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## Abstract

*Growth models predict that taxation may have permanent effects on* per capita *real GDP growth. We look at, and test this prediction for 21 OECD countries, over the period 1965-2010. We employ a semi-parametric technique – namely, a Finite Mixture model – to estimate an* augmented *version of the Barro (1990) model, in order to consider both* direct *and* indirect *effects of taxation on capital share parameters. The estimation technique allows to deal with unobserved heterogeneity and to perform a cluster analysis. Our results support the idea that taxes are generally harmful for growth. The coefficient estimates indicate that a cut in the corporate income tax rate by 10 % raises the GDP growth rate by 0.9% while a cut in the personal income tax rate by 10 % raises the GDP growth rate by 1%.*

**Keywords**: Economic growth; taxation; classification.
**JEL codes**: H30; O30; O40.

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# 1 Introduction

In this paper, we revisit a traditional issue in the empirics of growth and economic policy: whether taxation has long-lasting effects on real GDP dynamics. Growth theorists have proposed a variety of channels through which this can happen (see, among the others, Barro, 1990; Jones and Manuelli, 1990; Jones, et al., 1993; Stokey and Rebelo, 1995; Peretto, 2003, 2007). Here, we focus on the impact that taxes may have on the rates of physical *and* human capital accumulation. We propose an *augmented* version of the Barro (1990) model that allows for both *direct* and *indirect* effects of taxation on capital share parameters. From an econometric standpoint, our main departure from the existing literature is the use of a semi-parametric technique, which allows for countries' unobserved heterogeneity in the input effects on *per capita* GDP (see Alfò et al., 2008; Owen et al., 2009; Pittau et al., 2010; and Cohen-Cole et al., 2012, for related approach).

The analysis in this paper consists of two parts. In the first, we present our *augmented* Barro model and the Finite Mixture approach. Our underlying assumption is that countries can share some common unobserved economic structures (e.g. public debt sustainability, quality of institutions, natural resources, etc). Hence, countries can be seen as belonging to *hidden*, homogeneous clusters. Within each cluster, homogeneity holds, i.e. each country belongs to one of possible $K \geq 1$ groups of countries, sharing some common economic features represented by cluster-specific latent parameters (see Arminger et al., 1999; Fraley and Raftery, 2002; Alfò et al., 2008; Owen et al.,2009; Ng and Mclachlan, 2014). Following this approach, we can restrict the individual effects to a small discrete set of values accommodating extreme and/or strongly asymmetric departures from usual parametric assumptions (see e.g. Alfò and Trovato, 2004). The first contribution of the paper is, therefore, to set a model to estimate the impact of fiscal policy on growth, by allowing parameter heterogeneity among observations.

In the second part of the paper, we test our model, using a sample of 21 OECD countries over the period 1965-2010. The model assigns the countries in the sample to three different clusters and the effects of taxation on growth vary between them. Our main finding is that taxation negatively affect *per capita* GDP growth rates, both *directly* and *indirectly*, via physical and human capital saving rates. On average, the magnitude of such estimated effects, however, is not particularly large. Our estimates, which are robust to several modifications of the baseline setup, deliver the second contribution of the paper. In times in which several political leaders across the world have based their economic agenda on tax cuts, it is of particular importance to assess the effective role that taxes may have on growth. Our cross-country analysis makes a clear point on this, at least for our sample of OECD countries: on average, tax cuts produce a beneficial impact on GDP dynamics but of modest size. In our baseline specification, a cut by 10% in personal income tax rate generates an change in the real *per capita* GDP growth rate of +1% while a cut by 10% in corporate income tax rate increases the rate of growth of real *per capita* GDP by 0.9%.

The paper is structured as follows. Section 2 reviews the main empirical literature on the nexus between taxation and growth. Section 3 lays down the econometric strategy. Section 4 describes data, presents the estimation results and provides countries' classification. Section 5 concludes.

## 2 Literature review

Traditionally, the literature on economic growth identifies two main sources of economic development: i) investments in new capital, physical and/or human, and ii) technological change, i.e. improvements in the aggregate TFP. Taxation may have negative effects on the returns to investments and/or the expected profitability of R&D, which is one of the main driver of technological innovation. Therefore, taxation is naturally expected to exert a negative impact on the real GDP growth rate (see Lucas 1990). This negative effect, though, can be, in line of principle, counter-balanced by the gain in aggregate TFP arising from productive public expenditures (e.g. infrastructure, public R&D, etc.), which are (largely) financed through taxation.[1]

While the theoretical channels through which an increase in taxes may affect growth are clear, the large body of empirical works aimed at quantifying the effects of fiscal policy on macroeconomic performance has not produced yet a conclusive evidence. In particular, the correlation between taxation and real GDP growth is found often statistically non-significant. Nonetheless, a consensus has emerged on the fact that some fiscal instruments are indeed more harmful to economic growth than others. In this section, we briefly and separately review the main contributions on this topic.

**Taxation and growth** In an early work, Lucas (1990) shows that eliminating capital income taxation would produce a very small (about 0.03%) increase in real GDP long-run growth. For a sample of 18 OECD countries over the period 1965-1988, Mendoza et al. (1994) find no correlation between tax rates and growth rates. Similar results are found by Mendoza et al. (1997). Daveri and Tabellini (2000) found a negative effect of labor taxes on employment and growth while other studies do not find statistically significant effects. Koester and Kormendi (1989) Easterly and Rebelo (1993) obtain similar results. Tax revenue over GDP is found to be significantly and negatively correlated with GDP growth by Angelopoulos et al. (2007). For a sample of 21 OECD countries over the period 1971-2004, Arnold (2008) finds a substantial (negative) correlation between corporate/personal income taxation and growth, while property taxes seem to have a milder (but negative) effect. Through a “narrative approach”, Romer and Romer (2010, 2014) find that tax increases have a temporarily negative impact on GDP dynamics. More recently, Piketty et al. (2014) find no significant correlation between growth rates and the changes in marginal income tax rates that have been implemented in OECD countries since 1975.

**Tax composition and growth** Calibrating his model using US and East Asian NIC data, Kim (1998) shows that the difference in tax systems across countries explains a significant proportion (around 30%) of the difference in growth rates. For a sample of 22 OECD countries over the period 1970-1995, Kneller et al. (1999) find that shifting the revenue stance away from “distortionary”taxation (i.e. income tax, social security contribution, tax on property, and tax on payroll) toward “non-distortionary”taxation (i.e. consumption tax)

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[1] From the seminal paper of Barro (1990), the question of whether public expenditure has a significant impact on TFP and real GDP growth has been the object of a great deal in the economic literature. The evidence on this virtuous relationship, however, is mixed, at best.

has a slight growth-enhancing effect. Using data on 17 OECD countries, from the early 1970s to 2004, Bleaneyet al. (2001) obtain similar results, by taking explicitly into account disaggregated revenues and expenditures. For a sample of 23 OECD countries, over the period 1965-1990, Widmalm (2001), finds that the proportion of tax revenue raised by taxing personal income exhibits a robust negative correlation with economic growth. In a couple of paper, focused on high-income countries, Padovano and Galli (2001, 2002), find a strong link between lower income rates and faster economic growth. Li and Sarte (2004) find evidence that the decrease in progressivity associated to the *Tax Reform Act* of 1986 in the U.S. leads to small but non-negligible increases in US long-run growth (from 0.12% to 0.34%). For a sample of 70 countries over the period 1970-1997, Lee and Gordon (2005) find that higher corporate tax rates are significantly and negatively correlated with cross-sectional differences in average economic growth rates. According to their results, a cut in the corporate tax rate by 10% would raise the annual GDP growth rate by 1-2%. Using data for 116 countries, over the period 1972-2005, Martinez-Vasquez et al. (2009) find that an increase of 10% in the direct to indirect tax ratio reduces economic growth and FDI inflows by 0.39% and 0.57% respectively. Using an updated version of the dataset used by Bleaney et al. (2001), Gemmell et al. (2011) document rare episodes in which fiscal policy changes affect real GDP long-run growth rates. More recently, Jaimaovich and Rebelo (2017) show that low tax rates have a very small impact on long-run growth; however, as tax rates rise, their negative impact on growth may rise dramatically.

## 3 The econometric strategy

Following Barro (1990), we consider an aggregate technology in which capital accumulation adjusts in response to policy choices on taxation, i.e. we generalize the standard Barro-type regression model by allowing for a direct effect of tax policies on the magnitude of capital share parameters. Moreover, we assume that sources of country-specific unobserved heterogeneity may influence the growth process of the (country-specific) *per capita* GDP.[2] To capture the effects of unobserved heterogeneity, we let the coefficients in the production function to vary among countries. We assume that unobserved heterogeneity represents the effects of some unobserved covariates (see Wouterse, 2016; Mundlak et al., 2012; Phillips and Sul, 2007; Alfò et al., 2008; Pedroni, 2007; Fulginiti and Perrin, 1993; Engen and Skinner, 1992 and 1996). In particular, we consider potential correlation between the random effects and the covariates, and we adopt the *auxiliary regression* approach introduced by Mundlak (1988) to account for it.

We start by presenting the standard Barro model to test the effect of fiscal policy on *per capita* GDP growth. Subsequently, we introduce our *augmented* version of the model along with our assumptions on the way through which taxation affects capital shares.

**The Barro model** We assume a Cobb-Douglas production function, so that at each date $t$, with $t = 1, ..., T$, we have:

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[2] Caselli (2005) shows that about the 60 % of the differences in country income can be due to country-specific factors.

$$Y_{it} = (A_{it} L_i t)^{(1-\lambda-\nu)} K_{it}^{\lambda} H_{it}^{\nu} \tag{1}$$

where $Y$ is output, $K$ capital, $H$ human capital, $L$ is labor, $A$ the level of technology and $\lambda, \nu \in (0,1)$. In equation (1), $A_{it}$ reflects both technological progress and *unobservable* country-specific conditions (e.g. debt-to-GDP ratio, institutions, natural resources, etc.).

The model is based on the hypothesis that, in each country, the rates of investment in physical and human capital are determined by a constant fraction of output, with a common and constant depreciation rate ($d$), a constant and exogenous rate of growth for labor/population ($n$) and technological progress ($g$). Based on these assumptions and taking logs, the (estimable) equation for the level of *per capita* GDP, $y \equiv Y/L$, can be written as:

$$\begin{aligned} \log(y)_{it} &= \log(A)_{it} + gt + \frac{\nu}{(1-\lambda-\nu)} \log(s_h)_{it} + \frac{\lambda}{(1-\lambda-\nu)} \log(s_k)_{it} + \\ & \quad - \frac{\lambda+\nu}{1-\lambda-\nu} \log(n+g+d) \end{aligned} \tag{2}$$

where $s_h$ and $s_k$ are the exogenous shares of total income invested in human capital and physical capital. In Barro-type models, country-specific heterogeneity in technological parameters is meant to capture the differences in country-specific GDP dynamics. Mankiw et al. (1992) assume: $\log(A)_{it} = \alpha + \epsilon_i$, with $\epsilon_i \sim N(0,1)$ representing a country-specific shock. A possible way to *endogenize* the level of technology is to assume $\log(A)_{it} = f(\cdot) + \epsilon_{it}$, in which $f(\cdot)$ includes one or more explanatory variables (e.g., R&D investment). A more explicit way to model the effects of the explanatory variables on growth (via technological progress) is to rely on an additional *design* vector, say $\mathbf{z}_{it}$.

Assuming an endogenous process for $\log(A)_{it}$, the dynamics corresponding to equation (2) is given by:

$$E(\gamma_{it} \mid \mathbf{x}_{it}, \mathbf{z}_{it}) = \alpha_i + \beta_0 \log(y_{i,0}) + \mathbf{x}'_{it}\beta + \mathbf{z}'_{it}\delta \tag{3}$$

where $\gamma_{it} \propto (1/T)(\log(y)_{it} - \log(y)_{i,0})$ is the mean rate of growth of income in the time window $(0,t)$, while the intercept term, $\alpha_i$, measures country-specific innovation. The convergence rate over the country-specific balanced growth path is proxied by $\beta_0$. The vector $\mathbf{x}_i = \{\log(s_k)_{i,t}, \log(s_h)_{i,t}; \log(n+g+d)_{i,t}\}$ includes the *observed* Solow-type covariates (i.e. physical and human capital shares and effective units of labor growth adding depreciation rates). Finally, $\mathbf{z}_{it}$ includes other factors that may affect country-specific technological progress (e.g., tax structures, public debt sustainability, public sector's size and efficiency, political stability, etc).

There are several estimation issues worth noting (see e.g., Brock and Durlauf, 2000 and 2001). Correlation between independent variables in $\mathbf{z}_{it}$, $\mathbf{x}_{it}$ and initial conditions $\log(y_{i,0})$ as well as endogeneity issues may cause severe bias in parameter estimates. Regression results may be inflated by collinearity and, since initial GDP is likely correlated with capital saving rates, covariate effects – in our exercise, as we will see below, those measuring tax policies – may be ill-estimated (see Durlauf et al., 2005). Moreover, being based on macro-level measures, this class of models does not properly take into account the heterogeneity at micro-levels (see van Garderen et al., 2000; Blundel and Stocker, 2005). In this sense, micro-level interactions can be viewed as *hidden* relationships underlying the macro-level data generating process. Therefore, if taxation influences both capital accumulation and growth dynamics, the estimated coefficient for $\delta$ in equation (3) may mix different effects (Hauk, 2017). To deal with this issue, we modify this specification to allow for dependence between fiscal policy and capital stocks.

**The *augmented* Barro model** Following Barro (1990) and Engen and Skinner (1992), we assume that taxation affects GDP dynamics both *directly*, via aggregate efficiency, and *indirectly*, through its effect on aggregate saving rates. Accordingly, we estimate a linear model for the mean growth rate $\gamma_{it}$ under potential misspecification, since some covariates may be missing or collinear or may describe a non-linear relationships with GDP growth rates (see eg Aitkin et al., 2005, Lu et al., 2016 and Ng and McLachlan, 2014). When we allow for country-specific heterogeneity, equation (3) can be written as follows:

$$\mathrm{E}\left(\gamma_{it} \mid \mathbf{x}_{it}, \mathbf{w}_{it}, \phi_i\right) = \mathbf{x}'_{it}\beta + \mathbf{w}'_{it}\phi_i \tag{4}$$

where $\mathbf{x}_{it}$ is now the vector of observed covariates with constant non-individual effects, i.e. fiscal policy instruments $\tau_{it}$, and $\mathbf{w}_{it}$ is the vector of covariates associated to country-specific effects $\phi_i$, $i = 1, \ldots, n$. The country-specific effects $\phi_i$ are zero-mean deviation from effects associated to the corresponding elements in $\mathbf{x}_{it}$. We assume that $\phi_i$ is a i.i.d. drawn from a random variables with distribution $g_\phi$, zero mean and covariance matrix $\mathbf{\Sigma}_\phi$.

In equation (4), the intercept and slopes for capital shares are free to vary across countries. As the random parameters are unobserved, this model cannot be readily estimated. Since $\phi_i$ has (potentially) a dimension greater than 1, we proceed by employing a random effect estimator (see Wooldridge, 2009). When integrating the random parameters out of the model equation, however, we may need to account for potential dependence with observed covariates. When this is not accounted for, the random effect estimator may be inconsistent. To avoid this, we adopt a so-called *auxiliary* regression (as suggested by Mundlak 1978, 1988; and Chamberlain, 1980, 1984):

$$E(\phi_i \mid \mathbf{X}_i) = \mathbf{\Psi}\overline{\mathbf{x}}_i + \tilde{\phi}_i \tag{5}$$

where $\overline{\mathbf{x}}_i = T^{-1}\sum_{t=1}^{T}\mathbf{x}_{i,t}$, the parameter vector country-specific $\phi$ is now (linearly) free of independent variables and the matrix $\mathbf{\Psi}$ describes the dependence of each random parameter on each dimension of the mean value $\overline{\mathbf{x}}_i$. Since the vector of observed covariates $\mathbf{x}_{it}$ also includes the lagged response $\log(y)_{i,0}$, we assume the *sequential exogeneity* condition to ensure identification of elements in $\beta$ (Wooldridge, 2009):

$$E(\epsilon_{it} \mid \mathbf{x}_{it}, \tilde{\phi}_i) = 0, \quad \forall t \in T \tag{6}$$

This implies that the dynamics in the mean is completely specified when the lagged response is considered and $\mathbf{x}_{it}$ reacts to shocks affecting $\gamma_{it}$. Substituting (5) in equation (4), we obtain

$$\mu^{\gamma}_{it} = E\left(\gamma_{it} \mid \mathbf{x}_{it}, \mathbf{w}_{it}, \tilde{\phi}_i\right) = \quad \mathbf{x}'_{it}\beta + \mathbf{w}'_{it}\mathbf{\Psi}\bar{\mathbf{x}}_i + \mathbf{w}_{it}\tilde{\phi}_i \tag{7}$$

Equation (7) defines a random coefficient model corrected for potential endogeneity. As it can be easily evinced, the parameter vector $\beta$ in equation (7) measures the so-called *within* effect of the dynamics in $\mathbf{x}$ on the growth rate of *per capita* GDP.

Parameters in $\Psi$ measure the *indirect* effect of $\mathbf{x}$, mediated by the unobserved covariates through their correlation with the observed ones, and $\tilde{\phi}$ measures country-specific departures from the homogeneous model, not explained by the values of the observed covariates. In equation (7), not only the country-specific intercepts, but also the saving rates may be a function of taxation instruments. In this sense, we say that our model is an extension of the standard Barro-type model.

Equation (7) defines a two-level mixture regression model (Muthén and Asparouhov, 2009), where there are two different sources of variation: i) the residual variance, which is at the country level, and ii) the country-specific values for the regression parameters. These individual attributes lead to country-specific relationships between capital shares and the growth rate of *per capita* GDP.

To estimate the effects on growth we employ a Finite Mixture model (hereafter, FMM), relaxing the assumption of i.i.d. residuals, introducing marginal dependence between observations collected at different time points on the same statistical unit and imposing no constraints on the distribution of the random parameters (see e.g., Aitkin and Rocci, 2002). The random term $\tilde{\phi}_i$ can be defined as having a discrete distribution with masses $\pi_k$ associated to location $\zeta_k$, $k = 1, \ldots, K$, that is $\tilde{\phi}_i \sim \sum_k \pi_k \delta_\phi(\zeta_k)$, where $\delta_x(a) = 1$ if $x = a$, 0 otherwise. This prevents the effect of potential misspecification of the random effect distribution.[3] Details on the maximum likelihood estimation are provided in Appendix A.

**Modelling assumptions** Rather than assuming that mean tax levels of any type influence any of the effects in $\tilde{\phi}_i$, we restrict the non-zero values in $\mathbf{\Psi}$, in equation (5), according to the following assumptions on the mechanisms through which taxation may affects GDP dynamics. First, the overall tax burden, $\tau_T$, affects the country-specific coefficient associated to the Total Factor Productivity (see Gemmell et al., 2011). Second, the personal income tax share, $\tau_w$, impacts the country-specific parameter for the accumulation process of human capital.[4] Third, taxation on corporate income, $\tau_k$, influences the country-specific coefficient for physical capital share. Once the above assumptions have been included in the empirical model, equations (4) and (5) can be written in the following system

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[3] For a review, see Neuhaus and McCulloch (2006).

[4] Personal income tax influences income (and savings) but also the return on financial savings, and therefore the individual savings/investment process. High income tax and social security contributions on low-wage workers can reduce the individual incentive to work leading people to choose staying on social benefits rather than going to work, see eg Brewer et al. (2010). If this is true, people have not enough resources to invest in personal and/or children education.

$$\begin{cases} \gamma_{it} = \alpha_i + \beta_0 \log(y_{i0}) + \beta_i^h \log(s_h)_{it} + \beta_i^k \log(s_k)_{it} + \beta_3 \log(n+g+d)_{it} + \\ \qquad + \delta_1 \tau_{T,it} + \delta_2 \tau_{w,it} + \delta_3 \tau_{k,it} + \varepsilon_{it} \\ \alpha_i = \tilde{\phi}_i^A + \psi_{00} \overline{\tau}_{T,i} + \psi_{01} \overline{\log(s_h)}_i + \psi_{02} \overline{\log(s_k)}_i \\ \beta_i^h = \tilde{\phi}_i^h + \psi_{10} \overline{\tau}_{w,i} + \psi_{12} \overline{\log(s_k)}_i \\ \beta_i^k = \tilde{\phi}_i^k + \psi_{20} \overline{\tau}_{k,i} + \psi_{21} \overline{\log(s_h)}_i \end{cases} \tag{8}$$

where:

i) the $\tilde{\phi}$ terms capture the effect of omitted covariates, once we condition on the observed ones;

ii) $\alpha_i, \beta_i^k, \beta_i^h$ are allowed to vary across countries as a function of mean levels for tax policy measures $\overline{\tau}_{it} = (\overline{\tau}_{T,it}, \overline{\tau}_{w,it}, \overline{\tau}_{k,it})$, and capital shares $\overline{\log(s_k)}_i$ and $\overline{\log(s_h)}_i$;

iii) $\delta_1$, $\delta_2$ and $\delta_3$ measure the *direct* effects of taxes on growth rate of *per capita* GDP, while $\psi_{00}, \psi_{10}, \psi_{20}$ represent the *indirect* effect of tax policies on growth path;:[5]

iv) $\tilde{\phi}_i^A, \tilde{\phi}_i^h, \tilde{\phi}_i^k$ represent country-specific random terms that are linearly free of observed covariates.

After some algebraic steps, system (8) can be rewritten as follows:

$$\begin{aligned} \gamma_{it} &= \left(\tilde{\phi}_i^A + \psi_{00} \overline{\tau}_{T,i} + \psi_{01} \overline{\log(s_h)}_i + \psi_{02} \overline{\log(s_k)}_i\right) + \beta_0 \log(y_{i0}) + \\ &+ \left(\tilde{\phi}_i^h + \psi_{10} \overline{\tau}_{w,i} + \psi_{12} \overline{\log(s_k)}_i\right) \log(s_h)_{it} + \\ &+ \left(\tilde{\phi}_i^k + \psi_{20} \overline{\tau}_{k,i} + \psi_{21} \overline{\log(s_h)}_i\right) \log(s_k)_{it} + \\ &+ \beta_3 \log(n+g+d)_{it} + \delta_1 \tau_{T,it} + \delta_2 \tau_{w,it} + \delta_3 \tau_{k,it} + \varepsilon_{it} \end{aligned} \tag{9}$$

The FMM results in a (multivariate) discrete distribution on $\tilde{\phi}_i^A$, $\tilde{\phi}_i^h$ and $\tilde{\phi}_i^k$, obtained once we account for the effect of mean tax and shares levels on unobserved country-specific effects.

## 4 The empirical analysis

**Data set** Our sample is composed by a panel of 21 OECD countries, observed over the period 1965-2010. The Summers-Heston data set (PWT 9) provides information on *per capita* GDP, investment shares on physical capital and employment. The investment on human capital has been proxied by the Human Capital Index reported in PWT 9. OECD fiscal database (2017) provides information on fiscal policy. Following Arnold (2008), Gemmel et al. (2014), Kneller et al. (1999) and Lee and Gordon (2005), we focus on the following fiscal instruments: the personal income tax rate ($\tau_w$), the corporate income

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[5] This is an observational effect, linked to country-specific mean levels of taxation on the GDP growth path. Notice that the system of equations (8) is reminiscent to Pesaran and Smith (1995) and Pedroni (2007). Differently to them, however, we do not impose any restrictions on the distributions of the random terms ($\tilde{\phi}$), which are, instead, free to vary across countries according to an unspecified density function $g(\cdot)$.

tax rate ($\tau_k$) and the total tax burden, defined as total revenues over GDP ($\tau_T$). To describe the clusters, we also consider the following fiscal variables: the personal income taxes including social security contributions and taxes on payroll ($\tau_n$), the tax on consumption ($\tau_c$), the tax on sales ($\tau_s$) and the social security contributions ($ssc$). Tables 1 and 2 report variable definitions and descriptive statistics.[6]

To reduce the problem of endogeneity between future income and past tax rates in an inter-temporal allocation decision process, we build our covariate with a five years lag.[7]

Table 3 shows that the link between fiscal policy variables and growth rates of *per capita* GDP is not homogeneous across countries. The correlation between GDP growth rates and $\tau_T$ is negative for Germany, Spain and US but not for UK, Sweden or Switzerland; the correlation between GDP growth rates and $\tau_w$ is negative for Japan, Netherlands or United Kingdom but it is positive for Italy, Germany or US. Last, the correlation between GDP growth rates and $\tau_w$ is positive for US and Italy but not for Germany. In the next paragraph, we assess whether these different correlations are due to some country-specific characteristics. Figure 1 shows the clusters growth rates of *per capita* GDP during the analyzed period.

**Results** This paragraph uses the framework developed above to disentangle the sources of the cross-country relation between different taxation instruments and the growth rate of *per capita* GDP. We start by using the baseline specification (9) to proceed with the cluster analysis. In fact, FMM allows to group units into homogeneous components, sharing the same values of latent country-specific parameters (see and Ng and McLachlan, 2014; and Lu et al., 2016).[8] Here, each component is a cluster of countries and each country is assigned to a cluster according to a maximum *a posteriori* (MAP) rule, i.e. the $i$-th country is assigned to the $l$-th component if $\widehat{z}_{il} = \max(\widehat{z}_{i1}, \ldots, \widehat{z}_{iK})$. Table 4 presents the classification based on the MAP rule, along with the average rates of growth for the variables used in the regression. Since the Bayesian information criterion (BIC) for model in equation (9) achieves its minimum for a model with three components, we opt for a classification with three clusters of countries. Rootogram in Figure 2 for the posteriors shows that components are quite well separated. The average *per capita* GDP growth rates for each group are: 2.3% for Cluster 1, 3% for Cluster 2 and 2.2% for Cluster 3.

Table 5 reports the parameter estimates for our baseline model. The FMM has a better fit than the fixed-effect OLS model: to see this immediately, look at Figure 3 in which we overlay the empirical density functions of $\gamma$, obtained via FMM (dotted line) and via OLS Fixed Effects (dashed line), to that corresponding to observed data. Moreover, OLS estimates are biased because of the residuals' non-normality, i.e. the Shapiro-Wilk test rejects the normality hypothesis (with a value 0.955 and a p-value=0.000). On the contrary, the hypothesis is not rejected for all the three components identified via FMM.

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[6] For a complete definition of the taxation variables, the interested reader may refer to http://www.oecd.org/tax/tax-policy/global-revenue-statistics-database.htm.

[7] The choice of five-year periods lag is standard in the panel growth literature since it both ensures enough degrees of freedom and avoids the negative effects of strong autocorrelation of dependent variables (see, among others, Bond et al., 2001).

[8] This means that, conditionally on the observed covariates, countries belonging to the same cluster have shown a similar "structure", at least along the period under observation.

The coefficient on the initial level of income ($\log(y_0)$) is significantly negative (-2.45), i.e. there is a significant tendency toward convergence across OECD countries. The impact of savings rates, which is cluster-specific, when statistically significant is always positive. Unpleasantly, the parameter for $\log(s_k)$ is not statistically significant in the cluster composed by Ireland and Norway. A potential explanation is that, along the sample period, both countries have behaved as outliers in the distribution of one o more variables: Ireland has grown at the highest growth rate (4.3%) while Norway, despite its sustained growth (3%), has shown the largest decrease in $s_k$ (-54.5%). As we will see below, since $s_k$ and $s_h$ are cluster-specific, the effectiveness of fiscal policy on growth may vary across clusters.[9]

Overall, our estimates clearly indicate that taxes are negative for growth (see also the discussion on Table 10 below). In particular, taxes on personal income and corporate income exert a negative *direct* effect (-0.08 and -0.14, respectively) on *per capita* GDP growth; the total tax burden ($\tau_T$), instead, has no statistically significant effect on growth. This is in contrast to Angelopoulos et al. (2007) but in line with Kneller et al. (1999). Estimates for the interaction between capital shares and taxation instruments indicate a negative *indirect* effect of both $\tau_k$ (-0.04) and $\tau_w$ (-0.03). Qualitatively, these results are in line with those of Kneller et al. (1999), Arnold (2008), Lee and Gordon (2005) and Brewer et al. (2010).

The negative effects of $\overline{\log(s_k)}_i$ and $\overline{\log(s_h)}_i$ on growth (-4.46 and -12.81, respectively) reflect that countries with a greater initial endowment of physical and human capital grow less than those with an initial disadvantage.

**Robustness** Our results do not change when we divide the sample into two sub-periods "pre great moderation"(1965-1990) and "great moderation"(1990-2007) or when we exclude the years of the global financial crisis (2008-2010).[10] Qualitatively, our results hold even when we depart from the baseline specification (9). As a robustness check, we estimate four further specifications in which we modify the hypotheses about the channels through which taxation may affect GDP growth. In model (II), we assume that all fiscal instruments affect the aggregate TFP:

$$\alpha_i = \tilde{\phi}_i^A + \psi_{00}\overline{\tau}_{T,i} + \psi_{01}\overline{\tau}_{w,i} + \psi_{02}\overline{\tau}_{k,i} + \psi_{04}\overline{\log(s_h)}_i + \psi_{05}\overline{\log(s_k)}_i \tag{10}$$

In model (III), we assume that the aggregate TFP is affected by public capital accumulation $k_g$ (as a share of national GDP) while the capital shares are influenced by the income and investment tax rates as in equation (9):

$$\alpha_i = \tilde{\phi}_i^A + \psi_{00}\overline{k}_g + \psi_{01}\overline{\log(s_h)}_i + \psi_{02}\overline{\log(s_k)}_i \tag{11}$$

In model (IV), we assume that corporate taxation, by reducing the firms investment in incremental know-how, influences human capital accumulation:

$$\beta_i^h = \tilde{\phi}_i^h + \psi_{11}\overline{\tau}_{Ti} + \psi_{12}\overline{\tau}_{wi} + \psi_{13}\overline{\tau}_{ki} + \psi_{14}\overline{\log(s_h)}_i + \psi_{15}\overline{\log(s_k)}_i \tag{12}$$

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[9] The Jennrich (1970) test gives a $\chi^2 = 476.11$ (p-value=0.000), thus rejecting the hypothesis of an equal effects among components.

[10] These estimates are available upon request from the author.

In model (V), finally, we assume that the variability in country-specific parameters for physical capital can be partially explained by fiscal policy covariates:

$$\beta_i^k = \tilde{\phi}_i^k + \psi_{21}\overline{\tau}_{Ti} + \psi_{22}\overline{\tau}_{wi} + \psi_{23}\overline{\tau}_{ki} + \psi_{24}\overline{\log(s_h)}_i + \psi_{25}\overline{\log(s_k)}_i \qquad (13)$$

The results for models (II)-(V) are presented in Tables 6–9. The estimation of these models provides similar results in the random part and differences in the tax policy effects. For all model specifications, *direct* effects are found always negative: the coefficient of $\tau_w$ varies from from -0.08 and -0.09 while the coefficient for $\tau_k$ ranges from -0.13 and -0.14. The total tax burden $\tau_T$ is never statistically significant. Regarding the *indirect* effects on the GDP growth rate, we observe that in model (II) parameter estimates for $\tau_w$ and $\tau_k$ partially compensate those related to the *direct* effect, the "net"effect remaining negative. On the contrary, in model (III), parameters for the interactions between tax rates and saving rates reinforce the negative *direct* effects, even if only the one for $\tau_k \times \log(s_k)$ is statistically significant (-0.02). Globally, these results confirm the general negative impact of a higher taxation on GDP growth, and suggest that tax policy has quite homogenous effects (in magnitude, sign and significance) among countries. Further efforts, however, are needed to understand which covariate better discriminates between clusters.

**Discussion** The models presented above are (empirical) variations on a neoclassical theme, in which *per capita* GDP growth depends on the accumulation of physical and human capital and on the rate of technical changes. Fiscal policy modifications can generate output growth along the transition path. Transitions, however, can last for decades.[11]

The main message of our empirical exercise is that, across various samples and specifications, taxes are harmful for growth. Our estimates, however, call into question the effectiveness of tax cuts in boosting a more sustained growth. Table 10 reports the results of a "what if"exercise, in which we compute the change in GDP growth rate generated by a *ceteris paribus* cut by 10 % in $\tau_w$ and $\tau_k$. Despite the exercise is somewhat moot, it is instructive to quantify the impact of fiscal policy on GDP dynamics and allows to compare our results with those established by the existing literature. In the baseline model, these sizable tax cuts produce modest effects on growth, being associated to an increase of 1% in the GDP growth rate due to the cut in $\tau_w$ and of 0.9% due to the cut in $\tau_k$, respectively. These results partially contrast with those of Lee and Gordon (2005), who find a virtually zero impact for the cut in $\tau_w$ while a more beneficial effect for the cut in $\tau_k$ (around a 1.8% increase in the GDP growth rate). Despite effects are cluster-specific, differences across clusters are found negligible. Differently from the baseline model, a cut in the tax rate on corporate income is more beneficial for growth in model (III), in which the aggregate TFP is affected by public capital accumulation $k_g$, model (IV), in which $\tau_k$ also affects human capital accumulation, and model (V), in which

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[11] As pointed out by Lee and Gordon (2005), typically, fiscal policy adjusts in response to business-cycle fluctuations and this can cause short-run correlation between tax rates and the growth rate. Since our exercise focuses on the links between tax rates and average growth rates over more than thirty years, such short-run effects tend to average out.

both $\tau_w$ and $\tau_k$ interact with $\log(s_k)$.[12] The increase in the GDP growth is of 1% in models (II), (III) and (V) while it is larger in model (IV), +2%. In model (II), the two alternative policies deliver the same gain in terms of increase of the GDP growth rate (+1%).

Finally, for an additional reading of our results, we estimate a Multinomial Logit Model to assess the role of a set of explanatory variables in describing a country cluster's membership. In this exercise, we take the second cluster, $K$=2, as reference. The model evaluates the relative probability of being in one of the two remaining cluster against the reference, using a linear combination of predictors. The obtained MLE-estimated coefficients represent the effects of every predictor variable in the log-odds of being in any other regime versus the reference regime. As predictor variable we employ total tax burdern ($\tau_T$) tax on sales ($\tau_s$), tax on consumption ($\tau_c$) and social security contributions ($ssc$). Results in Table 11 indicate that the probability of being in the first Cluster, in response to a 1% increase

i) in $ssc$, increases by a multiplicative factor of $\exp(0.1342)=1.138$ (p-value=0.000) – i.e. the probability increases by 14%;

ii) in $\tau_s$, increases by a multiplicative factor of $\exp(-0.278)=0.763$ (p-value=0.000) – i.e. the probability decreases by 24%;

iii) in $\tau_T$, increases the probability of being in the first cluster, by a multiplicative factor of $\exp(-0.163)=0.852$ (p-value=0.000) – i.e. the probability decreases by 15%.

## 5 Concluding remarks

We propose and estimate an *augmented* Barro model to test the effects of taxation on growth. The model allows for heterogeneity in the capital (both physical and human) savings rates and in the intercept. The sources of unobserved heterogeneity are partially explained by country-specific taxation characteristics, through an auxiliary regression, controlling for potential endogeneity. In the Finite Mixture model, the random effect for the intercept captures country-specific institutional features, while the random effects for capital shares are affected by country-specific taxation instruments, such as the personal income tax rate and the corporate income tax.

Taxes affect the GDP growth both *directly* and *indirectly*. Direct effects refer to the impact that taxation may have on the level of technology while indirect effects are mediated by aggregate saving rates. By analyzing a variety of model specifications, we document a negative impact of taxation on real income dynamics. The effects are quite homogenous across countries. Their magnitude, however, is generally modest: on average, the *per capita* GDP growth rate raises of about 1% in response to a 10% cut in the considered tax rates. Our results are robust to changes in the sample period and survive to modifications of the baseline empirical model.

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[12] In model (III), in which TFP is a function public capital accumulation $k_g$, we make the conservative assumption that also $k_g$ drops by 10%.

## Compliance with Ethical Standards

**Conflict of Interest Statement**: the authors have no conflict of interest to declare.
**Ethical approval**: This article does not contain any studies with human participants performed by any of the authors.

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Table 1: Variable definition

| **Variable** | **Definition** |
|---|---|
| $\gamma$ | 5-years average *per capita* GDP growth rate |
| $\tau_T$ | total tax revenues as % of total GDP |
| $\tau_w$ | personal income tax, including personal income, social security contributions and taxes on payroll and workforce, categories 1100, 2000 and 3000 (OECD). |
| $\tau_k$ | corporate taxation as % of total tax revenues (tax category 1200, OECD) |
| $\tau_n$ | income taxes including social security contributions and taxes on payroll and workforce (categories 1110, 2000 and 3000, OECD). |
| $\tau_c$ | tax on consumption and property as % of total tax revenues, including tax on good and services, property and other tax (categories 5000 and 4000 and 6000, OECD). |
| $\tau_s$ | tax on sales as % of total tax revenues (category 5112, OECD). |
| $ssc$ | social security contributions as % of total tax revenues (category 2000, OECD) |

Table 2: Explanatory statistics (mean values) for used variables, 1965-2010

| **Country** | $\gamma$ | $s_h$ | $s_k$ | $n+g+d$ | $\tau_T$ | $\tau_k$ | $\tau_n$ | $\tau_w$ | $\tau_c$ | $ssc$ | $\tau_s$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Australia | 0.022 | 0.332 | 0.284 | 0.511 | 0.269 | 0.134 | 0.479 | 0.165 | 0.387 | 0.053 | 0.339 |
| Austria | 0.031 | 0.291 | 0.284 | 0.511 | 0.401 | 0.040 | 0.603 | 0.262 | 0.348 | 0.382 | 0.485 |
| Belgium | 0.027 | 0.271 | 0.281 | 0.505 | 0.421 | 0.058 | 0.634 | 0.292 | 0.305 | 0.312 | 0.409 |
| Canada | 0.022 | 0.323 | 0.252 | 0.520 | 0.328 | 0.096 | 0.493 | 0.197 | 0.403 | 0.136 | 0.392 |
| Denmark | 0.021 | 0.307 | 0.265 | 0.504 | 0.454 | 0.043 | 0.549 | 0.278 | 0.390 | 0.025 | 0.524 |
| Finland | 0.028 | 0.287 | 0.338 | 0.503 | 0.409 | 0.052 | 0.591 | 0.264 | 0.357 | 0.239 | 0.506 |
| France | 0.024 | 0.270 | 0.260 | 0.506 | 0.409 | 0.055 | 0.555 | 0.250 | 0.389 | 0.428 | 0.484 |
| Germany | 0.028 | 0.332 | 0.280 | 0.508 | 0.357 | 0.047 | 0.645 | 0.247 | 0.307 | 0.369 | 0.430 |
| Ireland | 0.043 | 0.268 | 0.262 | 0.523 | 0.314 | 0.071 | 0.435 | 0.159 | 0.493 | 0.144 | 0.607 |
| Italy | 0.033 | 0.248 | 0.264 | 0.504 | 0.348 | 0.083 | 0.579 | 0.231 | 0.337 | 0.348 | 0.395 |
| Japan | 0.035 | 0.313 | 0.333 | 0.497 | 0.253 | 0.194 | 0.536 | 0.184 | 0.271 | 0.305 | 0.224 |
| Luxembourg | 0.034 | 0.267 | 0.289 | 0.503 | 0.355 | 0.171 | 0.511 | 0.241 | 0.318 | 0.279 | 0.372 |
| Netherlands | 0.027 | 0.294 | 0.246 | 0.512 | 0.412 | 0.076 | 0.613 | 0.284 | 0.310 | 0.391 | 0.407 |
| New Zealand | 0.016 | 0.323 | 0.238 | 0.515 | 0.320 | 0.108 | 0.503 | 0.202 | 0.366 | . | 0.448 |
| Norway | 0.030 | 0.313 | 0.300 | 0.505 | 0.412 | 0.108 | 0.503 | 0.252 | 0.389 | 0.228 | 0.549 |
| Portugal | 0.036 | 0.218 | 0.304 | 0.508 | 0.304 | 0.097 | 0.441 | 0.163 | 0.459 | 0.265 | 0.654 |
| Spain | 0.032 | 0.238 | 0.266 | 0.512 | 0.276 | 0.070 | 0.587 | 0.182 | 0.339 | 0.398 | 0.356 |
| Sweden | 0.021 | 0.304 | 0.287 | 0.498 | 0.471 | 0.044 | 0.672 | 0.337 | 0.284 | 0.288 | 0.397 |
| Switzerland | 0.015 | 0.340 | 0.346 | 0.505 | 0.255 | 0.075 | 0.596 | 0.176 | 0.312 | 0.237 | 0.316 |
| United Kingdom | 0.027 | 0.316 | 0.216 | 0.504 | 0.349 | 0.088 | 0.485 | 0.199 | 0.427 | 0.184 | 0.442 |
| United States | 0.021 | 0.340 | 0.256 | 0.513 | 0.256 | 0.096 | 0.603 | 0.179 | 0.302 | 0.232 | 0.233 |
| Mean | 0.027 | 0.298 | 0.278 | 0.508 | 0.353 | 0.085 | 0.557 | 0.228 | 0.353 | 0.262 | 0.425 |

Figure 1: GDP growth rates by Groups

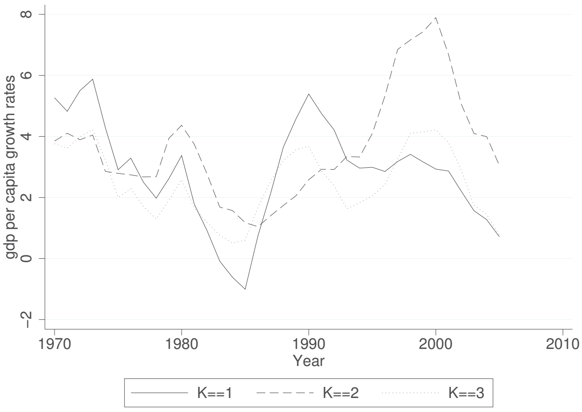


Table 3: Within country correlation between growth rate of *per capita* GDP and fiscal policy variables

| **Country** | $\rho_{\gamma\tau_T}$ | $\rho_{\gamma\tau_k}$ | $\rho_{\gamma\tau_w}$ | $\rho_{\gamma ssc}$ | $\rho_{\gamma\tau_c}$ | $\rho_{\gamma\tau_s}$ |
|---|---|---|---|---|---|---|
| Australia | 0.1781 | 0.4974 | -0.4376 | -0.2879 | -0.0496 | 0.0131 |
| Austria | -0.2293 | -0.018 | -0.3808 | -0.1649 | 0.2274 | -0.1515 |
| Belgium | -0.5532 | 0.3314 | -0.5003 | 0.0647 | 0.4753 | 0.2105 |
| Canada | -0.2542 | 0.7272 | -0.4217 | -0.4591 | 0.1107 | 0.2975 |
| Denmark | 0.1223 | 0.0293 | 0.0053 | 0.2219 | -0.0212 | -0.1832 |
| Finland | -0.1923 | 0.5496 | -0.6967 | -0.493 | 0.1716 | 0.2081 |
| France | -0.5433 | 0.6192 | -0.6526 | -0.5977 | 0.4915 | 0.4384 |
| Germany | -0.1431 | -0.1229 | -0.1384 | -0.3329 | 0.2389 | -0.0341 |
| Ireland | -0.2866 | 0.7286 | -0.0145 | -0.1402 | -0.3852 | -0.5499 |
| Italy | -0.5957 | -0.2245 | -0.3107 | 0.4804 | 0.2927 | 0.2182 |
| Japan | -0.4054 | 0.6047 | -0.6543 | -0.7717 | -0.1802 | -0.9426 |
| Luxembourg | -0.3556 | -0.0722 | -0.3682 | -0.2051 | 0.4054 | 0.2788 |
| Netherlands | -0.516 | 0.5411 | -0.4467 | -0.6938 | 0.3542 | 0.3079 |
| New Zealand | 0.3378 | 0.0322 | -0.4494 | . | 0.5114 | 0.5218 |
| Norway | 0.0441 | 0.2954 | -0.2765 | -0.5041 | -0.2504 | -0.1176 |
| Portugal | -0.3003 | 0.4125 | -0.2353 | -0.7761 | -0.4354 | -0.5523 |
| Spain | 0.0745 | 0.5621 | -0.4608 | -0.4036 | 0.3525 | 0.4374 |
| Sweden | 0.1364 | 0.3389 | -0.4209 | -0.2144 | 0.3647 | 0.167 |
| Switzerland | 0.3698 | 0.0588 | 0.2061 | 0.014 | -0.3427 | -0.434 |
| United Kingdom | 0.0485 | 0.3109 | -0.3693 | -0.0401 | 0.2492 | 0.3723 |
| United States | 0.3698 | 0.0588 | 0.2061 | 0.014 | -0.3427 | -0.434 |
| Legend: | † : 10%, $*$ : 5%, $**$ : 1%<br>The table reports country-specific correlations between the growth rate of *per capita* GDP and i) total tax revenues over GDP ($\rho_{\gamma\tau_T}$), ii) corporate tax revenues over total tax revenues ($\rho_{\gamma\tau_k}$), iii) personal income tax revenues over total tax revenues ($\rho_{\gamma\tau_w}$), iv) tax on sales revenues over total tax revenues ($\rho_{\gamma\tau_s}$), v) tax on social security revenues over total tax revenues $\rho_{\gamma ssc}$, vi) tax on consumption revenues over total tax revenues $\rho_{\gamma\tau_c}$. | | | | | |

Table 4: Clusters' composition

| **Country** | $\tau_w$ | $\tau_k$ | $\tau_T$ | $\tau_s$ | $ssc$ | $s_k$ | $s_h$ |
|---|---|---|---|---|---|---|---|
| | | | | **Cluster 1** | | | |
| Belgium | 0.110 | 0.145 | 0.314 | 0.682 | 0.065 | -0.046 | 0.301 |
| Italy | 0.157 | 0.046 | 0.579 | 0.059 | -0.186 | -0.144 | 0.396 |
| Japan | 0.260 | -0.410 | 0.424 | 0.914 | 0.653 | -0.364 | 0.222 |
| New Zealand | -0.066 | -0.060 | 0.421 | 0.624 | . | 0.153 | 0.067 |
| Spain | 0.050 | 0.310 | 1.264 | 0.230 | -0.109 | 0.323 | 0.323 |
| Mean | 0.102 | 0.006 | 0.600 | 0.399 | 0.106 | -0.016 | 0.262 |
| | | | | **Cluster 2** | | | |
| Ireland | 0.620 | 0.272 | 0.072 | -0.032 | 0.890 | 0.131 | 0.227 |
| Norway | -0.167 | 0.587 | 0.253 | -0.323 | 0.275 | -0.545 | 0.246 |
| Mean | 0.226 | 0.429 | 0.162 | -0.177 | 0.582 | -0.207 | 0.236 |
| | | | | **Cluster 3** | | | |
| Australia | 0.175 | -0.166 | 0.299 | -0.083 | 1.518 | -0.139 | 0.166 |
| Austria | 0.164 | 0.194 | 0.241 | 0.252 | 0.228 | 0.138 | 0.223 |
| Canada | 0.241 | -0.082 | 0.067 | -0.088 | 0.735 | 0.171 | 0.263 |
| Denmark | -0.021 | 1.908 | 0.325 | -0.100 | -0.198 | -0.104 | 0.222 |
| Finland | 0.102 | 0.423 | 0.391 | -0.134 | 1.037 | -0.290 | 0.341 |
| France | 0.197 | -0.126 | 0.289 | -0.338 | 0.058 | -0.219 | 0.287 |
| Germany | 0.094 | -0.096 | 0.111 | -0.030 | 0.291 | -0.492 | 0.239 |
| Luxembourg | -0.126 | -0.203 | 0.601 | 0.508 | -0.063 | 0.835 | 0.453 |
| Netherlands | -0.003 | 0.105 | 0.207 | -0.054 | 0.169 | -0.261 | 0.151 |
| Portugal | -0.025 | 0.221 | 0.064 | 0.037 | 0.030 | -0.047 | 0.090 |
| Sweden | -0.043 | 0.708 | 0.292 | 0.186 | 0.955 | -0.332 | 0.199 |
| Switzerland | 0.100 | 0.023 | 0.463 | -0.076 | 0.501 | -0.319 | 0.127 |
| United Kingdom | -0.041 | 0.075 | -0.034 | 0.423 | 0.022 | -0.213 | 0.315 |
| United States | 0.129 | -0.121 | 0.012 | -0.028 | 0.517 | 0.155 | 0.187 |
| Mean | 0.072 | 0.205 | 0.246 | 0.034 | 0.432 | -0.081 | 0.240 |

In table are reported the long run growth rates (from 1970 to 2005) of the variables used in the regressions

Table 5: *Augmented* Barro model (I), equation (9)

| | **OLS FE** | **Finite Mixture Model** | | |
|---|---|---|---|---|
| | | **Cluster 1** | **Cluster 2** | **Cluster 3** |
| | | *Country-specific parameters* | | |
| *Intercept* | 118.29*** | 35.13*** | 11.94 | 11.63 |
| $\log(s_k)$ | 1.997*** | 9.02*** | $-1.22$ | 3.68*** |
| $\log(s_h)$ | 17.232*** | 9.40*** | 19.42*** | 11.39*** |
| | | *Direct effects* | | |
| $\log(y_{0,i})$ | $-4.384^{***}$ | $-2.45^{***}$ | $-2.45^{***}$ | $-2.45^{***}$ |
| $\log(n+g+d)$ | $-7.277^{**}$ | $-6.22^{**}$ | $-6.22^{**}$ | $-6.22^{**}$ |
| $\tau_T$ | $-0.003$ | 0.02 | 0.02 | 0.02 |
| $\tau_w$ | $-0.067^{***}$ | $-0.08^{***}$ | $-0.08^{***}$ | $-0.08^{***}$ |
| $\tau_k$ | $-0.053$ | $-0.14^{***}$ | $-0.14^{***}$ | $-0.14^{***}$ |
| | | *Indirect effects* | | |
| $\overline{\tau}_{T,i}$ | | $-0.02$ | $-0.02$ | $-0.02$ |
| $\overline{\tau}_{w,i} \times \log(s_h)$ | | $-0.03^{***}$ | $-0.03^{***}$ | $-0.03^{***}$ |
| $\overline{\tau}_{k,i} \times \log(s_k)$ | | $-0.04^{***}$ | $-0.04^{***}$ | $-0.04^{***}$ |
| $\overline{\log(s_h)}_i$ | | $-12.81^{***}$ | $-12.81^{***}$ | $-12.81^{***}$ |
| $\overline{\log(s_k)}_i$ | | $-4.46^{***}$ | $-4.46^{***}$ | $-4.46^{***}$ |
| $\hat{\sigma}^2$ | | 1.6 | | |
| $\hat{\pi}_k$ | | 0.252 | 0.096 | 0.652 |
| $\hat{z}_k$ | | 0.249 | 0.099 | 0.651 |
| Log-likelihood | | -1392.547 | | |
| BIC | | 2930.14 | | |
| $R^2$ | 0.001 | | | |
| Breusch-Pagan LM test | $\chi^2 = 143^{***}$ | | | |
| Pesaran CD test | $Z = 29.427^{***}$ | | | |
| Observations | 730 | 730 | | |

Significance levels: $***$: 0.001 $**$ : 0.01 $^*$ 0.05.

Note: $\hat{\sigma}^2$, variance of the random terms; $\hat{\pi}_k$, estimated prior probabilities; $\hat{z}_k$, estimated posterior probabilities.

Table 6: Robusteness check, *Augmented* Barro model (II) “effects only on TFP”, equations (8) + (10)

| | **Cluster 1** | **Cluster 2** | **Cluster 3** |
|---|---|---|---|
| | | *Country-specific parameters* | |
| *Intercept* | 25.73** | 46.26*** | $-$23.78* |
| $\log(s_k)$ | 3.18*** | 8.98*** | $-$1.48 |
| $\log(s_h)$ | 14.62*** | 10.91*** | 8.02** |
| | | *Direct effects* | |
| $\log(y_{0,i})$ | $-$2.94*** | $-$2.94*** | $-$2.94*** |
| $\log(n+g+d)$ | $-$5.05* | $-$5.05* | $-$5.05* |
| $\tau_T$ | 0.02 | 0.02 | 0.02 |
| $\tau_w$ | $-$0.09*** | $-$0.09*** | $-$0.09*** |
| $\tau_k$ | $-$0.15*** | $-$0.15*** | $-$0.15*** |
| | | *Indirect effects* | |
| $\overline{\tau}_{T,i}$ | $-$0.019 | $-$0.019 | $-$0.019 |
| $\overline{\tau}_{w,i}$ | 0.08** | 0.08** | 0.08** |
| $\overline{\tau}_{k,i}$ | 0.14** | 0.14** | 0.14** |
| $\overline{\log(s_h)}_i$ | $-$14.64*** | $-$14.64*** | $-$14.64*** |
| $\overline{\log(s_k)}_i$ | $-$3.70*** | $-$3.70*** | $-$3.70*** |
| $\hat{\sigma}$ | 1.6 | | |
| $\hat{\pi}_k$ | 0.652 | 0.247 | 0.098 |
| $\hat{z}_k$ | 0.647 | 0.251 | 0.102 |
| Log-likelihood | -1399.72 | | |
| BIC | 2944.487 | | |
| Observations | 730 | | |

Significance levels: $***$: 0.001 $**$ : 0.01 $^*$ 0.05.

Note: $\hat{\sigma}^2$, variance of the random terms; $\hat{\pi}_k$, estimated prior probabilities; $\hat{z}_k$, estimated posterior probabilities.

Table 7: Robusteness check, *Augmented* Barro model (III), “with public capital”, equations (8) + (11)

| | **Cluster 1** | **Cluster 2** | **Cluster 3** |
|---|---|---|---|
| | | *Country-specific Parameters* | |
| *Intercept* | 34.79*** | 51.89*** | −13.45 |
| $\log(s_h)$ | 16.83*** | 12.82*** | 10.54*** |
| $\log(s_k)$ | 3.34*** | 8.74*** | −1.31 |
| | | *Direct effects* | |
| $\log(y_{0,i})$ | −3.00*** | −3.00*** | −3.00*** |
| $\log(n+g+d)$ | −4.42* | −4.42* | −4.42* |
| $k_g$ | −0.02*** | −0.02*** | −0.02*** |
| $\tau_w$ | −0.08*** | −0.08*** | −0.08*** |
| $\tau_k$ | −0.13*** | −0.13*** | −0.13*** |
| | | *Indirect effects* | |
| $\overline{k}_{g,i}$ | 0.02* | 0.02* | 0.02* |
| $\overline{\tau}_{w,i} \times \log(s_h)$ | −0.02 | −0.02 | −0.02 |
| $\overline{\tau}_{k,i} \times \log(s_k)$ | −0.02*** | −0.02*** | −0.02*** |
| $\overline{\log(s_h)}_i$ | −15.19*** | −15.19*** | −15.19*** |
| $\overline{\log(s_k)}_i$ | −3.38*** | −3.38*** | −3.38*** |
| $\hat{\sigma}^2$ | 1.61 | | |
| $\hat{\pi}_k$ | 0.6455 | 0.2584 | 0.0953 |
| $\hat{z}_k$ | 0.647 | 0.2531 | 0.0995 |
| Log-likelihood | -1396.957 | | |
| BIC | 2938.962 | | |
| Observations | 730 | | |

Significance levels: $***$: 0.001 $**$ : 0.01 $^{*}$ 0.05.

Note: $\hat{\sigma}^2$, variance of the random terms; $\hat{\pi}_k$, estimated prior probabilities; $\hat{z}_k$, estimated posterior probabilities.

Table 8: *Robusteness check, Augmented* Barro model (IV), “effects only through the coefficient for $\log(s_h)$”, equations (8) + (12)

| | **Cluster 1** | **Cluster 2** | **Cluster 3** |
|---|---|---|---|
| | | *Country-specific parameters* | |
| *Intercept* | 19.13* | 34.44*** | −4.47 |
| $\log(s_k)$ | 3.89*** | 8.74*** | −1.55* |
| $\log(s_h)$ | 13.43*** | 9.87*** | 15.51*** |
| | | *Direct effects* | |
| $\log(y_{0,i})$ | −2.87*** | −2.87*** | −2.87*** |
| $\log(n+g+d)$ | −6.12** | −6.12** | −6.12** |
| $\tau_T$ | 0.02 | 0.02 | 0.02 |
| $\tau_w$ | −0.08*** | −0.08*** | −0.08*** |
| $\tau_k$ | −0.14*** | −0.14*** | −0.14*** |
| | | *Indirect effects* | |
| $\overline{\tau}_{T,i} \times \log(s_h)$ | 0.01 | 0.01 | 0.01 |
| $\overline{\tau}_{w,i} \times \log(s_h)$ | −0.03*** | −0.03*** | −0.03*** |
| $\overline{\tau}_{k,i} \times \log(s_h)$ | −0.06*** | −0.06*** | −0.06*** |
| $\overline{\log(s_h)}_i$ | −12.34*** | −12.34*** | −12.34*** |
| $\overline{\log(s_k)}_i$ | −4.83*** | −4.83*** | −4.83*** |
| $\hat{\sigma}$ | 1.593 | | |
| $\hat{\pi}_k$ | 0.591 | 0.264 | 0.145 |
| $\hat{z}_k$ | 0.597 | 0.254 | 0.149 |
| Log-likelihood | -1392.126 | | |
| BIC | 2929.298 | | |
| Observations | 730 | | |

Significance levels: $***$: 0.001 $**$ : 0.01 $^*$ 0.05.

Note: $\hat{\sigma}^2$, variance of the random terms; $\hat{\pi}_k$, estimated prior probabilities; $\hat{z}_k$, estimated posterior probabilities.

Table 9: *Robusteness check, Augmented* Barro model (V), “effects only through the coefficient fo log($s_k$)”, equations (8) + (13))

| | **Cluster 1** | **Cluster 2** | **Cluster 3** |
|---|---|---|---|
| | *Country-specific parameters* | | |
| *Intercept* | 17.75$^*$ | 34.20$^{***}$ | $-5.91$ |
| $\log(s_k)$ | 4.97$^{***}$ | 10.04$^{***}$ | $-0.45$ |
| $\log(s_h)$ | 10.89$^{***}$ | 7.28$^{***}$ | 12.91$^{***}$ |
| | *Direct effects* | | |
| $\log(y_{0,i})$ | $-2.44^{***}$ | $-2.44^{***}$ | $-2.44^{***}$ |
| $\log(n+g+d)$ | $-6.52^{**}$ | $-6.52^{**}$ | $-6.52^{**}$ |
| $\tau_T$ | 0.03 | 0.03 | 0.03 |
| $\tau_w$ | $-0.08^{***}$ | $-0.08^{***}$ | $-0.08^{***}$ |
| $\tau_k$ | $-0.13^{***}$ | $-0.13^{***}$ | $-0.13^{***}$ |
| | *Indirect effects* | | |
| $\overline{\tau}_{T,i} \times \log(s_k)$ | 0.00 | 0.00 | 0.00 |
| $\overline{\tau}_{w,i} \times \log(s_k)$ | $-0.02^{***}$ | $-0.02^{***}$ | $-0.02^{***}$ |
| $\overline{\tau}_{k,i} \times \log(s_k)$ | $-0.04^{***}$ | $-0.04^{***}$ | $-0.04^{***}$ |
| $\overline{\log(s_h)}_i$ | $-11.86^{***}$ | $-11.86^{***}$ | $-11.86^{***}$ |
| $\overline{\log(s_k)}_i$ | $-4.81^{***}$ | $-4.81^{***}$ | $-4.81^{***}$ |
| $\hat{\sigma}$ | 1.593 | | |
| $\hat{\pi}_k$ | 0.596 | 0.269 | 0.146 |
| $\hat{z}_k$ | 0.597 | 0.254 | 0.149 |
| Log-likelihood | 2832.366 | | |
| BIC | 2933.413 | | |
| Observations | 730 | | |

Significance levels: $***$: 0.001 $**$ : 0.01 $^*$ 0.05.
Note: $\hat{\sigma}^2$, variance of the random terms; $\hat{\pi}_k$, estimated prior probabilities; $\hat{z}_k$, estimated posterior probabilities.

Table 10: Effect on *per capita* GDP growth rate of a 10% cut in $\tau_w$ and $\tau_k$

| | **Baseline model** | | **Model (II)** | | **Model (III)** | | **Model (IV)** | | **Model (V)** | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $\tau_w$ | $\tau_k$ | $\tau_w$ | $\tau_k$ | $\tau_w$ | $\tau_k$ | $\tau_w$ | $\tau_k$ | $\tau_w$ | $\tau_k$ |
| **Cluster 1** | 1% | 0.9% | 1% | 1% | 0.6% | 1% | 1% | 2% | 0.5% | 0.8% |
| **Cluster 2** | 1% | 0.9% | 1% | 1% | 0.6% | 1% | 1% | 2% | 0.5% | 0.8% |
| **Cluster 3** | 1% | 0.9% | 1% | 1% | 0.6% | 1% | 1% | 2% | 0.5% | 0.8% |

Table 11: Multinomial Logit Model for cluster membership

| | **Cluster 1** | **Cluster 2** |
|---|---|---|
| *Intercept* | 0.227$^{**}$ | 0.237$^{**}$ |
| $\tau_T$ | -0.163$^{**}$ | -0.140$^{**}$ |
| $ssc$ | 0.134$^{**}$ | 0.293 |
| $\tau_c$ | -0.141$^{\dagger}$ | -0.138$^*$ |
| $\tau_s$ | -0.278$^{**}$ | -0.199$^{**}$ |
| $\gamma$ | 0.001 | -0.298$^{**}$ |

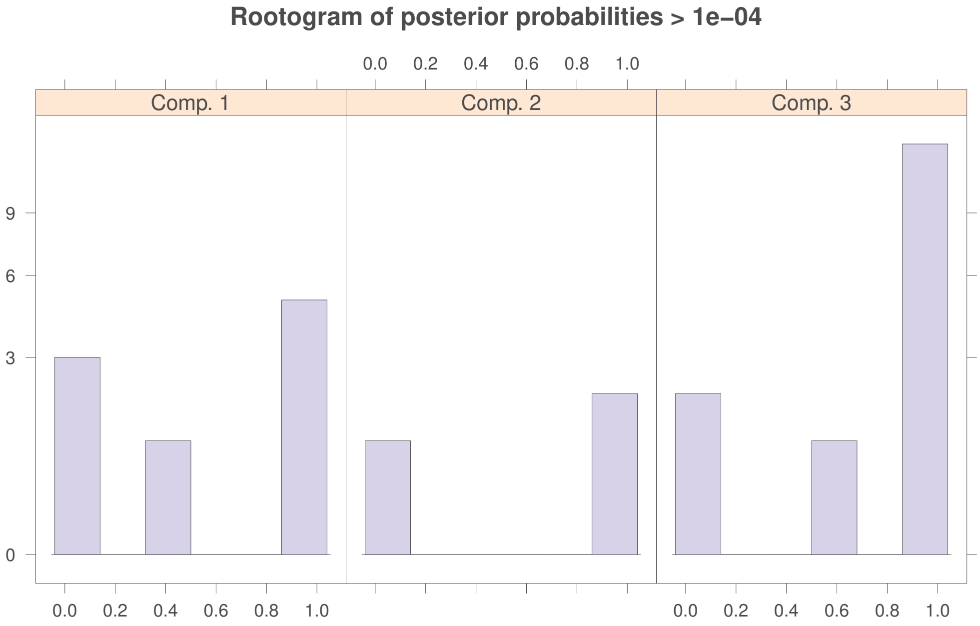


Figure 2: Rootogram for posterior component membership

# Appendix

## A ML parameter estimation

Our specification includes unobserved country-specific heterogeneity through country-specific parameters. As discussed by Aitkin et al. (2005), through this approach, we may consider several sources of model misspecification, ranging from omitted covariates, to wrong assumptions on either the link function or the conditional response distributions (eg Cobb-Douglas vs CES production function).

Using equation (7) and assuming conditional independence for the measurements corresponding to the same country, the probability density function for the country profile $\gamma_i$ can be written as:

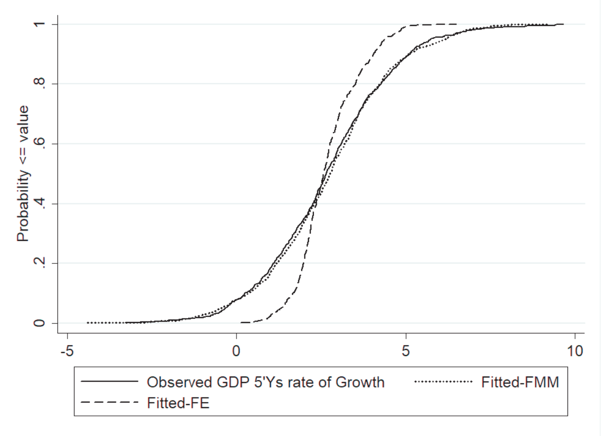
$$f\left(\gamma_i \mid \mathbf{x}_i, \tilde{\phi}_i\right) = \prod_{t=1}^{T} \left\{ \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[ -\frac{1}{2\sigma^2} \left(\gamma_{it} - \mu_{it}^{\gamma}\right)^2 \right] \right\}$$

Let us assume that $\tilde{\phi}_i \sim g(\cdot)$; treating the latent effects as nuisance parameters, and integrating them out, we obtain the following expression for the marginal likelihood:

$$L(\cdot) = \prod_{i=1}^{n} \left\{ \int_{\oplus} f(\gamma_i \mid \mathbf{x}_i, \tilde{\phi}_i) \mathrm{d}G(\tilde{\phi}_i | \mathbf{x}_i) \right\} \simeq \prod_{i=1}^{n} \left\{ \int_{\oplus} f(\gamma_i \mid \mathbf{x}_i, \tilde{\phi}_i) \mathrm{d}G(\tilde{\phi}_i) \right\} \quad (14)$$

since, as we showed before, $g(\tilde{\phi}_i | \mathbf{x}_i) \simeq g(\tilde{\phi}_i)$. Rather than using a parametric

Figure 3: Empirical cumulative functions for FMM in Table 5 and OLS FE (not reported)



specification, we leave for $G(\cdot)$ unspecified and provide a nonparametric maximum likelihood estimator for this term, see Laird (1978) and Lindsay (1983a, 1983b). According to such an approach, see Lindsay and Lesperance (1995) for a review, the integral in eq (14) may be approximated by the following weighted sum:

$$L(\cdot) = \prod_{i=1}^{n} \left\{ \sum_{k=1}^{K} f(\gamma_i \mid \mathbf{x}_i, \zeta_k)\pi_k \right\} = \prod_{i=1}^{n} \left\{ \sum_{k=1}^{K} f_{ik}\pi_k \right\} \tag{15}$$

where, as mentioned above, $\tilde{\phi}_i \sim \sum_{k=1}^{K} \pi_k \delta_k(\zeta_k)$, $K$ is the number locations $\zeta_k$, $k = 1, \dots, K$ (see McLachlan and Peel, 2000). The likelihood in equation (15) resembles the likelihood for a finite mixture of regression models, where groups of countries are associated to specific values of parameters. Since component memberships are unobserved, they may be thought of as missing data. For a fixed number of components $K$, we denote by $\mathbf{z}_i = (z_{i1}, \dots, z_{iK})$ the latent component-indicator vector, with elements

$$z_{ik} = \begin{cases} 1 & \text{if } \tilde{\phi}_{\mathrm{i}} = \zeta_{\mathrm{k}} \\ 0 & \text{otherwise} \end{cases} \tag{16}$$

Were this source of heterogeneity observed, the indicator variables would be known, and the model would reduce to a simple GLM regression model with group-specific parameters. The hypothetical space defined by the complete data problem is given by $(\gamma_i, \mathbf{x}_i, \mathbf{z}_i)$. Using a multinomial distribution for the unobserved vector of component indicators, $\mathbf{z}_i$, the log likelihood for the complete data can be written as:

$$\ell_c(\cdot) = \sum_{i=1}^{n} \sum_{k=1}^{K} z_{ik} \left\{ \log(\pi_k) + \log f_{ik} \right\} \tag{17}$$

By taking derivatives with respect to the vector of model parameters, $\theta$, we obtain:

$$\frac{\partial \log[L(\theta)]}{\partial \theta} = \frac{\partial \ell(\theta)}{\partial \theta} = \sum_{i=1}^{n} \sum_{k=1}^{K} \frac{\pi_k f_{ik}}{\sum\limits_{k=1}^{K} \pi_k f_{ik}} \frac{\partial \log f_{ik}}{\partial \theta} = \sum_{i=1}^{n} \sum_{k=1}^{K} \hat{z}_{ik} \frac{\partial \log f_{ik}}{\partial \theta} \tag{18}$$

where $\hat{z}_{ik}$ represents the posterior probability that the $i-th$ country comes from the $k-th$ component of the mixture, $f_{ik} = f(\gamma_i \mid \zeta_k)$ denotes the response distribution in that component, $k = 1, \ldots, K$, $i = 1, \ldots, n$, and $\theta = (\alpha_i, \beta_i^h, \beta_i^k, \Sigma_\phi)$. The corresponding likelihood equations are weighted sums of those for an ordinary regression model with log link and weights $\hat{\mathbf{z}}_{ik}$. Solving these equations for a given set of weights, and updating the weights from the current parameter estimates defines an EM algorithm, see eg McLachlan and Peel (2000).

Alfò et al. (2008) describes the EM algorithm in the context of Solow growth models. The mixture model explicitly considers country-specific growth paths, without any need to define, a priori, any threshold. It helps capture the country-specific structure, allowing for correlation between observed covariates and country-specific random parameters. A side result of FMMs is that we may provide a partition of countries in clusters characterized by homogeneous unobserved characteristics, based on the posterior probabilities $\hat{z}_{ik}$. According to a simple *maximum a posteriori* (MAP) rule, in fact, the $i$-th country may be classified into the $l$-th component if:

$$\hat{z}_{il} = \max(\hat{z}_{i1}, \ldots, \hat{z}_{iK}).$$

It is worth noticing that each component is characterized by homogeneous values of the estimated latent effects; that is, conditionally on the observed covariates, countries from the same group show a similar structure, at least in the steady state. Penalized likelihood criteria such as Akaike information criterion (Akaike, 1973), Bayesian information Criterion (Schwarz, 1978) or Consistent Akaike information criterion (Bodzogan, 1994) can be used to choose the number of mixture components used to approximate the (potentially continuous) distribution of the random parameters. Usually, attempts to estimate the model with too many components results either in one mass having an estimated probability approaching zero or two masses having nearly the same estimated location.

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