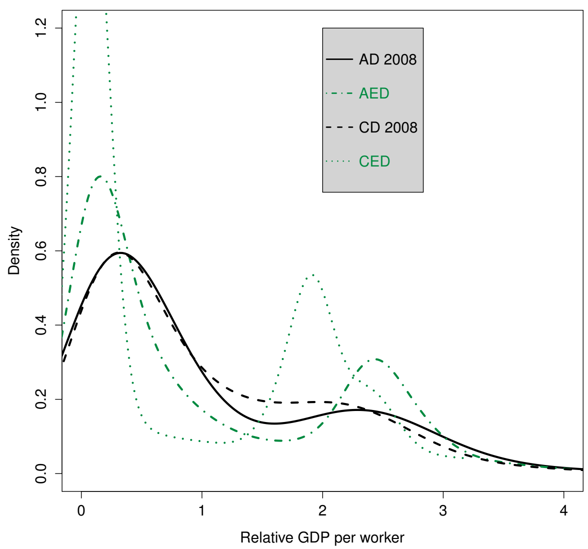
(b) Variable: log.n. Actual and counterfactual distributions in 2008 (whole sample and growth regimes)



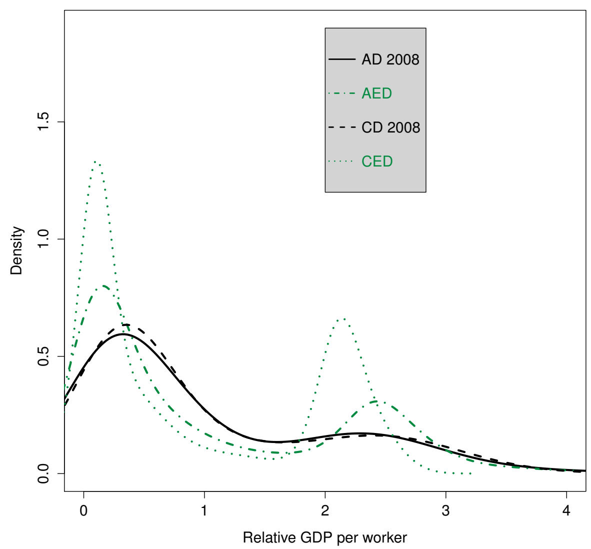
(c) Variable: log.i/y. Actual and counterfactual distributions in 2008 (whole sample and growth regimes)



(d) Variable: log.y0. Actual and counterfactual final and ergodic distributions.



(e) Variable: log.n. Actual and counterfactual final and ergodic distributions.



(f) Variable: log.i/y. Actual and counterfactual final and ergodic distributions.

Figure 13: Actual and counterfactual distributions.

Table 5: Mean and standard deviation of growth rate, deep and proximate determinants.

	g	GDPpw.1960	PRI.60	SEC.60	LE.60	DEM.60.65	CON.60.65	ELF.61	ABS.LAT	ME	TROP.AR
Mean	0.02	11759.63	0.55	0.15	54.83	1.02	0.32	0.47	24.56	3.72	0.54
SD	0.03	11214.42	0.32	0.16	12.48	7.3	12.48	0.28	17.99	6.76	0.48
	LND100CR	AR.FR	5.FR.DAYS	PROT.65	CAT.65	ISLAM.65	ANI.65	log.y0	log.n	log.i/y	log.h
Mean	0.47	7.12	0.4	0.11	0.39	0.17	0.09	9.24	-2.64	-1.57	1.52
SD	0.38	9.04	0.45	0.22	0.4	0.32	0.17	1.25	0.17	0.43	0.74

Table 6: Correlations among growth rate, deep and proximate determinants.

	g	PRI.60	SEC.60	LE.60	DEM.60.65	CON.60.65	ELF.61	ABS.LAT	ME	TROP.AR	LND100CR
g	1	0.170	0.130	0.200	0.110	0.060	-0.210	0.190	-0.200	-0.230	0.170
PRI.60	0.170	1	0.710	0.910	0.710	0.290	-0.490	0.630	-0.570	-0.500	0.530
SEC.60	0.130	0.710	1	0.690	0.600	0.270	-0.310	0.520	-0.390	-0.520	0.340
LE.60	0.200	0.910	0.690	1	0.670	0.240	-0.580	0.670	-0.610	-0.610	0.550
DEM.60.65	0.110	0.710	0.600	0.670	1	0.240	-0.240	0.410	-0.390	-0.300	0.510
CON.60.65	0.060	0.290	0.270	0.240	0.240	1	-0.120	0.220	-0.170	-0.170	0.090
ELF.61	-0.210	-0.490	-0.310	-0.580	-0.240	-0.120	1	-0.600	0.560	0.560	-0.460
ABS.LAT	0.190	0.630	0.520	0.670	0.410	0.220	-0.600	1	-0.460	-0.900	0.260
ME	-0.200	-0.570	-0.390	-0.610	-0.390	-0.170	0.560	-0.460	1	0.510	-0.370
TROP.AR	-0.230	-0.500	-0.520	-0.610	-0.300	-0.170	0.560	-0.900	0.510	1	-0.170
LND100CR	0.170	0.530	0.340	0.550	0.510	0.090	-0.460	0.260	-0.370	-0.170	1
AR.FR	0.220	0.540	0.530	0.560	0.380	0.230	-0.480	0.870	-0.410	-0.820	0.100
5.FR.DAYS	0.220	0.500	0.510	0.600	0.310	0.160	-0.530	0.900	-0.480	-0.940	0.210
PROT.65	-0.020	0.420	0.290	0.400	0.400	0.160	-0.220	0.480	-0.150	-0.260	0.040
CAT.65	-0.120	0.260	-0.030	0.210	0.070	0.010	-0.160	-0.060	-0.310	0.130	0.220
ISLAM.65	0.010	-0.510	-0.320	-0.420	-0.340	-0.120	0.150	-0.080	0.240	-0.030	-0.210
ANI.65	-0.150	-0.530	-0.360	-0.570	-0.350	-0.110	0.450	-0.430	0.680	0.390	-0.420
GDPpw.1960	0.010	0.710	0.680	0.760	0.620	0.300	-0.370	0.650	-0.420	-0.550	0.330
log.y0	0.010	0.740	0.620	0.810	0.570	0.270	-0.480	0.640	-0.510	-0.590	0.490
log.n	-0.350	-0.480	-0.330	-0.470	-0.340	-0.180	0.410	-0.570	0.260	0.490	-0.250
log.i/y	0.310	0.340	0.230	0.390	0.090	0.030	-0.190	0.240	-0.250	-0.290	0.140
log.h	0.050	0.760	0.620	0.760	0.540	0.250	-0.380	0.470	-0.550	-0.440	0.430

	AR.FR	5.FR.DAYS	PROT.65	CAT.65	ISLAM.65	ANI.65	GDPpw.1960	log.y0	log.n	log.i/y	log.h
g	0.220	0.220	-0.020	-0.120	0.010	-0.150	0.010	0.010	-0.350	0.310	0.050
PRI.60	0.540	0.500	0.420	0.260	-0.510	-0.530	0.710	0.740	-0.480	0.340	0.760
SEC.60	0.530	0.510	0.290	-0.030	-0.320	-0.360	0.680	0.620	-0.330	0.230	0.620
LE.60	0.560	0.600	0.400	0.210	-0.420	-0.570	0.760	0.810	-0.470	0.390	0.760
DEM.60.65	0.380	0.310	0.400	0.070	-0.340	-0.350	0.620	0.570	-0.340	0.090	0.540
CON.60.65	0.230	0.160	0.160	0.010	-0.120	-0.110	0.300	0.270	-0.180	0.030	0.250
ELF.61	-0.480	-0.530	-0.220	-0.160	0.150	0.450	-0.370	-0.480	0.410	-0.190	-0.380
ABS.LAT	0.870	0.900	0.480	-0.060	-0.080	-0.430	0.650	0.640	-0.570	0.240	0.470
ME	-0.410	-0.480	-0.150	-0.310	0.240	0.680	-0.420	-0.510	0.260	-0.250	-0.550
TROP.AR	-0.820	-0.940	-0.260	0.130	-0.030	0.390	-0.550	-0.590	0.490	-0.290	-0.440
LND100CR	0.100	0.210	0.040	0.220	-0.210	-0.420	0.330	0.490	-0.250	0.140	0.430
AR.FR	1	0.880	0.500	-0.150	-0.130	-0.270	0.580	0.530	-0.500	0.250	0.460
5.FR.DAYS	0.880	1	0.320	-0.130	-0.010	-0.350	0.580	0.600	-0.480	0.290	0.450
PROT.65	0.500	0.320	1	-0.260	-0.240	-0.110	0.490	0.330	-0.330	0.070	0.300
CAT.65	-0.150	-0.130	-0.260	1	-0.480	-0.310	0.160	0.240	0.040	-0.030	0.190
ISLAM.65	-0.130	-0.010	-0.240	-0.480	1	-0.010	-0.280	-0.230	0.220	-0.070	-0.400
ANI.65	-0.270	-0.350	-0.110	-0.310	-0.010	1	-0.430	-0.550	0.250	-0.290	-0.420
GDPpw.1960	0.580	0.580	0.490	0.160	-0.280	-0.430	1	0.820	-0.330	0.240	0.590
log.y0	0.530	0.600	0.330	0.240	-0.230	-0.550	0.820	1	-0.340	0.380	0.730
log.n	-0.500	-0.480	-0.330	0.040	0.220	0.250	-0.330	-0.340	1	-0.130	-0.240
log.i/y	0.250	0.290	0.070	-0.030	-0.070	-0.290	0.240	0.380	-0.130	1	0.390
log.h	0.460	0.450	0.300	0.190	-0.400	-0.420	0.590	0.730	-0.240	0.390	1

Table 7: AICc of the best model for each possible couple of deep determinants referred to the only best models for each couple of deep determinants.

1st/**2**nd	None	GDPpw.60	PRI.60	SEC.60	LE.60	DEM.60.65	CON.60.65	ELF.61	ABS.LAT	ME	TROP.AR	LND100CR	AR.FR	5.FR.DAYS	PROT.65	CAT.65	ISLAM.65	ANI.65
GDPpw.60	-2104.28	-2109.40	-2187.54	-2172.28	-2210.70	-2137.10	-2113.81	-2147.36	-2179.52	-2157.81	-2120.22	-2134.45	-2180.14	-2170.48	-2160.17	-2158.22	-2129.14	-2119.46
PRI.60	-2172.00	-2182.22	-2183.28	-2183.78	-2204.35	-2182.48	-2182.74	-2172.48	-2180.25	-2177.56	-2180.87	-2181.46	-2188.38	-2188.52	-2188.21	-2208.98	-2185.44	-2180.17
SEC.60	-2145.59	-2190.45	-2183.04	-2166.20	-2203.97	-2161.63	-2159.50	-2165.16	-2178.53	-2153.58	-2159.81	-2158.41	-2166.88	-2166.90	-2173.22	-2178.41	-2156.85	-2155.55
LE.60	-2189.19	-2201.71	-2192.33	-2197.46	-2210.83	-2192.17	-2193.01	-2198.05	-2200.34	-2200.36	-2200.34	-2195.76	-2205.15	-2205.48	-2201.64	-2230.50	-2198.04	-2196.54
DEM.60.65	-2140.51	-2165.58	-2173.29	-2170.23	-2193.75	-2153.29	-2149.78	-2160.87	-2191.90	-2155.48	-2160.04	-2163.46	-2173.57	-2174.71	-2177.15	-2167.32	-2149.17	-2151.49
CON.60.65	-2109.06	-2117.40	-2182.74	-2159.50	-2200.95	-2149.78	-2119.12	-2153.75	-2175.53	-2146.63	-2144.02	-2125.23	-2168.22	-2160.98	-2151.82	-2147.36	-2119.13	-2120.49
ELF.61	-2133.86	-2151.65	-2170.31	-2162.97	-2196.17	-2161.43	-2148.03	-2130.25	-2156.23	-2146.01	-2136.06	-2148.91	-2157.13	-2142.10	-2184.01	-2152.28	-2144.15	-2146.05
ABS.LAT	-2150.10	-2186.77	-2180.61	-2170.46	-2212.17	-2183.60	-2164.32	-2170.37	-2161.62	-2159.61	-2163.55	-2163.04	-2172.48	-2173.07	-2198.74	-2184.38	-2160.68	-2146.09
ME	-2124.77	-2186.08	-2177.56	-2153.58	-2200.36	-2150.11	-2137.46	-2156.24	-2159.61	-2142.05	-2149.61	-2132.83	-2149.47	-2149.47	-2175.13	-2162.63	-2137.53	-2129.80
TROP.AR	-2119.33	-2186.77	-2183.79	-2169.59	-2212.17	-2183.60	-2150.67	-2171.59	-2152.19	-2152.76	-2119.33	-2140.26	-2134.10	-2129.18	-2165.25	-2157.53	-2141.54	-2125.19
LND100CR	-2099.70	-2131.22	-2168.56	-2149.06	-2184.26	-2151.14	-2137.66	-2148.91	-2160.79	-2132.83	-2140.64	-2134.41	-2158.96	-2136.04	-2157.58	-2147.15	-2119.51	-2116.60
AR.FR	-2125.11	-2190.42	-2196.09	-2172.44	-2219.16	-2190.76	-2156.95	-2175.45	-2159.20	-2166.33	-2128.95	-2148.01	-2146.36	-2139.02	-2171.52	-2159.73	-2143.87	-2141.33
5.FR.DAYS	-2125.11	-2190.42	-2190.39	-2175.33	-2216.98	-2190.76	-2156.95	-2179.35	-2158.49	-2166.88	-2129.18	-2148.01	-2140.18	-2130.77	-2171.52	-2162.92	-2158.24	-2133.74
PROT.65	-2161.39	-2175.44	-2186.78	-2173.79	-2193.22	-2173.97	-2163.78	-2173.74	-2175.26	-2163.74	-2173.76	-2174.14	-2178.93	-2178.94	-2182.20	-2197.74	-2175.15	-2168.22
CAT.65	-2120.41	-2136.94	-2218.46	-2187.61	-2212.88	-2179.11	-2140.22	-2171.70	-2189.82	-2174.68	-2154.27	-2132.33	-2162.48	-2170.95	-2185.29	-2139.66	-2166.07	-2128.66
ISLAM.65	-2101.56	-2155.84	-2185.44	-2156.55	-2198.04	-2147.90	-2131.46	-2144.13	-2188.00	-2152.03	-2144.24	-2117.48	-2167.13	-2178.62	-2175.15	-2161.23	-2117.23	-2111.26
ANI.65	-2097.91	-2111.74	-2184.55	-2174.81	-2210.99	-2151.49	-2114.23	-2149.27	-2146.09	-2146.32	-2120.07	-2111.33	-2145.24	-2125.82	-2168.22	-2136.43	-2117.90	-2100.51

Table 8: Bayesian model posterior probability of the best model for each possible couple of deep determinants referred to the only best models for each couple of deep determinants.

1st/**2**nd	None	GDPpw.60	PRI.60	SEC.60	LE.60	DEM.60.65	CON.60.65	ELF.61	ABS.LAT	ME	TROP.AR	LND100CR	AR.FROST	5.FR.DAYS	PROT.65	CAT.65	ISLAM.65	ANI.65
GDPpw.60	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PRI.60	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SEC.60	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LE.60	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**0.992**	0.000	0.000
DEM.60.65	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
CON.60.65	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ELF.61	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ABS.LAT	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ME	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
TROP.AR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LND100CR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR.FR	0.000	0.000	0.000	0.000	**0.003**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
5.FR.DAYS	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PROT.65	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
CAT.65	0.000	0.000	**0.002**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ISLAM.65	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ANI.65	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Regime H	**Regime LH**	**Regime LL**
Australia	Algeria	China
Austria	Argentina	Egypt
Belgium	Benin	Gambia, The
Canada	Bolivia	Greece
Cyprus	Brazil	India
Denmark	Burundi	Indonesia
Finland	Cameroon	Iran
France	Central African Republic	Japan
Ireland	Chile	Jordan
Israel	Colombia	Korea, Republic of
Italy	Congo, Democratic Republic	Malaysia
Luxembourg	Congo, Republic of	Mali
Netherlands	Costa Rica	Mauritania
New Zealand	Cote d'Ivoire	Nepal
Norway	Dominican Republic	Niger
Spain	Ecuador	Thailand
Sweden	El Salvador	Turkey
Switzerland	Gabon	
United Kingdom	Ghana	
United States of America	Guatemala	
	Haiti	
	Honduras	
	Jamaica	
	Kenya	
	Malawi	
	Mexico	
	Morocco	
	Nicaragua	
	Panama	
	Paraguay	
	Peru	
	Philippines	
	Portugal	
	Romania	
	Rwanda	
	Senegal	
	Singapore	
	South Africa	
	Sri Lanka	
	Syria	
	Tanzania	
	Togo	
	Trinidad & Tobago	
	Uganda	
	Uruguay	
	Venezuela	
	Zambia	

Table 9: Lists of countries in the three growth regimes for the best model

	Regime H		
Dep. Var:	**log.n**	**log.i/y**	**log.h**
	Pooled GAM **1960-2008**	Pooled GAM **1960-2008**	Pooled GAM **1960-2008**
Parametric coefficients:	Estimate	Estimate	Estimate
Intercept	-2.671***	-1.451***	2.019***
$D_{1970-1980}$	-0.061	0.0432	0.104***
$D_{1980-1990}$	-0.101**	-0.036	0.184***
$D_{1990-2000}$	-0.182***	-0.006	0.239***
$D_{2000-2008}$	-0.185**	0.067	0.278***
Semi-parametric coefficients:	EDF	EDF	EDF
log.y	1.000***	2.241**	1.000***
log.n.1960	2.858	3.019**	3.548***
log.i/y.1960	7.833***	4.885***	1.000
log.h.1960	1.000	1.000	1.000***
REML score	-45.784	-40.97	-85.68
Scale est.	0.011	0.014	0.006
Obs.	100	100	100
Countries.	20	20	20

Table 10: First-stage regressions of potentially endogenous determinants. Significance codes: 0.01"***" 0.05"**" 0.1"*". **EDF**: estimated degrees of freedom that reflect the flexibility of the model (when the EDFs of a term are equal to one, the smooth term can be substituted by a linear function). **REML score**: score of the restricted maximum likelihood estimation providing the fundamental information on the specification of the model. **Scale est.**: scale parameter, corresponding to the residual variance of the estimation. **Obs.**: number of observations. **Countries**: number of countries.

	Regime LH		
Dep. Var:	**log.n**	**log.i/y**	**log.h**
	Pooled GAM **1960-2008**	Pooled GAM **1960-2008**	Pooled GAM **1960-2008**
Parametric coefficients:	Estimate	Estimate	Estimate
Intercept	-2.625***	-1.692***	0.798***
$D_{1970-1980}$	0.051**	0.193***	0.350***
$D_{1980-1990}$	0.064***	0.068	0.663***
$D_{1990-2000}$	0.067***	-0.035	0.877***
$D_{2000-2008}$	0.009	0.039	1.019***
Semi-parametric coefficients:	EDF	EDF	EDF
log.y	1.000*	1.000	3.192**
log.n.1960	3.725***	3.053**	1.147
log.i/y.1960	1.000	4.020***	4.163***
log.h.1960	3.930***	1.000	1.631***
Gen. R^2	0.42	0.56	0.89
REML score	-158.53	65.823	-8.135
Scale est.	0.011	0.084	0.004
Obs.	235	235	235
Countries.	47	47	47

Table 11: First-stage regressions of potentially endogenous determinants. Significance codes: 0.01"***" 0.05"**" 0.1"*". **EDF**: estimated degrees of freedom that reflect the flexibility of the model (when the EDFs of a term are equal to one, the smooth term can be substituted by a linear function). **REML score**: score of the restricted maximum likelihood estimation providing the fundamental information on the specification of the model. **Scale est.**: scale parameter, corresponding to the residual variance of the estimation. **Obs.**: number of observations. **Countries**: number of countries.

	Regime LL		
Dep. Var:	**log.n**	**log.i/y**	**log.h**
	Pooled GAM **1960-2008**	Pooled GAM **1960-2008**	Pooled GAM **1960-2008**
Parametric coefficients:	Estimate	Estimate	Estimate
Intercept	-2.699***	-1.877***	0.440***
$D_{1970-1980}$	0.056	0.363***	0.399***
$D_{1980-1990}$	0.131***	0.429***	0.796***
$D_{1990-2000}$	0.109***	0.416***	1.074***
$D_{2000-2008}$	0.055	0.488***	1.306***
Semi-parametric coefficients:	EDF	EDF	EDF
log.y	1.000*	1.000	4.414**
log.n.1960	2.104***	3.053**	2.725
log.i/y.1960	2.115***	4.020***	1.000
log.h.1960	3.348***	1.000	6.312***
REML score	-37.85	30.175	24.739
Scale est.	0.014	0.076	0.050
Obs.	85	85	85
Countries.	17	17	17

Table 12: First-stage regressions of potentially endogenous determinants. Significance codes: 0.01"***" 0.05"**" 0.1"*". **EDF**: estimated degrees of freedom that reflect the flexibility of the model (when the EDFs of a term are equal to one, the smooth term can be substituted by a linear function). **REML score**: score of the restricted maximum likelihood estimation providing the fundamental information on the specification of the model. **Scale est.**: scale parameter, corresponding to the residual variance of the estimation. **Obs.**: number of observations. **Countries**: number of countries.