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Growth in regions

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Abstract We use a newly assembled sample of 1,528 regions from 83 countries to compare the speed of per capita income convergence within and across countries. Regional growth is shaped by similar factors as national growth, such as geography and human capital. Regional convergence rate is about 2 % per year, comparable to that between countries. Regional convergence is faster in richer countries, and countries with better capital markets. A calibration of a neoclassical growth model suggests that significant barriers to factor mobility within countries are needed to account for the evidence.

Keywords Convergence · Mobility barriers · Human capital

JEL Classification O43 · O47 · R11

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1 Introduction

Since the fundamental work of Barro (1991), the question of convergence of income levels between countries has received enormous attention (Barro et al. 1995; Caselli et al. 1996; Aghion et al. 2005; Barro 2012). Several papers also analyze convergence between regions of the same country, as in the case of Japanese prefectures, Canadian provinces, Australian regions, Russian regions, or U.S. states (Barro and Sala-I-Martin 1991, 1992, 1995; Blanchard and Katz 1992; Cashin 1995; Coulombe and Lee 1995; Sala-i-Martin 1996; Ganong and Shoag 2012; Guriev and Vakulenko 2012; Spilimbergo and Che 2012), but data availability has limited this kind of exercise. In this paper, we systematically study regional convergence by using a large sample of sub-national regions. To this end, we expand the dataset from Gennaioli et al. (2013) by collecting time-series data on regional GDP. Using data on 1,528 regions in 83 countries, we analyze the patterns of convergence among regions and compare them to convergence across countries.

There is substantial inequality among regions of the same country that needs to be understood. In Brazil, which is typical in terms of regional inequality among developing countries, the mean (median) region has per capita income in 2010 of about US $6,636 (US $4,859), and the standard deviation of regional GDP per capita is $3,205. In the average country in our dataset, the richest region is 4.7 times richer than the poorest one (roughly the difference between the US and South Africa in 2010), but sometimes differences are more extreme. For example, GDP per capita in the richest Mexican state, Campeche, is 16.4 times higher than that in the poorest, Chiapas, a difference roughly similar to that between US and Guyana in 2010. If we avoid extremely poor regions, which typically have small populations, and extremely rich regions, which typically have natural resources, inequality within countries is lower but still substantial. Moreover, poor countries display greater dispersion of regional GDP levels than rich countries. The average standard deviation of (log) per capita income in the 20 poorest countries is 1.64 times larger than the average dispersion of per capita income in the 20 richest countries (40 vs. 24 %).

These findings raise the question of whether the substantial within-country inequality is fictitious, in the sense that it reflects measurement problems. We show, however, that similar levels of inequality obtain if we look at satellite data from night-time lights as a proxy for per capita income (Henderson et al. 2012), or at living standards as proxied for by patterns of durable goods consumption (Young 2012). For a sub-sample of countries, we also use data on housing costs as a crude correction for cost-of-living differences, and find that the overwhelming part of regional inequality is real. Controlling for differences in housing costs, we estimate that, in an average country in our dataset, the richest region is 3.7 times richer than the poorest one, compared to the 4.7 times without the price level correction.

Because these income differences summarize past growth trajectories, understanding the speed of regional convergence can shed light on the persistence of regional inequality. Going back to the example of Brazil, even if all regions have the same steady state income, a region temporarily falling one standard deviation (36 %) below steady state income would take about 23 years to close the gap when the speed of catch up is Barro's "iron law" rate of 2 % per year.[1] In the meantime, inequality will persist.

These considerations raise four questions. What is the speed of regional convergence? How does it compare to the speed of convergence between countries? What factors determine it?

[1] The meta-analysis of Abreu et al. (2005) finds that across 48 studies the average convergence rate is 4.3 %, much higher than Barro's 2 %. In part, this finding is due to smaller samples. In part, it is due to the use of fixed effect estimation, which raises the convergence coefficient. Given our findings, a cross-country convergence rate above 2 % only deepens the puzzle of why regions don't converge faster than countries.

Is it consistent with patterns of regional inequality? Our data allows us to systematically address these questions. The focus on regional convergence also allows us to better assess the explanatory power of the neoclassical growth model. The estimates of cross-country convergence rates are potentially subject to severe omitted variable problems, owing to large heterogeneity between countries. This problem does not disappear in the case of sub-national regions, but it is less severe than at the national level. Regions are more homogeneous than countries in terms of productivity, institutions, and access to technology.

To organize the discussion, we present a neoclassical model of regional growth related to the earlier work of Barro et al. (1995), Braun (1993), and Ganong and Shoag (2012). To account for persistent disparities in regional incomes, we incorporate into the model a stylized process of mobility of human and physical capital from regions where it is abundant to regions where it is scarce subject to an exogenous mobility friction. This model generates a modified growth equation, which predicts that the speed of regional convergence decreases in the severity of mobility frictions. The model also predicts that a region's per capita income growth should rise with country-level income to an extent that increases in factor mobility. A region can attract more capital, and thus grow faster, when integrated into a richer country. Both of these predictions are new and empirically testable.

Empirically, we find that doubling national income raises regional growth by about 1.5 %. Regional convergence is about 2 % per year, exactly the "iron law" rate found by Barro (2012). In our sample of countries, national convergence rate is slightly faster than 1 %, only slightly slower than the regional rate. This result, which is not substantially affected by country fixed effects, is puzzling. Barriers to the mobility of human and physical capital are arguably much less important within than between countries, implying, contrary to what we find, much faster regional than national convergence. Slow regional convergence is the key finding of our growth accounting exercise.

Slow regional convergence is not the result of obvious measurement problems. As in Barro (2012), we estimate our equation for regional growth using lagged GDP as an instrument for current GDP, because the latter might be measured with error. The estimated regional convergence rate falls to 1.9 %, but due to decline in sample size, not the use of IV. We also show that slow convergence is robust to accounting for cost-of-living differences.[2] Finally, the similarity between regional and national convergence rates is unlikely to be due to the omitted variables problem, because this problem is surely less severe at the regional than at the national level. Omitted variables should cause a relative overstatement of regional convergence rates.

Motivated by the evidence of limited regional convergence, we explore whether slow regional convergence is the product of institutional barriers to regional mobility of resources. To this end, we run regional growth regressions by including interactions of regional GDP with proxies for national market institutions as well as government transfers. We find that regional convergence is faster in richer countries, consistent with the latter having lower regional inequality, and in countries with better-regulated capital markets and fewer trade barriers. However, even the statistically significant determinants of the speed of convergence do not move the convergence rate much beyond Barro's "iron law". Mapping estimated coefficients into the parameters of the model points to rather slow mobility of capital in

2 Different limits to mobility have different consequences for welfare. In the case of non-tradability of certain locally produced goods, such as housing, perfect mobility of labor would suffice to equalize the living standards of workers across regions (as differences in price levels would offset nominal income differences). Barriers to mobility of labor would in contrast entail differences in the living standards of workers across regions. In our analysis, we try to directly measure living costs as well as potential regulatory barriers to mobility and look at migration of productive factors.

response to within-country return differences. The elasticity of migration to yearly regional return differentials implied by our model is about 0.85, not far from the cross country elasticity of migration documented by Ortega and Peri (2009).

This evidence seems at odds with the findings of high regional mobility in the U.S. To further investigate mobility in our sample of countries, we collect direct evidence—for 33 countries—on the share of employees, as well as of skilled employees, who are recent migrants. Consistent with our growth regressions, we show that these shares are on average rather small, and smaller for poorer regions and in countries with poorly-regulated capital markets.

As a final robustness check, we estimate fixed effects growth regressions. From cross country studies, it is well known that fixed effects boost the estimated speed of convergence. In our sample, the introduction of country fixed effects increases national convergence rates by roughly 2 percentage points. If we include regional fixed effects, the speed of regional convergence rises substantially, by anywhere from 1.5 to 8 percentage points. We concur with Barro (2012) that fixed effects estimates likely lead to a large Hurwicz bias, particularly at the sub-national level, where the omitted variable problem is much less severe. We therefore emphasize the OLS estimates in the presentation of the results. Even with fixed effects, regional convergence is only slightly faster than national convergence, so substantial within-country mobility barriers are required to make sense of the data. Although our analysis does not include potentially critical factors accounting for regional growth such as structural transformation or technology diffusion, it raises a puzzle of whether the causes of low mobility and slow regional convergence are regulation, technology, or externalities.

The paper is organized as follows. Section 2 lays out a model of regional convergence and migration. Section 3 describes the data. Section 4 estimates the model's equations for regional convergence. Section 5 interprets the model in light of the empirical findings. Section 6 concludes.

2 The model

We present a model of convergence across regions that allows for limited factor mobility. Time is discrete $t = 0, 1, \ldots$. A country consists of a measure one of regions, indexed by $i \in [0, 1]$ and characterized by regional total factor productivity (TFP) A_i, population L_i and an initial *per capita* capital endowment $\hat{h}_{i,0}$. Capital is a broad construct, combining human and physical inputs (we do not have data on regional physical capital). We distinguish a region's time t capital endowment $\hat{h}_{i,t}$ from the amount of capital $h_{i,t}$ employed at time t in the same region. The two will tend to differ due to mobility of physical capital and labor (and thus of human capital). We could allow for growth of A_i over time (owing to technological progress and diffusion), but we do not model this possibility because our dataset does not allow us to directly assess the role of TFP growth. We also neglect structural transformation, again due to lack of data.

Each region has a Cobb–Douglas technology to combine "raw" labor L_i and aggregate composite capital $L_i \cdot h_{i,t}$ to produce output. If at time t region i employs an amount $h_{i,t}$ of capital per-capita, its output per capita $y_{i,t}$ is determined by a diminishing returns Cobb–Douglas technology:

$$y_{i,t} = A_i h_{i,t}^{\alpha}, \quad \alpha < 1. \tag{1}$$

In expression (1), α stands for the regional income share remunerating broad capital, while $(1 - \alpha)$ is the income share remunerating raw labor. We expect α to be close to 1, due to the fact that most labor productivity is due to physical capital, human capital and skills. Krueger (1999) estimates that after netting out the roles of education and experience, raw labor accounts for 5–10 % of the total U.S. wage bill. Our estimates end up slightly higher than Krueger's, perhaps because we focus on developing countries.

Equation (1) can be seen as a reduced form for the production function $Y_i = A_i K_i^{\theta} H_i^{\gamma} L_i^{1-\theta-\gamma}$, where K_i is physical capital, H_i human capital, and L_i is raw labor. Per capita output is then equal to $y_i = (K_i/L_i)^{\theta}\,(H_i/L_i)^{\gamma}$. This yields Eq. (1) after defining composite capital as $h_i = (K_i/L_i)^{\frac{\theta}{\theta+\gamma}}\,(H_i/L_i)^{\frac{\gamma}{\theta+\gamma}}$ and $\alpha = \theta + \gamma < 1$. In principle, regional human capital H_i can be mapped into years of schooling in the region S_i according to the usual mincerian equation $H_i = e^{\mu S_i}$. In Sect. 4.1, we introduce human capital in our regression analysis, we discuss the implications of our estimates for μ.

Regions with higher A_i are more productive, due for instance to better geography or institutions. The competitive remuneration of capital is then equal to $w_{i,t} = \alpha A_i h_{i,t}^{\alpha-1}$. With perfect mobility, capital migrates towards regions where $w_{i,t}$ is higher. Human capital moves with labor. We do not explicitly model migration, but we have in mind a setting where, as in Gennaioli et al. (2013), skills are heterogeneous in the population and only the most skilled workers choose to migrate. An inflow of skilled migrants would thus tend to raise a region's per capita human capital. We present some data on migration in Sect. 4.

When capital moves to a region, it is employed with the regions' production function and is paid its marginal product there. Under perfect mobility, the remuneration of capital would be equalized across regions, which implies:

$$h_{i,t}^{free} = \hat{A}_i \cdot h_t, \tag{2}$$

where $\hat{A}_i = \frac{A_i^{\frac{1}{1-\alpha}}}{\int A_i^{\frac{1}{1-\alpha}} di}$ captures region i's relative TFP and $h_t = \int \hat{h}_{i,t} di$ is the aggregate capital in the country. Intuitively, return equalization occurs when relatively more productive regions employ more capital than less productive ones. Capital mobility costs, however, prevent return equalization.

2.1 Migration and human capital accumulation

To close the model, we must specify how capital evolves over time, both in the aggregate and across regions. To obtain closed form solutions, in our main specification we assume that capital depreciates fully in one period and that population growth is zero. When we interpret our estimates in Sect. 5, we also consider a model with capital depreciation and population growth, which we analyze in "Appendix 2". Allowing for positive population growth and depreciation rates does not tangibly affect our findings. In the spirit of the Solow model, we assume that at time t each region i invests the same exogenous share s of income in education or physical investment. The endowment of capital of region i at time $t+1$ is then given by:

$$\hat{h}_{i,t+1} \equiv s y_{i,t} = s A_i h_{i,t}^{\alpha}, \tag{3}$$

where $h_{t+1} = s \int A_i h_{i,t}^{\alpha} di$ is the resulting aggregate capital endowment at $t+1$.[3]

The link between the initial capital endowment $\hat{h}_{i,t+1}$ and employment $h_{i,t+1}$ depends on migration. Migration occurs after new capital is created but before production. If mobility costs are infinite, each region employs its endowment, so that $h_{i,t+1} = \hat{h}_{i,t+1}$. If mobility

[3] One can view Eq. (3) as resulting from a two-period OLG structure in which the young are endowed with raw labor and invest its remuneration into physical and human capital whose return they consume when old.

is perfect, the remuneration of capital is equalized across regions and, by Eq. (2), $h_{i,t+1} = \hat{A}_i \cdot h_{t+1}$. To capture in a tractable way intermediate degrees of mobility, we assume that capital employed in region i at time $t+1$ is given by:

$$h_{i,t+1} = v_{t+1} \cdot \left(\hat{h}_{i,t+1}\right)^{\tau} \left(\hat{A}_i \cdot h_{t+1}\right)^{1-\tau}, \tag{4}$$

where $\tau \in [0, 1]$ and $v_{t+1} \equiv \frac{h_{t+1}^{\tau}}{\int \left(\hat{h}_{i,t+1}\right)^{\tau} \left(\hat{A}_i\right)^{1-\tau} di}$ is a normalization factor common to all regions.

In Eq. (4), parameter τ proxies for mobility costs.[4] At $\tau = 1$, these costs are so high that there is no mobility at all. At $\tau = 0$, these costs are absent and the allocation of capital adjusts so that its remuneration is equalized across regions. In less extreme cases, there is an intermediate degree of mobility (and thus of convergence in returns). Equation (4) is admittedly ad-hoc, but it allows us to tractably account for the costs of capital mobility in the regressions.

2.2 Steady state and growth regressions

We can now explore the dynamics of our economy to derive the implications for growth regressions. Equation (1) implies that the growth rate of region i between times t and $t+1$ is given by $y_{i,t+1}/y_{i,t} = \left(h_{i,t+1}/h_{i,t}\right)^{\alpha}$. Per capita income growth is pinned down by per capita capital growth (i.e., post migration), which we can derive from Eqs. (3) and (4):

$$\frac{h_{i,t+1}}{h_{i,t}} = v_{t+1} \cdot h_{i,t}^{\alpha\tau-1} \cdot (sA_i)^{\tau} \left(\hat{A}_i \cdot s \cdot \int A_j h_{j,t}^{\alpha} dj\right)^{1-\tau}. \tag{5}$$

The growth rate of capital employment in region i increases in: (i) the savings rate s, (ii) the region's TFP, (iii) aggregate investment $s \cdot \int A_j h_{j,t}^{\alpha} dj$. This growth rate decreases, due to diminishing returns, with the initial capital stock $h_{i,t}$. The dynamics of the economy are identified by the evolution of the regions' capital endowment and migration patterns. These in turn determine the evolution of the aggregate capital endowment h_t and output $y_t = \int A_i h_{i,t}^{\alpha} di$. The appendix proves the following result:

Proposition 1 *There is a unique steady state characterized by (non-zero) regional per capita incomes $\left(y_i^*\right)_i$ and aggregate per capita income $y^* = \int y_i^* di$. In this steady state, there is no migration. Starting from non-zero income, each region converges to this steady state according to the difference equation:*

$$\frac{y_{i,t+1}}{y_{i,t}} = s^{\alpha} \cdot v_{t+1}^{\alpha} \cdot A_i \cdot \hat{A}_i^{\alpha(1-\tau)} \cdot y_{i,t}^{\alpha\tau-1} \cdot y_t^{\alpha(1-\tau)}. \tag{6}$$

Proposition 1 shows that per-capita income growth is temporary: diminishing returns cause regional incomes to eventually converge to their steady state. In Appendix 2, we extend Eq. (6) to the case of positive population growth and finite depreciation.

By taking logs and relabeling terms, we can rewrite (6) as:

$$ln\left(\frac{y_{i,t+1}}{y_{i,t}}\right) = a_{t+1} + b_i - (1-\alpha\tau)\, lny_{i,t} + \alpha\,(1-\tau)\, lny_t + \in_{i,t+1}, \tag{7}$$

[4] In this one-good model, there is no trade in goods across regions, but in a multi-goods model of Hecksher–Ohlin type, imperfect capital mobility would be isomorphic to imperfect trade in goods.

where $\in_{i,t+1}$ is a random shock hitting region i at time $t+1$.[5] We estimate Eq. (7) directly to back out values for α and τ.

The constant b_i in Eq. (7) captures region specific productivity: more productive regions should ceteris paribus grow faster. Indeed, according to the model, $b_i = [1+\alpha(1-\alpha)(1-\tau)]\, ln(A_i)$, which increases in the region's TFP. Unless all determinants of productivity are controlled for, OLS estimation of (7) is subject to an omitted variables problem that creates a downward bias in the convergence rate. This is a severe problem for national growth regressions, owing to large cross country differences in institutions, culture, etc. To overcome this difficulty, researchers have tried to use fixed effects estimates. It is however well known that this strategy creates a potentially severe opposite Hurwicz (1950) bias (especially in short time series), overstating the rate of convergence. Because of this bias, Barro (2012) and others prefer estimating cross country growth regression without country fixed effects. In the sub-national context, the omitted variables bias is less severe than across countries, since differences in institutions or culture are arguably smaller within countries. Accordingly, the case for not using regional fixed effects in this context is much stronger than in cross country regressions (after country fixed effects are controlled for). Our preferred estimates for Eq. (7) thus use OLS with country fixed effects, but we show how the results change when we use regional fixed effects.

Holding productivity constant, Eq. (7) predicts that economic growth decreases in the initial level of income (recall that $\alpha\tau < 1$). This is the standard convergence result of neoclassical models, due to diminishing returns. The novel twist is that the speed of convergence $(1-\alpha\tau)$ decreases with mobility costs (i.e. decreases in τ). Mobility of capital to poorer regions accelerates convergence. Finally, holding regional income constant, regional growth increases in aggregate per capita income y_t. This is also an implication of mobility: higher national income raises investment and thus the amount of capital available for employment in the region. The strength $\alpha(1-\tau)$ of this effect falls in τ. These effects are absent in conventional cross country studies because mobility costs are assumed to be prohibitive ($\tau = 1$). Of course, the quantitative relevance of capital mobility costs in a regional context is an empirical question, and the estimation of Eq. (7) can shed light on their magnitude.

To investigate limited within country factor mobility, we also allow τ to vary across countries, due to differences in factor market development and government transfers. We specify that $\tau_c = 1 - \beta \cdot d_c$, where d_c is a proxy capturing the extent of factor market development or government transfers in country c and $\beta > 0$ is a parameter linking that proxy to the effective mobility cost. This leads to the interactive equation:

$$ln\left(\frac{y_{i,t+1}}{y_{i,t}}\right) = a_{t+1} + b_i - (1-\alpha)\, lny_{i,t} - \alpha\cdot\beta\cdot d_c\cdot lny_{i,t} + \alpha\cdot\beta\cdot d_c\cdot lny_t + \epsilon_{i,t+1}. \quad (8)$$

We then estimate Eq. (8) by selecting empirical proxies d_c for each of these factors and then estimate Eq. (8) to back out parameters α and β. This exercise allows us to link the speed of convergence to regional inequality within countries. By Eq. (8), assuming that all regions (in all countries) are subject to the same variance σ of the random shock and that the variance of regional constants (i.e. productivities) is equal to z, we find that long run inequality in country c is equal to:

$$Var\left(lny_{i,t}\right) = \frac{z+\sigma}{1-\alpha^2(1-\beta\cdot d_c)^2}. \quad (9)$$

[5] We view this random shock as stemming from a transitory (multiplicative) shock to regional productivity A_i.

Regional inequality is lower in countries with lower barriers to regional factor mobility (higher d_c).

We conclude by mapping our mobility parameter τ into the elasticity of migration to return differentials. To do so, suppose that the economy is in a steady state with return w and region i experiences a drop in its wage level to $w_i < w$. This situation represents a developed economy that has already converged but faces an adverse shock in one region. Starting from an initial factor endowment $h_{i,0}$, out migration adjusts the actual resources stock to h_i, to satisfy:

$$ln\left(\frac{h_i}{h_{i,0}}\right) = -\frac{1-\tau}{1-\alpha} \cdot ln\left(\frac{w}{w_{i,0}}\right) = -\frac{\beta \cdot d_c}{1-\alpha} \cdot ln\left(\frac{w}{w_{i,0}}\right). \quad (10)$$

Equation (10) characterizes the percentage outmigration flow from region i as a function of the return differential. The coefficient $\frac{1-\tau}{1-\alpha}$ has the intuitive interpretation of "elasticity of outmigration" to the return difference $w/w_{i,0}$. For a given τ, elasticity increases in α: when returns are less diminishing, capital should be allocated less equally across regions. This boosts mobility in Eq. (4) and thus the elasticity of migration in Eq. (10). Our regional regressions yield values for the parameters α and τ that can be used to obtain a reference value for the elasticity in (10), which can then be compared to direct estimates obtained from developed economies to evaluate whether our regressions are consistent with higher mobility frictions in developing countries.

3 Data and summary statistics

3.1 The dataset

Our analysis is based on measures of regional GDP, years of schooling, and geography in up to 1,528 regions in 83 countries for which we found regional GDP data. We begin by gathering GDP data at the most disaggregated administrative division available (typically states or provinces), or, when such data does not exist, at the most disaggregated statistical division level (e.g. the Eurostat NUTS in Europe) for which such data is available (see the Online Appendix for a list of sources). During our sample period (see below), the number of regions with GDP data increased in 35 of the countries in our sample. For example, GDP data for Nova Scotia, Nunavut, and Yukon was reported as an aggregate before 1998 and broken down after that. To make the data comparable over time, we compute all of our statistics for the regions that existed during the period when GDP first became available (see online Appendix 1 for a list of the regions in our dataset and how they map into existing administrative and statistical divisions). Figure 1 shows that our sample coverage is extensive outside of Africa.

We collect all the yearly data on regional GDP we find. Table 1 lists the years for which we have found regional GDP data and shows that typically there are gaps in the data. For example, regional GDP for Brazilian states is available for 1950–1966, 1970, 1975, 1980, and 1985–2010. The average country in our sample has regional GDP data for 20.0 time points spanning 33.2 years. We first convert all regional GDP data into (current purchasing power) US$ values by multiplying national GDP in PPP terms by the share of each region in national GDP and then use regional population to compute per capita GDP in each region. Regional price deflators are generally unavailable. We follow the standard practice and compute the average annual growth rate of per capita GDP for each region over 5-year intervals (Barro 2012).

Next we gather data on the highest educational attainment of the population 15 years and older, primarily from population censuses (see online Appendix 3 for a list of sources).

Fig. 1 Sample coverage

We estimate the number of years of schooling associated with each level of educational attainment. We use UNESCO data on the duration of primary and secondary school in each country and assume: (a) zero years of school for the pre-primary level, (b) 4 additional years of school for tertiary education, and (c) zero additional years of school for post-graduate degrees. We do not use data on incomplete levels because it is only available for about half of the countries in the sample. For example, we assume zero years of additional school for the lower secondary level. For each region, we compute average years of schooling as the weighted sum of the years of schooling required to achieve each educational level, where the weights are the fraction of the population aged 15 and older that has completed each level of education.

Table 1 lists the years for which we have data on educational attainment. Data on years of schooling is typically available at ten year intervals. In some cases, data on educational attainment starts after regional GDP data. For example, data on regional educational attainment for Argentinian provinces starts in 1970 while regional GDP data is available for 1953. In our empirical work, we use interpolated data on years of schooling matching 80 % (27,000/33,738) of the region-year observations with regional GDP.

We also collect data on geography, natural resources, and the disease environment as proxies for unobserved differences in productivity. Appendix 3 describes the variables in detail, here we summarize them briefly. We use three measures of geography computed directly from GIS maps. They include the area of each region, the latitude for the centroid of each region, and the (inverse) average distance between cells in a region and the nearest coastline. We use data from the USGS World Petroleum Assessment Data to estimate per capita cumulative oil and gas production. We measure the disease environment using GIS data on the dominant vector species of mosquitoes from Kiszewski et al. (2004) to capture the component of malaria variation that is exogenous to human intervention. Lastly, we keep track of the region of the country's capital city.

Table 2 presents a full list of the 83 countries in the sample, with the most recent year for which we have regional data. The countries are listed from poorest to richest. Table 2 also

Table 1 Sample coverage for GDP and years of schooling

Country	Sample period	
	Data on GDP	Data on years of schooling
Albania	1990, 2001, 2009	1989, 2001
Argentina	1953, 1970, 1980, 1993–2005	1970, 1980, 1991, 2001, 2010
Australia	1953, 1976, 1989–2010	1966, 2006
Austria	1961–1992, 1995–2010	1964, 1971, 1981, 1991, 2001, 2009
Bangladesh	1982, 1993, 1995, 1999, 2005	1981, 2001
Belgium	1960–1968, 1995–2010	1961, 2001
Benin	1992, 1998, 2004	1992, 2002
Bolivia	1980–1986, 1988–2010	1976, 1992, 2001
Bosnia and Herzegovina	1963, 2010	1961, 1991
Brazil	1950–1966, 1970, 1975, 1980, 1985–2010	1950, 1960, 1970, 1980, 1991, 2000, 2010
Bulgaria	1990, 1995–2010	1965, 1992, 2011
Canada	1956, 1961–2010	1961, 1971, 1981, 1991, 2001, 2006
Chile	1960–2010	1960, 1970, 1982, 1992, 2002
China	1952–2010	1982, 1990, 2000, 2010
Colombia	1950, 1960–2010	1964, 1973, 1985, 1993, 2005
Croatia	1963, 2000–2010	1961, 2001
Czech Republic	1993, 1995–2010	1993, 2011
Denmark	1970–1991, 1993–2010	1970, 2006
Ecuador	1993, 1996, 1999, 2001–2007	1962, 1974, 1982, 1990, 2001, 2010
Egypt, Arab Rep.	1992, 1998, 2007	1986, 1996, 2006
El Salvador	1996, 1999, 2002, 2010	1992, 2007
Estonia	1996–2010	1997, 2009
Finland	1960, 1970, 1983–1992, 1995–2010	1960, 1980, 1985, 2010
France	1950, 1960, 1962–1969, 1977–2010	1962, 1968, 1975, 1982, 1990, 1999, 2006
Germany, East	1991–2010	1970, 1971, 1981, 1987, 2009
Germany, West	1950, 1960, 1970–2010	1970, 1971, 1981, 1987, 2009
Greece	1970, 1974, 1977–2010	1971, 1981, 1991, 2001
Guatemala	1995, 2004–2008	1994, 2002
Honduras	1988–2003	1988, 2001
Hungary	1975, 1994–2010	1970, 2005
India	1980–1993, 1999–2010	1971, 2001
Indonesia	1971, 1983, 1996, 2004–2010	1971, 1976, 1980, 1985, 1990, 1995, 2000, 2005, 2010

Table 1 continued

Country	Sample period	
	Data on GDP	Data on years of schooling
Iran, Islamic Republic	2000–2010	1996, 2006
Ireland	1960, 1979, 1991–2010	1966, 1971, 1979, 1981, 1986, 1991, 1996, 2002, 2006
Italy	1950, 1977–2009	1951, 1961, 1971, 1981, 1991, 2001
Japan	1955–1965, 1975–2009	1960, 2000, 2010
Jordan	1997, 2002, 2010	1994, 2004
Kazakhstan	1990–2010	1989, 2009
Kenya	1962, 2005	1962, 1989, 1999, 2009
Korea, Rep.	1985–2010	1970, 1975, 1980, 1985, 1990, 1995, 2000, 2005, 2010
Kyrgyz Republic	1996–2000, 2002–2007	1989, 1999, 2009
Latvia	1995–2006	1989, 2001
Lesotho	1986, 1996, 2000	1976, 2006
Lithuania	1995–2010	1989, 2001
Macedonia	1963, 1990, 2000–2010	1989, 2001
Malaysia	1970, 1975, 1980, 1990, 1995, 2000, 2005–2010	1970, 1980, 1991, 2000
Mexico	1950, 1960, 1970, 1975, 1980, 1993–2010	1950, 1960, 1970, 1990, 1995, 2000, 2005, 2010
Mongolia	1989–2004, 2006, 2007, 2010	1989, 2000
Morocco	1990, 2000–2007, 2009, 2010	2004
Mozambique	1996–2009	1997, 2007
Nepal	1999, 2006	2001
Netherlands	1960, 1965, 1995–2010	2001
Nicaragua	1974, 2000, 2005	2001
Nigeria	1992, 2008	1991, 2006
Norway	1973, 1976, 1980, 1995, 1997–2010	1960, 2010
Pakistan	1970–2004	1973, 1981, 1998
Panama	1996–2008	1960, 1970, 1980, 1990, 2000, 2010
Paraguay	1992, 2002, 2008	1992, 2002
Peru	1970–1995, 2001–2010	1961, 1993, 2007
Philippines	1975, 1980, 1986, 1987, 1992, 1997, 2006–2010	1970, 1990, 1995, 2000, 2007
Poland	1990, 1995–2010	1970, 2002
Portugal	1977–2010	1960, 1981, 1991, 2001, 2011
Romania	1995–2010	1977, 1992, 2002
Russian Federation	1995–2010	1994, 2010
Serbia	1963, 2002	1961, 2002

Table 1 continued

Country	Sample period	
	Data on GDP	Data on years of schooling
Slovak Republic	1995–2010	1991, 2001, 2011
Slovenia	1963, 1995–2010	1961, 2002, 2011
South Africa	1970, 1975, 1980–1989, 1995–2010	1970, 1996, 2001, 2007
Spain	1981–2008, 2010	1981, 1991, 2001
Sri Lanka	1990, 1991, 1993, 1995, 1997, 1999, 2001, 2003, 2005, 2009, 2010	1981, 2001
Sweden	1985–2010	1985, 2010
Switzerland	1965, 1970, 1975, 1978,1980–1995, 1998–2005, 2008–2010	1970, 1980, 1990, 2000, 2010
Tanzania	1980, 1985, 1990, 1994, 2000–2010	1978, 1988, 2002
Thailand	1981–2010	1970, 1980, 1990, 2000
Turkey	1975–2001	1965, 1985, 1990, 2000
Ukraine	1990, 2004–2010	1989, 2001
United Arab Emirates	1981, 1982, 1988–1991 2001–2009	1980, 2005
United Kingdom	1950, 1960, 1970, 1995–2010	1951, 1991, 2001
United States	1950–2010	1960, 1970, 1980, 1990, 2000, 2005
Uruguay	1961, 1991–2002	1963, 1975, 1985, 1996, 2006
Uzbekistan	1995–2005	1989
Venezuela	1950, 1961, 1971, 1981, 1990	1971, 1981, 1990, 2001
Vietnam	1990, 1995, 2000, 2006, 2008	1989, 1999, 2009

reports per capita regional income in the poorest, 25th percentile, mean, 50th percentile, 75th percentile, and the richest region in each country, the standard deviation of (log) GDP per capita, as well as the ratio of richest to poorest, and 75th to 25th percentile regions. Several points come out in the data. First, if we look across countries, inequality is immense. The 2010 GDP per capita of Norway, the richest country in our sample, is 59 times higher than that of Mozambique, the poorest. Even in the middle of the distribution there is substantial inequality among countries. The 2010 GDP per capita in South Korea, at the 75th percentile, is 5.1 times higher than that of Jordan, at the 25th percentile.

Second, inequality is smaller but still substantial within countries. At the extreme, in Thailand, the 2010 GDP per capita of Rayong is 20.7 higher than that of Sakon Nakhon ($43,288 vs. $2,093). To put this difference in perspective, Sakon Nakhon is as rich as an average Sub-Saharan country, while Rayong is similar to the US. Similar patterns of inequality show up in Russia, Mexico, and other countries with extremely wealthy mining and exploration regions. Using the Theil index to measure inequality, it is possible to compare the extent of regional inequality to country-level inequality. The Theil population-weighted index of inequality of GDP per capita is .42, of which .37 can be attributed to between country inequality, and .05 to within-country regional inequality. Put differently, within-country regional inequality explains roughly 12 % of total world income inequality. Although

Table 2 Dispersion of regional GDP per capita

Country	Year	Minimum	25th pctl	Mean	Median	75th pctl	Maximum	75th pctl/25th pctl	Max/min	σ Ln GDP pc (%)	Country GDP/World
Mozambique	2009	$423	$475	$768	$562	$860	$2,033	1.8	4.8	50	0.06
Nepal	2006	$647	$754	$917	$934	$993	$1,258	1.3	1.9	26	0.08
Bangladesh	2005	$760	$819	$995	$896	$1,037	$1,830	1.3	2.4	23	0.10
Tanzania	2010	$727	$780	$1,125	$1,072	$1,311	$2,615	1.7	3.6	32	0.10
Lesotho	2000	$675	$766	$923	$845	$1,178	$1,228	1.5	1.8	24	0.11
Benin	2004	$600	$798	$1,171	$1,280	$1,529	$1,542	1.9	2.6	40	0.11
Kenya	2005	$669	$703	$1,765	$1,182	$1,798	$4,472	2.6	6.7	78	0.11
Kyrgyz Republic	2007	$967	$1,123	$2,154	$1,813	$2,533	$4,870	2.3	5.0	54	0.15
Nigeria	2008	$1,149	$1,461	$1,929	$1,916	$2,398	$2,736	1.6	2.4	36	0.15
Uzbekistan	2005	$1,178	$1,398	$1,917	$1,714	$2,321	$3,203	1.7	2.7	34	0.17
Pakistan	2004	$1,585	$1,606	$1,836	$1,750	$2,067	$2,261	1.3	1.4	16	0.17
Vietnam	2008	$1,249	$1,588	$2,120	$1,856	$2,619	$4,504	1.6	3.6	32	0.21
India	2010	$1,453	$2,853	$4,713	$4,125	$5,611	$12,831	2.0	8.8	53	0.24
Nicaragua	2005	$1,410	$1,700	$1,908	$1,780	$1,888	$3,023	1.1	2.1	23	0.25
Honduras	2003	$1,733	$1,991	$2,733	$2,692	$3,340	$3,984	1.7	2.3	28	0.27
Philippines	2010	$1,157	$1,827	$3,070	$2,124	$2,882	$8,940	1.6	7.7	64	0.28
Mongolia	2010	$867	$1,177	$2,154	$1,418	$2,309	$8,044	2.0	9.3	58	0.29
Indonesia	2010	$934	$2,447	$4,103	$2,968	$3,704	$16,115	1.5	17.2	65	0.30
Bolivia	2010	$2,863	$3,153	$4,097	$3,383	$4,619	$7,716	1.5	2.7	32	0.33
Morocco	2010	$2,399	$2,834	$3,357	$3,147	$3,889	$4,871	1.4	2.0	23	0.33
Guatemala	2008	$1,756	$2,510	$4,591	$3,440	$6,049	$14,331	2.4	8.2	56	0.34
Sri Lanka	2010	$2,411	$2,847	$3,434	$3,187	$3,378	$6,451	1.2	2.7	28	0.36
Paraguay	2008	$2,361	$2,982	$3,748	$3,581	$4,307	$7,443	1.4	3.2	29	0.39
Egypt, Arab Rep.	2007	$3,463	$4,118	$4,381	$4,467	$4,606	$5,417	1.1	1.6	11	0.40

Table 2 continued

Country	Year	Minimum	25th pctl	Mean	Median	75th pctl	Maximum	75th pctl/25th pctl	Max/min	σ Ln GDP pc (%)	Country GDP/World
Jordan	2010	$3,178	$3,723	$4,133	$4,027	$4,425	$5,717	1.2	1.8	17	0.41
El Salvador	2010	$3,890	$4,465	$5,229	$4,786	$5,754	$8,401	1.3	2.2	23	0.46
Ukraine	2010	$2,646	$3,520	$5,084	$4,004	$6,048	$17,454	1.7	6.6	41	0.47
China	2010	$3,127	$5,249	$8,012	$6,408	$9,974	$17,622	1.9	5.6	46	0.53
Bosnia and Herzegovina	2010	$3,760	$4,571	$5,829	$5,157	$6,184	$12,575	1.4	3.3	31	0.57
Ecuador	2007	$1,775	$2,932	$6,339	$3,584	$5,896	$26,066	2.0	14.7	73	0.57
Albania	2009	$4,932	$5,578	$6,338	$5,804	$6,617	$10,846	1.2	2.2	20	0.60
Thailand	2010	$2,093	$2,827	$6,358	$4,182	$7,345	$43,288	2.6	20.7	67	0.62
Serbia	2002	$1,612	$4,517	$5,466	$5,062	$6,318	$9,439	1.4	5.9	37	0.65
Colombia	2010	$3,125	$4,147	$6,311	$5,564	$7,019	$14,876	1.7	4.8	43	0.66
Peru	2010	$2,382	$3,511	$6,008	$4,960	$6,965	$16,401	2.0	6.9	49	0.66
Macedonia	2010	$3,568	$4,769	$6,932	$7,461	$8,034	$11,363	1.7	3.2	39	0.71
South Africa	2010	$5,836	$6,279	$7,048	$6,848	$7,817	$8,659	1.2	1.5	16	0.74
Uruguay	2002	$3,640	$5,142	$6,156	$6,103	$6,917	$10,745	1.3	3.0	24	0.77
Brazil	2010	$2,892	$4,080	$6,636	$4,859	$9,869	$12,705	2.4	4.4	49	0.79
Iran, Islamic Rep.	2010	$2,589	$4,963	$7,786	$5,738	$8,401	$22,245	1.7	8.6	52	0.83
Romania	2010	$4,342	$6,398	$8,097	$7,038	$9,612	$24,053	1.5	5.5	32	0.84
Turkey	2001	$1,989	$4,598	$6,215	$5,881	$7,467	$14,759	1.6	7.4	44	0.85
Kazakhstan	2010	$3,489	$7,237	$12,986	$11,275	$13,681	$43,931	1.9	12.6	66	0.85
Panama	2008	$2,737	$3,857	$6,797	$4,829	$5,335	$17,713	1.4	6.5	61	0.86
Bulgaria	2010	$5,041	$5,918	$7,679	$6,576	$8,329	$25,206	1.4	5.0	32	0.90
Argentina	2005	$3,704	$4,651	$10,179	$8,403	$12,652	$28,358	2.7	7.7	64	0.90
Mexico	2010	$5,130	$8,033	$13,442	$10,276	$12,823	$84,158	1.6	16.4	53	0.97

Table 2 continued

Country	Year	Minimum	25th pctl	Mean	Median	75th pctl	Maximum	75th pctl/25th pctl	Max/min	σ Ln GDP pc (%)	Country GDP/World
Venezuela	1990	$2,924	$3,719	$6,921	$5,159	$8,577	$17,106	2.3	5.9	55	1.06
Malaysia	2010	$4,098	$7,451	$11,086	$10,422	$13,515	$20,500	1.8	5.0	45	1.08
Russian Federation	2010	$3,099	$7,495	$12,854	$10,460	$13,372	$58,690	1.8	18.9	53	1.11
Chile	2010	$4,878	$8,324	$13,189	$9,908	$14,874	$42,174	1.8	8.6	55	1.13
Latvia	2006	$3,048	$5,550	$8,030	$7,831	$9,082	$21,320	1.6	7.0	44	1.18
Lithuania	2010	$7,770	$9,356	$11,925	$10,625	$13,479	$20,615	1.4	2.7	29	1.21
Croatia	2010	$7,772	$9,752	$12,231	$11,445	$12,011	$27,054	1.2	3.5	30	1.24
Estonia	2010	$7,675	$8,821	$11,327	$9,945	$11,667	$25,866	1.3	3.4	31	1.30
Hungary	2010	$7,531	$10,441	$13,453	$12,152	$14,292	$36,285	1.4	4.8	33	1.32
Poland	2010	$11,210	$12,294	$15,098	$14,102	$17,357	$27,120	1.4	2.4	23	1.36
Slovak Republic	2010	$11,050	$14,893	$19,978	$16,655	$19,457	$46,762	1.3	4.2	43	1.57
Portugal	2010	$15,997	$16,507	$19,843	$18,367	$20,546	$27,797	1.2	1.7	22	1.70
Czech Republic	2010	$16,832	$18,793	$21,571	$19,528	$20,590	$50,496	1.1	3.0	27	1.84
Greece	2010	$18,747	$19,081	$22,270	$19,936	$24,874	$31,629	1.3	1.7	19	1.87
Slovenia	2010	$16,363	$18,229	$22,009	$20,956	$23,324	$35,166	1.3	2.1	21	1.96
Korea, Rep.	2010	$16,738	$21,924	$25,703	$23,941	$30,724	$34,461	1.4	2.1	21	2.09
Spain	2010	$18,919	$21,801	$25,854	$24,229	$30,165	$39,722	1.4	2.1	19	2.10
Italy	2010	$17,843	$20,679	$27,537	$29,200	$33,140	$37,175	1.6	2.1	26	2.11
France	2010	$23,319	$24,399	$27,055	$25,492	$27,380	$51,628	1.1	2.2	17	2.31
Japan	2009	$19,510	$25,290	$27,581	$26,845	$29,208	$52,074	1.2	2.7	15	2.36
Finland	2010	$24,781	$28,561	$32,086	$29,272	$37,851	$39,964	1.3	1.6	20	2.45
Denmark	2010	$19,873	$23,268	$36,691	$25,206	$53,383	$61,723	2.3	3.1	52	2.53
United Kingdom	2010	$25,630	$27,032	$30,926	$29,175	$31,623	$47,274	1.2	1.8	18	2.56

Table 2 continued

Country	Year	Minimum	25th pctl	Mean	Median	75th pctl	Maximum	75th pctl/25th pctl	Max/min	σ Ln GDP pc (%)	Country GDP/World
Belgium	2010	$23,178	$25,463	$31,639	$29,054	$33,406	$50,249	1.3	2.2	26	2.56
Germany, East	2010	$26,631	$27,256	$27,290	$27,274	$27,304	$27,983	1.0	1.1	2	2.63
Germany, West	2008	$26,532	$28,755	$34,692	$31,989	$38,602	$52,740	1.3	2.0	21	2.63
Sweden	2010	$27,996	$30,999	$32,974	$31,580	$33,421	$49,114	1.1	1.8	12	2.66
Australia	2010	$32,602	$37,430	$43,708	$39,579	$53,063	$56,915	1.4	1.7	21	2.70
Austria	2010	$26,272	$32,574	$37,517	$38,179	$40,940	$49,943	1.3	1.9	20	2.75
Canada	2010	$27,838	$29,686	$36,802	$33,942	$38,562	$55,778	1.3	2.0	22	2.75
Ireland	2010	$20,268	$20,569	$29,948	$27,894	$42,343	$44,581	2.1	2.2	32	2.87
Netherlands	2010	$27,424	$31,559	$36,910	$35,205	$41,353	$52,997	1.3	1.9	20	2.88
Switzerland	2010	$26,312	$31,062	$38,380	$34,338	$37,387	$81,077	1.2	3.1	29	3.05
United Arab Emirates	2009	$13,253	$17,188	$37,176	$22,038	$53,496	$112,294	3.1	8.5	75	3.24
United States	2010	$32,190	$35,999	$41,080	$39,587	$44,123	$73,257	1.2	2.3	16	3.43
Norway	2010	$35,597	$37,175	$45,800	$42,795	$49,402	$87,858	1.3	2.5	22	3.65
Average 20 poorest countries		$1,200	$1,560	$2,302	$1,947	$2,616	$5,353	1.70	4.7	40	0.20
Average 20 richest countries		$25,108	$28,155	$34,515	$31,508	$39,262	$57,086	1.45	2.5	24	2.74

country-level inequality takes the lion's share, regional inequality is substantial even from the vantage point of world income inequality.

Third, inequality within countries is much lower if we compare 75th and 25th percentile regions. In Thailand, the ratio of incomes in 75th and 25th percentile regions is only 2.6; it is 1.8 in Russia and 1.6 in Mexico. Clearly, enormous within-country inequality is driven to a substantial extent by natural resources. Fourth, even ignoring the extremes, regional inequality within countries is substantial and appears to decline with development. The ratio of incomes of 75th to 25th percentile regions is 1.70 in the poorest countries, but declines to 1.45 in the richest ones. The standard deviation of (log) GDP per capita is 40 % in the poorest 20 countries, but declines to 24 % in the richest 20 countries.

3.2 Are differences in regional GDP per capita real?

Before we turn to the growth analysis, we check whether the substantial regional income inequality documented in Table 2 is due to measurement problems. On the one hand, regional GDP estimates may be noisy. On the other hand, regional income differences may be largely offset by regional purchasing power differences, because higher observed nominal GDP in a region might merely reflect the region's higher costs of housing or other non-traded goods. To examine the extent of measurement problems, we gather satellite data on nighttime lights as a proxy for real GDP (Henderson et al. 2012), as well as proxies for living standards based on ownership of durable goods (Young 2012). For 28 countries, we also find data on regional housing costs. We cannot use regional price indexes because these are unavailable for most of the countries in our sample.

Data on night-time lights are collected from satellite images and are available for the period 1992–2010 for all countries in our sample. Satellites measure night-time lights on a scale from 0 (no light) to 63 over areas of roughly 0.86 square kilometers. We measure regional per capita night time lights as the ratio of the integral of the lights in a region to the region's population.

Data on the ownership of durable goods for 29 of the countries in our sample countries is available from the Demographic and Health Survey (DHS).[6] Panel data on living standards is available for 19 of the 29 countries. We focus on the percentage of households in a region that: (1) use piped water, (2) use a flush toilet, (3) use electricity, (4) own a radio, (5) own a television, (6) own a refrigerator, and (7) own a car. Finally, data on housing costs (i.e. actual and imputed rental rates) is available from the Luxembourg Income Survey for selected regions in 28 of our sample countries (Table 4 lists them).

We first examine the variation in night-time lights and living standards within countries. Panel A of Table 3 reports sample average values of various statistics, treating each country-year as an observation. The results show that night-time lights and living standards vary enormously within countries. On average, night-time lights per capita range from 0.01 to 0.06. Similarly, averaging across country-years, the fraction of households that own a refrigerator ranges from 20 to 57 % while that who own a car ranges from 5 to 18 %. Interestingly, the ratio of the 75th to 25th percentile values for night-time lights and for all 7 living standard variables is higher than the corresponding ratio for GDP per capita. To illustrate, the average ratio of 75th to 25th percentile values of nighttime lights is 2.45, while that ratio for GDP per capita is 1.65.

To assess more precisely the relationship between GDP per capita and these alternative measures, we run univariate regressions of night-time lights and the 7 living standards vari-

[6] See the Online Appendix 4 for a list of sample countries and years with DHS data.

Table 3 Regional GDP per capita and living standards

Variables	Minimum	25th pctl	Mean	Median	75th pctl	Maximum	75th pctl/25th pctl	Max/min
Panel A: Averages the for statistics listed below								
Regional GDP pc	1,461	1,939	2,827	2,451	3,222	6,836	1.65	5.50
Night-time lights intensity/ population	0.01	0.01	0.02	0.02	0.03	0.06	2.45	12.89
% households using piped water	19 %	27 %	35 %	34 %	41 %	59 %	2.75	49.23
% households using flush toilet	25 %	32 %	40 %	38 %	46 %	65 %	2.62	35.66
% households with electricity	46 %	57 %	63 %	63 %	70 %	83 %	1.86	7.85
% households possessing a radio	47 %	56 %	63 %	63 %	68 %	80 %	1.27	2.06
% households possessing a television	36 %	44 %	52 %	50 %	59 %	73 %	1.93	10.31
% households possessing a refrigerator	20 %	27 %	34 %	32 %	40 %	57 %	2.57	13.27
% households possessing a private car	5 %	6 %	9 %	8 %	12 %	18 %	3.31	17.14

					Prediction Errors by GDP pc Quartile			
Dependent Variables	Slope	S.E.	R^2-Within (%)	R^2-Between (%)	Quartile 1 (%)	Quartile 2 (%)	Quartile 3 (%)	Quartile 4 (%)
Panel B: Univariate Regressions for Regional GDP per capita								
Night-time lights intensity/ population	0.3061[a]	(0.0518)	4 %	3 %	−3.6	0.7	−1.5	2.5
% households using piped water	0.1359[a]	(0.0097)	19 %	60 %	0.2	−1.0	0.2	1.3
% households using flush toilet	0.1869[a]	(0.0092)	34 %	44 %	−0.3	−0.3	2.6	−2.4
% households with electricity	0.1479[a]	(0.0090)	25 %	63 %	−1.4	1.0	1.4	−0.3
% households possessing a radio	0.0993[a]	(0.0076)	17 %	36 %	−0.4	0.5	0.7	−0.9
% households possessing a television	0.1776[a]	(0.0077)	39 %	63 %	−1.3	−0.2	1.9	0.3
% households possessing a refrigerator	0.1722[a]	(0.0077)	38 %	53 %	−0.3	−0.8	1.4	−0.1
% households possessing a private car	0.0541[a]	(0.0031)	28 %	34 %	−0.3	−1.1	0.9	0.8

All regressions include country-year fixed effects plus a constant
[a] Significant at the 1 % level; [b] significant at the 5 % level; and [c] significant at the 10 % level

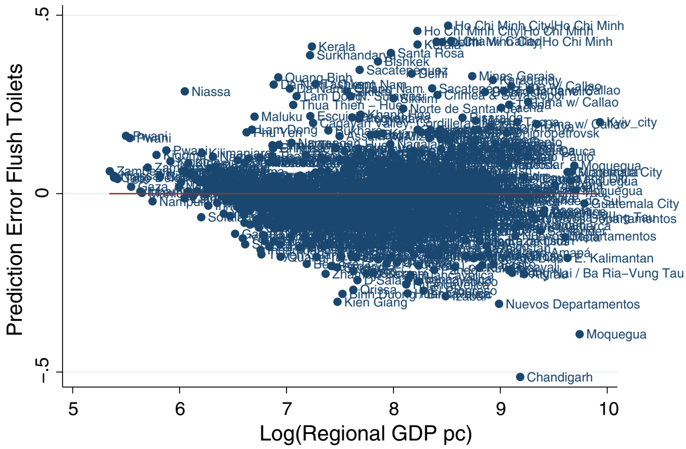

Fig. 2 Prediction errors from a regression of flush toilets on regional GDP per capita and country fixed effects

ables on (log) GDP per capita plus country-year fixed effects (Fig. 2 shows the prediction errors generated by such regression for flush toilets). Panel B shows that (nominal) GDP per capita explains much of the variation in night-time lights and living standards: within R squares range from 8 % (for lights) to 68 % (for flush toilets), while between R squares range from 4 % (for lights) to 48 % (for toilets). The hypothesis that real GDP per capita is understated (overstated) for poor (rich) regions predicts that lights and living standards should be higher (lower) than expected based on the level of regional GDP per capita. To further look at this issue, we group regions into quartiles based on regional GDP per capita and report the predictions errors generated by the univariate regressions. We find that nighttime lights are 3.5 percentage points *lower* than predicted in poor regions and 2.5 % *higher* than predicted in rich regions. Focusing on rich regions, we find that the fraction of households that have flush toilets, electricity, radios, and refrigerators in rich regions is below the predicted level. In contrast, rich regions have more light intensity and a higher fraction of households with piped water, televisions, and cars than the predicted level. Poor regions also show a similar mixed pattern. In sum, lights and living standards vary a great deal within countries and much of that variation is driven by GDP per capita. Prediction errors are economically small and their pattern does not support the hypothesis that GDP per capita severely overstates the relative living standards in rich versus poor regions.

The results on Table 3 should allay concerns that the large variation in regional GDP per capita that we see on Table 2 is spurious. The data on regional housing costs confirm this point. Table 4 provides direct evidence on how the cost of housing—the key non-tradeable good—varies across regions. To illustrate, consider the case of Brazil. We have a single cross-section (2006) and data for all (20) Brazil's regions in our dataset. Housing costs in the most expensive region (Rio Grande do Sul) are roughly 2.71 times higher than in the least expensive region (Paraíba). In the subsample of countries with housing data, housing costs in the most expensive region are 2.93 times higher than in the least expensive region of a country. These figures likely overstate differences in housing costs since-to keep things simple and transparent—we do not adjust housing costs for differences in housing quality, which is positively correlated with GDP per capita.

Taking these data on housing costs at face value, we compute crude regional price deflators based on the assumption that households allocate 30 % of their budget to housing and that

Table 4 Housing cost

Country	Number cross-sections	Number regions	*Housing cost index*			Deflated Regional GDP per capita			Regional GDP per capita		
			75th/25th pctl	Max/min	SD (%)	75th/25th pctl	Max/min	SD (%)	75th/25th pctl	Max/min	SD (%)
Australia	4	6	1.39	2.19	29.57	1.15	1.52	17.56	1.17	1.64	17.79
Austria	2	9	1.16	1.49	12.55	1.18	2.15	22.77	1.23	2.14	22.48
Brazil	1	20	1.45	2.71	27.43	2.04	4.34	44.27	2.50	4.86	49.93
Canada	1	10	1.40	2.71	39.49	1.19	1.67	16.88	1.42	1.81	20.76
China	1	11	1.76	4.48	64.33	2.06	3.56	47.57	2.08	5.39	66.78
Colombia	2	24	1.82	4.51	37.67	1.69	3.79	37.93	1.75	4.71	45.21
Czech Republic	1	14	1.09	1.39	8.64	1.10	2.54	32.30	1.13	2.67	35.60
Denmark	5	5	1.08	1.32	10.22	2.21	2.72	48.40	2.17	2.71	48.88
Estonia	2	15	3.98	11.15	73.73	1.39	3.76	32.74	1.27	3.15	34.10
Finland	6	5	1.05	1.25	9.58	1.46	6.44	47.80	1.32	1.74	23.21
France	4	21	1.10	1.54	10.63	1.14	1.89	15.66	1.13	2.05	18.38
Germany, East	5	5	1.11	1.30	9.95	1.04	1.10	3.63	1.02	1.06	2.36
Germany, West	7	10	1.18	1.30	9.11	1.24	1.80	20.38	1.30	1.86	22.24
Greece	3	8	1.07	1.30	7.72	1.21	1.57	15.34	1.24	1.63	15.84
Guatemala	1	22	1.36	3.71	33.10	2.30	5.85	52.78	2.38	7.71	61.56
Hungary	2	18	1.49	2.98	30.76	1.37	3.07	32.66	1.50	3.72	39.35
India	1	27	1.68	4.22	39.03	1.75	6.52	46.29	1.79	7.83	54.47
Ireland	7	7	1.31	2.24	31.84	1.49	1.81	21.75	1.61	1.83	24.31
Italy	10	20	1.54	2.92	28.93	1.42	2.01	20.15	1.62	2.13	24.80
Mexico	9	32	1.71	5.68	45.64 %	1.65	4.44	40.05 %	1.94	5.83	46.84 %
Netherlands	1	12	1.27	2.85	25.59 %	1.33	1.59	15.38 %	1.26	1.41	13.06 %
Poland	3	15	1.12	1.33	7.41 %	1.30	1.91	19.11 %	1.32	2.16	22.47 %

Table 4 continued

Country	Number cross-sections	Number regions	*Housing cost index*			Deflated Regional GDP per capita			Regional GDP per capita		
			75th/25th pctl	Max/min	SD (%)	75th/25th pctl	Max/min	SD (%)	75th/25th pctl	Max/min	SD (%)
South Africa	2	4	2.79	6.66	68.04	1.44	1.70	22.51	1.25	1.49	16.88
Sweden	2	21	1.07	1.34	7.13	1.09	1.70	12.69	1.09	1.80	14.25
Switzerland	1	24	1.47	2.40	26.48	1.23	1.90	17.15	1.20	2.19	20.30
United Kingdom	8	9.5	1.21	1.95	20.70	1.09	1.46	11.41	1.12	1.62	15.57
United States	5	51	1.47	2.65	29.83	1.14	1.85	11.94	1.22	2.08	15.92
Uruguay	1	19	1.27	2.44	22.58	1.28	2.66	19.77	1.35	2.95	24.73
Average	3.46	15.86	1.48	2.93	27.42	1.43	2.76	26.67	1.48	2.93	29.22

housing is the only price that varies across regions.[7] Calculations using this price deflator are instructive. Continuing with the Brazilian example, deflated GDP per capita in the richest region (São Paulo) is roughly 4.3 times higher than in the poorest region (Piauí). In contrast, nominal GDP per capita in the richest region is roughly 4.9 times higher than in the poorest region. Brazil is representative of other countries in the sample. Across countries in this sub-sample with housing cost data, the ratio of the highest to lowest regional deflated GDP per capita is 2.76, as compared to 2.93 when ignoring differences in housing costs. Such differences in "real" versus "nominal" GDP per capita largely disappear when comparing regions with GDP per capita in the 75th percentile versus the 25th percentile (i.e. the ratio drops from 1.48 to 1.43). Housing costs dampen differences in nominal regional GDP per capita but real GDP per capita is far from being equalized across regions. Nevertheless, since nominal income differences seem to overstate differences in living standards, it is important to correct for this factor in our growth regressions. As reported in the next section, adjusting for cost of living differences does not materially affect our convergence results.

In sum, regional differences in GDP per capita are largely real. To understand these patterns of inequality within countries, we try to see how they evolve over time. To this end, we use our model to assess the speed of convergence and its determinants.

4 Growth regressions

We now present our basic empirical results across both regions and countries. The estimation of Eq. (7) with OLS implicitly assumes that regional income $y_{i,t}$ is uncorrelated with the error term. As we already discussed at length in Sect. 2.2 after Eq. (7), this assumption is problematic in cross country regressions, which suffer from severe omitted variable problems that understate the speed of convergence. Our focus on regions does not eliminate the omitted variable problem, but it arguably makes it less severe: by controlling for country fixed effects, we can effectively control for the large cross country heterogeneity in productivity, institutions, and technology. Following the recommendation of Barro (2012), our basic results do not include country fixed effects in cross-country regressions and region fixed effects in cross-region regressions. As we show in the robustness section, such fixed effects estimates lead to much faster convergence rates, but probably for spurious econometric reasons (Hurwicz 1950; Nickell 1981). Barro (2012) also uses lagged per capita GDP as an instrument for current per capita GDP to address an errors-in-variables concern. For comparability purposes, we also present results using instrumental variables, which make little difference for parameter estimates but sharply cut sample size.

4.1 Basic results

To begin, Table 5 presents the basic regional regressions, using all the data we have. Following Barro (2012), we estimate panel regressions with 5-year average annual growth rates of real per capita regional GDP as dependent variables. To get at convergence, we control for beginning of period levels of per capita income. To get at spillovers from national income, which are implied by our model, we also control for national per capita GDP at the beginning of the period. To take into account the fact that different regions might have different steady states, we use the usual geographic controls, such as latitude, inverse distance to coast, malaria ecology, log of the cumulative oil and gas production, log of population density, and a dummy

[7] Specifically, we compute the deflator as $(HC_{i,j,t}/HC_{j,t})^{0.3}$, where $HC_{i,j,t}$ is the housing cost in region i of country j on period t and $HC_{j,t}$ is the average cost of housing in country j and period t.

for whether the national capital is in the region. In some specifications, we also control for the beginning of each 5-year period years of education in the region.

In the first four columns of Table 5, we present results with no fixed effects. To examine the role of outliers, in column (4) we exclude observations where per capita GDP growth is either below the 5th percentile or above the 95th percentile. In columns (5)–(7), we control for country fixed effects. We correct standard errors for heteroskedasticity, autocorrelation, and correlation across regions following Driscoll and Kraay (1998). Because it is customary to insert in growth equations time controls to capture time variation in growth rates (again, see Barro 2012), in column (8) we also include year fixed effects. Finally, we present the IV specification in column (10), and the OLS specification for the same (smaller) sample in column (9).

The results on control variables in Table 5 confirm some well-known findings. Without country fixed effects, latitude, inverse distance to coast, natural resource endowments, and population density all influence regional growth rates in expected ways, while malaria ecology is insignificant. The economic significance of these four variables on per capita GDP growth ranges from .49 percentage points for a one-standard deviation increase in latitude to .13 percentage points for a one-standard deviation increase in oil. These results are much weaker, or disappear, when country fixed effects are added. We also find that, with country fixed effects, regions that include a national capital have grown about 1% faster during this period.

The main result of OLS specifications in Table 5 is the confirmation of the "iron law" convergence rate of about 2 % per year in this regional sample. Excluding outliers lowers the point estimate for the convergence rate to 1.2 % (see column 4). Without country fixed effect, we also find that doubling the country's per capita income raises the region's growth rate by about 0.9 %, consistent with our model. Interestingly, the inclusion of country fixed effects leaves the convergence coefficient almost unaffected, while rendering regional controls such as geography insignificant. This suggests that the regional information contained in the controls is accounted for by country fixed effects, but the latter in turn contain little additional information relative to the controls themselves. Consistent with our priors, the omitted variable bias does not appear to be very large at the regional level once country effects are controlled for.

Years of education also enter significantly in the regional growth regressions, with the usual sign. Increasing average education by 5 years (a big change) raises the annual growth rate by between 0.85 % (without country fixed effects) and 2.8 % (with country fixed effects), depending on the specification. This effect of education on regional growth is consistent with the standard findings in a cross-section of countries (Barro 1991; Mankiw et al. 1992), but also with the cross-sectional evidence that differences in education explain by far the largest share of differences in per capita incomes across sub-national regions (Gennaioli et al. 2013).[8] Using firm-level production function estimates, Gennaioli et al. (2013) advance the hypothesis that managerial human capital is a critical, but so far neglected, determinant of productivity.

[8] In column [7], the coefficient on years of schooling is 0.0056 while the coefficient on regional GDP per capita is 0.0227. This implies that one extra year of schooling increases steady-state GDP per capita by about 24 % (=0.0056/0.0227). To interpret the implication of this coefficient in terms of mincerian returns to schooling, take our production function where per capita output is $y = Ah^{\alpha}$. Given that h combines human and physical capital, but we do not have data on the latter, assume that physical capital is a linear function of human capital, namely $K = zH$. Then, given the formula for h laid out in Sect. 2 and the mincerian equation $H = e^{\mu S}$, we can approximate $y \approx A(1 + z^{\alpha \frac{\theta}{\theta+\gamma}})e^{\alpha\mu\bar{S}}$, where $\bar{S}$ is average years of schooling. This formula implies that $dlny = \alpha\mu d\bar{S}$. To match the regression estimate, coefficients should be such that $\alpha\mu = 0.24$. Given that α is close to one, the country-wide mincerian return μ should be about 0.25, which is the ballpark of the values accounted for in Gennaioli et al. (2013) by using managerial human capital. The same calculation implies that in our preferred specification in column (3) the mincerian return is close to 10% .

Table 5 Determinants of regional growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Regression estimates										
Ln(GDP pc region)	−0.0093[a]	−0.0181[a]	−0.0195[a]	−0.0116[a]	−0.0165[a]	−0.0188[a]	−0.0227[a]	−0.0208[a]	−0.0160[a]	−0.0192[a]
	(0.0025)	(0.0033)	(0.0041)	(0.0040)	(0.0038)	(0.0033)	(0.0042)	(0.0038)	(0.0027)	(0.0051)
Ln(GDP pc country)		0.0105[a]	0.0089[b]	0.0016		0.0048	−0.0121	−0.0291[b]	0.0000	0.0029
		(0.0027)	(0.0037)	(0.0022)		(0.0089)	(0.0108)	(0.0133)	(0.0026)	(0.0045)
Latitude	0.0003[b]	0.0003[c]	0.0002	0.0001[c]	0.0001	0.0002	0.0001	0.0001	0.0004[a]	0.0004[b]
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0002)
Inverse distance to coast	0.0427[a]	0.0459[a]	0.0546[a]	0.0397[a]	0.0135	0.0173	0.0219[b]	0.0234[b]	0.0404[b]	0.0425[b]
	(0.0157)	(0.0161)	(0.0182)	(0.0116)	(0.0104)	(0.0112)	(0.0109)	(0.0105)	(0.0182)	(0.0207)
Malaria ecology	0.0003	0.0004	0.0004	0.0001	0.0008	0.0009	0.0012	0.0011	0.0002	0.0002
	(0.0005)	(0.0005)	(0.0006)	(0.0005)	(0.0007)	(0.0007)	(0.0009)	(0.0008)	(0.0007)	(0.0009)
Ln(Cum oil and gas prod)	0.1685[a]	0.2019[a]	0.1950[a]	0.1026[b]	0.1058	0.1085	0.0942	0.0829	0.0192	0.0372
	(0.0531)	(0.0572)	(0.0458)	(0.0489)	(0.0842)	(0.0891)	(0.0926)	(0.0911)	(0.0620)	(0.0869)
Ln(Population density)	0.0016[a]	0.0017[a]	0.0008	0.0004	0.0003	0.0003	−0.0011	−0.0013[c]	−0.0002	−0.0002
	(0.0006)	(0.0006)	(0.0007)	(0.0005)	(0.0005)	(0.0005)	(0.0008)	(0.0007)	(0.0006)	(0.0009)
Capital is in region	0.0009	0.0059	0.0062	0.0047[b]	0.0102[a]	0.0116[a]	0.0091[a]	0.0099[a]	0.0050[c]	0.0064[c]
	(0.0038)	(0.0037)	(0.0039)	(0.0020)	(0.0031)	(0.0028)	(0.0031)	(0.0027)	(0.0029)	(0.0035)
Years of education			0.0019[c]	0.0017[c]			0.0056[a]	0.0045[a]	0.0027[a]	0.0029[a]
			(0.0011)	(0.0010)			(0.0018)	(0.0015)	(0.0009)	(0.0011)
Constant	0.0895[a]	0.0721[a]	0.0922[b]	0.0931[a]	0.1624[a]	0.1386[c]	0.2955[a]	0.3832[a]	0.1346[a]	0.1347[a]
	(0.0212)	(0.0214)	(0.0403)	(0.0344)	(0.0308)	(0.0707)	(0.0847)	(0.0985)	(0.0410)	(0.0292)

Table 5 continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Observations	7,947	7,947	6,820	6,145	7,947	7,947	6,820	6,820	4,396	4,396
R^2	6 %	7 %	7 %	8 %	6 %	6 %	8 %	19 %	11 %	11 %
Within R^2					6 %	6 %	8 %	19 %		
Between R^2					7 %	8 %	6 %	6 %		
Fixed effects	None	None	None	None	Country	Country	Country	Ctry, Year	None	None
Estimation	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	IV
Instrument	NA	NA	NA	NA	NA	NA	NA	NA	NA	Lagged GDP
Panel B: Implied Values for α and τ										
alfa	0.9907	0.9924	0.9894	0.9894	0.9835	0.9852	0.9653	0.9501	0.9840	0.9828
tau	1.0000	0.9894	0.9910	0.9990	1.0000	0.9959	1.0124	1.0306	1.0000	0.9980

[a] Significant at the 1 % level; [b] significant at the 5 % level; and [c] significant at the 10 % level

Column (9) presents the OLS results on the smaller sample for which we can instrument GDP with lagged GDP. The estimated convergence rate drops to 1.6 % per year for this smaller sample. Column (10) presents an IV regression similar to Barro (2012), but for regions. The use of instrumental variables for regional data does not materially affect the convergence rate, now estimated at 1.9 %. Since IV has a minor impact on convergence, we emphasize the OLS estimates for a larger sample.

The estimates of the average convergence rate hide substantial heterogeneity among countries. Some of the most rapidly growing countries in the sample, such as India, China, and Chile, actually exhibit regional divergence. Later, we investigate national determinants of regional convergence rates.

The results obtained from the estimation of Eq. (8) are quite surprising. A regional convergence rate of 2 % is comparable to the cross country convergence rate documented by Barro (2012). One might think that mobility of human and physical capital should be much higher within than across countries, leading to much faster convergence across regions than across countries. To see whether this finding is not an artifact of our sample, and thus to better compare regional and national convergence, Table 6 presents the basic cross-country results for 89 countries that have per capita GDP data going back to at least 1965. Columns (1)–(4) include no fixed effects, whereas in column (5) we include year fixed effects. Column (6) shows the results where income is instrumented with past income. We take data from the standard period over which these results are usually considered, 1960–2010. We use 5-year economic growth rates as independent variables. We use beginning-of-the-period national income to get at convergence. We use the same geographic controls as in Table 3 and, consistent with the earlier literature, find several statistically significant effects, especially for inverse distance to coast. In the context of national growth, we cannot identify the spillover effect predicted by Eq. (7), and so we exclude world income in specifications with year fixed effects.

In specifications including only geographic controls, the estimated convergence rate between countries is only .3–.4 %. As we add additional controls, especially life expectancy, investment-to-GDP, and fertility (which of course are correlated with initial per capita income), we can raise estimated convergence rates to about 1.8 % per year in OLS specifications. An instrumental variable specification in column (6) yields a very similar 1.7 %, showing that, again, IV does not matter. These are slightly slower than regional convergence rates, but comparable to Barro's 2 %. We also find that greater human capital is associated with faster growth when we control for geography but not when we add additional controls such as life expectancy, investment-to-GDP, and fertility.

We draw two tentative conclusions from these specifications. First, a comparison of estimated convergence rates in Tables 5 and 6 points to higher estimates within countries than between countries, by about 1 % per year, in OLS specifications. This result is supportive of the model because: (i) resources such as human and physical capital are more mobile within than between countries, and (ii) productivity differences between regions of a country are likely to be smaller than those between countries, which implies that the downward bias in the estimated convergence rate is likely smaller in within-country estimates. Both considerations imply that convergence should be faster at the regional than at the national level. The second message is that, although higher, the rate of convergence between regions is puzzlingly close to that estimated between countries. In this sense, the OLS difference in these convergence rates of about 1 % can be viewed as an upper bound on the role of regional mobility.[9]

[9] A 1 % difference in convergence rates has a substantial impact on the length of time to converge. For example, per capita GDP in the poorest region in the median country in our sample is 40 % below the country mean. Closing a 40 % gap with the steady state level of income would take 25 years at a 2 % convergence rate but only 17 years at a 3 % convergence rate.

Table 6 Determinants of national GDP growth (Countries that have initial GDP data no later than 1965)

	(1)	(2)	(3)	(4)	(5)	(6)
Ln(GDP pc Ctry)	−0.0043[a]	−0.0029[c]	−0.0050[b]	−0.0177[a]	−0.0165[a]	−0.0169[a]
	(0.0015)	(0.0015)	(0.0021)	(0.0021)	(0.0020)	(0.0021)
Ln(GDP pc World)		−0.0160[a]	−0.0233[a]	−0.0400[a]		
		(0.0052)	(0.0062)	(0.0066)		
Latitude	0.0003[a]	0.0002[a]	0.0002[b]	−0.0000	−0.0000	−0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Inverse distance to coast	0.1389[a]	0.1281[a]	0.1222[a]	0.0251	0.0279	0.0280
	(0.0320)	(0.0315)	(0.0340)	(0.0235)	(0.0234)	(0.0235)
Ln(Cum oil and gas prod)	−0.0003	−0.0015	−0.0017	0.0019	0.0014	0.0017
	(0.0025)	(0.0025)	(0.0025)	(0.0037)	(0.0035)	(0.0036)
Malaria environment	−0.0009[a]	−0.0008[a]	−0.0007[a]	−0.0006[b]	−0.0004	−0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Years education			0.0016[b]	−0.0004	−0.0007	−0.0006
			(0.0008)	(0.0008)	(0.0008)	(0.0008)
1/(life expectancy at birth)				−1.9446[a]	−2.2905[a]	−2.3255[a]
				(0.6455)	(0.6296)	(0.6319)
Fertility				−0.0264[a]	−0.0258[a]	−0.0261[a]
				(0.0046)	(0.0046)	(0.0047)
Law and order				0.0137[c]	0.0126	0.0127[c]
				(0.0073)	(0.0076)	(0.0077)
Investment-to-GDP ratio				0.0723[a]	0.0730[a]	0.0732[a]
				(0.0125)	(0.0130)	(0.0131)
Government-consumption-to-GDP ratio				−0.0577[b]	−0.0445[c]	−0.0451[c]
				(0.0276)	(0.0267)	(0.0268)
Openness				0.0061[b]	0.0050[c]	0.0051[c]
				(0.0027)	(0.0028)	(0.0028)
(Change in terms of trade) × openness				0.0231	0.0187	0.0191
				(0.0152)	(0.0153)	(0.0154)
Democracy				0.0124[b]	0.0085[c]	0.0088[c]
				(0.0051)	(0.0048)	(0.0048)
Democracy squared				−0.0010[a]	−0.0007[b]	−0.0007[b]
				(0.0003)	(0.0003)	(0.0003)
Inflation				−0.0042[a]	−0.0037[a]	−0.0037[a]
				(0.0012)	(0.0013)	(0.0013)
Constant	0.0485[a]	0.1731[a]	0.2439[a]	0.5476[a]	0.2268[a]	0.2306[a]
	(0.0122)	(0.0404)	(0.0524)	(0.0664)	(0.0216)	(0.0219)
Observations	868	868	868	868	868	868

Table 6 continued

	(1)	(2)	(3)	(4)	(5)	(6)
Adjusted R^2	7%	8%	9%	27%	27%	31%
Number of countries	89	89	89	89	89	89
Fixed effects	No	No	No	No	Year	Year
Instrumental variables	None	None	None	None	None	Lagged GDP

[a] Significant at the 1 % level; [b] significant at the 5 % level; and [c] significant at the 10 % level

4.2 Implied values of α and τ and the role of cost of living differences

To see the implications of our results for factor mobility, the bottom rows of Table 5 present the values of the structural parameters α and τ implied by the regressions. Recall that Table 5 uses both cross-regional variation in initial incomes, and some residual cross-country variation, to estimate convergence. The (negative of the) coefficient on beginning-of-period income is an estimate of the "convergence" rate $(1 - \alpha\tau)$ in Eq. (7), while the coefficient on national income is an estimate of "aggregate externality" $\alpha(1 - \tau)$ in Eq. (7). In effect, we have two equations with two unknowns. Using as a benchmark the estimates in column (3), we obtain $\alpha = .989$ and $\tau = .991$. In other words, the data point to a model in which broadly defined human and physical capital captures the lion's share of national income and there are significant barriers to capital mobility, in the precise sense that τ is very close to 1.

Consider these parameter values one by one. It is hard to precisely estimate the contribution of raw labor, but its low income share $(1 - \alpha) \approx 1\%$ implied by our estimate of α is in the ballpark of existing estimates. Krueger (1999) calculated that in the U.S. the raw labor share is between 5 and 10 %, but this number may be inflated by minimum wage regulations. As we show in "Appendix 2", the raw labor share implied by our estimates rises a bit once we account for population growth and finite depreciation. In our benchmark parameterization with an annual depreciation rate of 6 % and population growth rate of 2 %, we obtain coefficients $\alpha = 0.87$ and $\tau = 0.87$. In this case, the income share going to raw labor increases to 13 %.

The most puzzling finding is the high within-country mobility cost implied by $\tau = .99$. We later come back to this parameter value to discuss its implication for the elasticity of migration in Eq. (10). For now, we just note that, even within countries, the model in which every sub-national region converges at its own speed seems to be a good approximation.

One important issue is whether differences in regional costs of living can account for slow convergence. Put differently, can it be the case that, once we account for cost of living differences, the implied interregional mobility would be much higher? To address this question, we estimate for each country in which regional housing cost data are available the regression:

$$ln\left(1 + def_{i,t}\right) = c_0 + c_1 \ln\left(\frac{y_{i,t}}{y_t}\right) + u_t + v_{i,t}. \tag{11}$$

In Eq. (11), $1 + def_{i,t}$ is the price deflator in region i at time t, $y_{i,t}$ is the regional GDP per capita of region i, u_t is a country-year fixed effect, and $v_{i,t}$ is a random error. Figure 3 illustrates the relationship between our price deflator and the log of regional GDP per capita. The estimated coefficient of log regional GDP per capita is 0.15, and captures the elasticity of housing costs with respect to regional income. This estimate can be used to obtain a rough quantification of the effect of price differences on regional convergence.

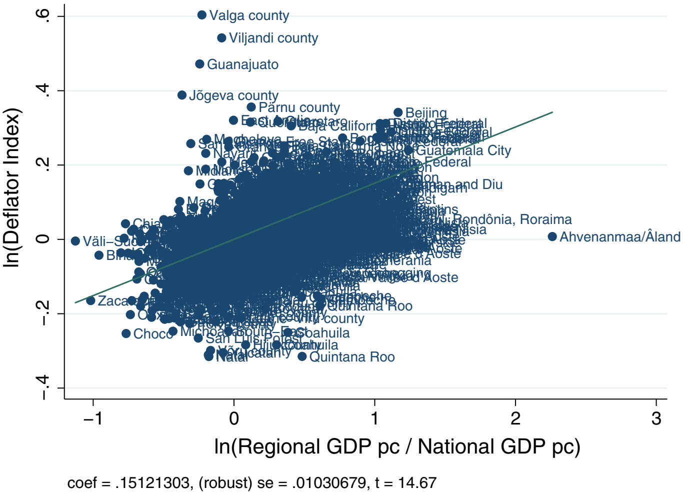

Fig. 3 Deflator Index versus Regional GDP per capita

To see this, note that when we allow for regional price differences and assuming that these differences stay constant over time, Eq. (7) becomes:

$$ln\left(\frac{y_{i,t+1}}{y_{i,t}}\right) = \tilde{a}_{t+1} + \tilde{b}_i - (1 - \alpha\tau)\, ln\left(\frac{y_{i,t}}{1 + def_{it}}\right) + \alpha\,(1 - \tau)\, ln y_t + \tilde{\in}_{i,t+1}. \quad (12)$$

Simply put, a region's nominal income level is replaced by its deflated counterpart. By replacing the deflator fitted in Eq. (11) into (12), we obtain the estimating equation:

$$ln\left(\frac{y_{i,t+1}}{y_{i,t}}\right) = \tilde{a}_{t+1} + \tilde{b}_i - .85\,(1 - \alpha\tau)\, ln\left(\frac{y_{i,t}}{1 + def_{it}}\right)$$
$$+ [\alpha\,(1 - \tau) - .15(1 - \alpha\tau)]\, ln y_t + \tilde{\in}_{i,t+1}. \quad (13)$$

By equating the estimated coefficients in Table 5 with the corresponding parameters in Eq. (13), we can back out values of α and τ that take regional price differences into account. Reinterpreting the parameter estimates of Table 5 column (3) in this way has no meaningful impact on parameter values, which become $\alpha = 0.987$ and $\tau = 0.990$. Accounting for price differences only marginally increases mobility, reducing τ from 0.991 to 0.990. If we hypothetically increase the GDP per capita elasticity of the deflator from 0.15 to 0.50, then, following the same methodology, we obtain $\alpha = 0.981$ and $\tau = 0.980$. As a final robustness check, since Tables 3 and 4 show that differences in purchasing power across regions are fairly minimal excluding the lowest and highest quartile of GDP per capita, we drop observations from the 1st and 4th quartile of GDP per capita and re-run the regressions in Table 5. Results are qualitatively similar. For example, in this case the specification in column (3) of Table 5 yields $\alpha = 0.989$ and $\tau = 0.985$ (compared with 0.989 and 0.991 for the full sample). Even accounting for differences in housing costs, regional mobility seems puzzlingly low. In Sect. 5, we map our parameter values into the more economically interpretable notion of elasticity of migration with respect to wage differentials.

Table 7 Country-level determinants of the speed of convergence

	Ln(GDP pc)	English Legal Origin	Financial Regulation	Trade Tariffs	Labor	Transf/Gov	Gov/GDP	Years Educ (Regional)
Panel A: Basic specification								
Ln(GDP pc Region)	0.0420[b]	−0.0182[a]	−0.0076[b]	−0.0021	−0.0052	−0.0033	−0.0068	−0.0161[a]
	(0.0191)	(0.0047)	(0.0034)	(0.0045)	(0.0116)	(0.0143)	(0.0103)	(0.0040)
Interaction var	0.0701[a]		0.1908[a]	0.2229[a]	0.1329	0.4069[c]	0.4298	0.0179[a]
	(0.0257)		(0.0350)	(0.0481)	(0.1527)	(0.2305)	(0.5288)	(0.0059)
Ln(GDP pc region) × interaction var	−0.0071[a]	0.0072	−0.0197[a]	−0.0238[a]	−0.0195	−0.0413[c]	−0.0596	−0.0015[b]
	(0.0024)	(0.0054)	(0.0037)	(0.0055)	(0.0177)	(0.0231)	(0.0550)	(0.0006)
Latitude	0.0002	0.0002	0.0001	0.0001	0.0001	0.0001	0.0001	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Inverse distance to coast	0.0148	0.0111	0.0187	0.0187[c]	0.0118	0.0193	0.0163	0.0234[c]
	(0.0114)	(0.0096)	(0.0114)	(0.0105)	(0.0100)	(0.0176)	(0.0110)	(0.0120)
Malaria ecology	0.0008	0.0006	0.0009	0.0009	0.0003	−0.0020[c]	0.0009	0.0012
	(0.0007)	(0.0006)	(0.0008)	(0.0007)	(0.0003)	(0.0010)	(0.0007)	(0.0009)
Ln(Cum oil and gas prod)	0.1287	0.0971	0.1350	0.1456[c]	0.1414	0.0739	0.1374	0.1319
	(0.0979)	(0.0887)	(0.1102)	(0.0874)	(0.1888)	(0.1146)	(0.0910)	(0.1104)
Ln(Population density)	0.0001	0.0003	−0.0000	0.0000	−0.0004	0.0001	0.0001	−0.0011
	(0.0006)	(0.0005)	(0.0007)	(0.0006)	(0.0006)	(0.0010)	(0.0006)	(0.0009)
Capital is in region	0.0126[a]	0.0102[a]	0.0127[a]	0.0117[a]	0.0142[a]	0.0210[a]	0.0118[a]	0.0128[a]
	(0.0031)	(0.0031)	(0.0031)	(0.0025)	(0.0026)	(0.0043)	(0.0031)	(0.0030)
Constant	−0.4129[b]	0.1619[a]	0.0824[a]	0.0329	0.0877	0.0367	0.0973	0.1364[a]
	(0.2033)	(0.0300)	(0.0280)	(0.0367)	(0.0969)	(0.1346)	(0.0954)	(0.0332)
Observations	7,947	7,947	5,731	6,469	2,722	2,242	7,219	6,820
Adjusted R^2	18 %	16 %	19 %	20 %	20 %	25 %	16 %	20 %
Fixed effect	Country	Country	Country	Country	Country	Country	Country	Country

Table 7 continued

	Ln(GDP pc)	English legal origin	Financial regulation	Trade tariffs	Labor	Transf/Gov	Gov/GDP	Years Educ (Regional)
Panel B: Control for both level and interactions of GDP per capita								
Ln(GDP pc region)	0.0420[b]	0.0417[b]	0.0084	−0.0062	−0.0338	0.0804[c]	0.0593[a]	0.0437
	(0.0191)	(0.0186)	(0.0236)	(0.0173)	(0.0400)	(0.0417)	(0.0211)	(0.0313)
Ln(GDP pc country)	0.0701[a]	0.0726[a]	−0.0094	−0.0194	−0.0503	0.0661	0.0918[a]	0.0610
	(0.0257)	(0.0260)	(0.0289)	(0.0248)	(0.0488)	(0.0542)	(0.0340)	(0.0445)
ln(GDP pc region) × Ln(GDP pc country)	−0.0071[a]	−0.0074[a]	−0.0017	0.0007	0.0037	−0.0102[b]	−0.0094[a]	−0.0082[c]
	(0.0024)	(0.0023)	(0.0028)	(0.0025)	(0.0039)	(0.0050)	(0.0030)	(0.0043)
Interaction Var			0.1754[a]	0.2156[a]	0.1750	0.2513	−0.2122	0.0008
			(0.0300)	(0.0765)	(0.1211)	(0.2455)	(0.4331)	(0.0081)
Ln(GDP pc Region) × Interaction Var		0.0097[b]	−0.0160[a]	−0.0219[b]	−0.0229	−0.0236	0.0151	0.0006
		(0.0047)	(0.0036)	(0.0089)	(0.0146)	(0.0250)	(0.0468)	(0.0009)
Latitude	0.0002	0.0002	0.0000	0.0000	0.0001	0.0002	0.0002	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Inverse Distance to Coast	0.0148	0.0117	0.0134	0.0146	0.0120	0.0184	0.0179	0.0197[c]
	(0.0114)	(0.0116)	(0.0105)	(0.0100)	(0.0104)	(0.0176)	(0.0115)	(0.0108)
Malaria Ecology	0.0008	0.0005	0.0007	0.0007	0.0004	−0.0021[b]	0.0010	0.0011
	(0.0007)	(0.0006)	(0.0007)	(0.0006)	(0.0003)	(0.0009)	(0.0007)	(0.0009)
Ln(Cum Oil and Gas Prod)	0.1287	0.1180	0.1253	0.1352	0.1292	0.0913	0.1610	0.0989
	(0.0979)	(0.1063)	(0.1044)	(0.0813)	(0.1882)	(0.1207)	(0.1017)	(0.0939)
Ln(Population density)	0.0001	0.0001	−0.0000	0.0001	−0.0004	0.0002	0.0000	−0.0013
	(0.0006)	(0.0006)	(0.0007)	(0.0006)	(0.0006)	(0.0010)	(0.0006)	(0.0009)
Capital is in region	0.0126[a]	0.0127[a]	0.0110[a]	0.0099[a]	0.0132[a]	0.0209[a]	0.0139[a]	0.0092[a]
	(0.0031)	(0.0029)	(0.0031)	(0.0026)	(0.0032)	(0.0044)	(0.0031)	(0.0033)
Constant	−0.4129[b]	−0.4344[b]	0.1556	0.1844	0.4951	−0.4743	−0.5624[b]	−0.2961
	(0.2033)	(0.2085)	(0.2452)	(0.1811)	(0.4617)	(0.4566)	(0.2477)	(0.3339)
Observations	7,947	7,947	5,731	6,469	2,722	2,242	7,219	6,820
Adjusted R^2	18%	18%	19%	20%	20%	26%	19%	21%
Fxd Effect	Country	Country	Country	Country	Country	Country	Country	Country

[a] Significant at the 1 % level; [b] Significant at the 5 % level; and [c] Significant at the 10 % level

4.3 Barriers to regional mobility and convergence

The previous findings indicate that barriers to regional mobility are important. As a first pass towards assessing this possibility, here we identify direct proxies for legal and regulatory barriers to factor mobility across regions. Lucas (1990) has famously asked why physical capital does not move across international borders. Reasons include the lack of proper institutions and of complementary factors of production, such as human capital, in poor countries. In the regional context, these explanations are problematic, because: (i) institutional differences are small within countries (and do not explain differences in regional development, Gennaioli et al. 2013), and (ii) scarcity of complementary inputs itself relies on regional immobility of human capital. At the same time, country-wide regulations such as overly regulated financial, labor and goods markets may create barriers to factor mobility and can be measured directly.

To get at this issue, we proxy for the barriers to factor mobility using the following measures of a country's market infrastructure: an index of the regulation of domestic financial markets from Abiad et al. (2008), an index of international trade tariffs from Spilimbergo and Che (2012), an index of labor regulations from Aleksynska and Schindler (2011). We also use a dummy equal to 1 if the country's laws are of English Legal Origin. According to La Porta et al. (1998, 2008), English Legal Origin is a broad indicator of a market-supporting regulatory stance. To assess whether the public sector has a direct effect on regional convergence, we also proxy for determinants of mobility using two measures of redistribution: a measure of government transfers and subsidies as a fraction of total government spending, and the ratio of government spending to GDP. Finally, we check Lucas's hypothesis by investigating the effect of regional human capital on mobility and the region's speed of convergence.[10]

To evaluate the influence of institutional barriers to mobility on convergence, we estimate Eq. (8) by interacting the (log) level of regional GDP with the previously described institutional proxies for d_c. As a first step, we check how the rate of regional convergence depends on the (log) level of GDP in the country (formally, this is akin to setting $d_c = y_c$). We also test Lucas' hypothesis that limited convergence is explained by local scarcity of human capital by replacing d_c with a *region-specific* interactive variable: the region's human capital as proxied by its average level of schooling. All regressions include country fixed effects to capture time-invariant determinants of productivity.

The results of this exercise are reported in Table 7. All regressions include our standard geography controls, regional per capita GDP, country fixed effects, and proxies for d_c entered separately. In Panel A, the regressions also include the interaction between each proxy and regional GDP per capita. In Panel B, we add to the previous specification the level of GDP per capita as well as the interaction between regional and national GDP per capita. The regressions omit the interaction between national GDP per capita and proxies for d_c, because national and regional GDP per capita are highly correlated.[11]

Begin with Panel A. We find that higher (log) GDP per capita is associated with faster regional convergence (see Column 1, Panel A). Our estimates suggest that boosting national

[10] We also tried: (1) an index of the regulation of capital flows from Abiad et al. (2008), (2) an index of the regulation of the banking from Abiad et al. (2008), (3) an index of capital controls from Schindler (2009), and (4) the number of months of severance payments for a worker with 9 years of tenure on the job from Aleksynska and Schindler (2011).

[11] Formally, the regressions in Panel A of Table 7 do not include the term $\alpha \cdot \beta \cdot d_c \cdot lny_t$ appearing in Eq. (8). The reason is that national and regional incomes are strongly correlated. Thus, having a set of interactions between national income and country-level determinants of the speed of convergence creates multicollinearity problems. Nevertheless, the results on interactions are qualitatively similar if we add national income as a control (Table 7B).

GDP per capita by 20 % while keeping regional per capita GDP constant adds 1.31 percentage points to the region's convergence rate. Columns 2–8 in Panel A introduce one at the time the interactions with proxies for national market infrastructure and government transfers. More liberalized financial markets, lower international trade tariff rates, and higher government transfers all increase the speed of convergence. A region that is 20 % below the steady state converges 5.69 percentage points faster when the domestic finance (de)regulation index is one standard deviation higher than the sample average, 5.91 percentage points faster when tariffs are one standard deviation below their sample average, and 8.87 percentage points faster when government transfers are one standard deviation higher than the sample average.[12] The results generally support the model's prediction that frictions slow the convergence rate. The exception is the effect of common law since it implies that—despite having more favorable market infrastructure—a region 20 % below the steady state converges 0.16 percentage points *slower* in common law than in civil law countries. There is no evidence that the speed of convergence is associated with labor regulation or government expenditure. Although the effect of English Legal Origin is puzzling, these results suggest that economic and financial development, international trade, and government transfers do, ceteris paribus, reduce regional inequality.

Because the quality of institutions and government redistribution may be products of economic development, in Panel B we include these proxies while controlling for the interaction between regional and national per capita GDP as well as the level of (log) per capita GDP. Neither trade tariffs nor government transfers play a role here. The coefficient of the interaction between regional GDP and domestic financial regulation index, tariffs, and English Legal Origin are roughly unchanged and remain statistically significant, while the interaction between regional GDP and government transfers lose statistical significance. Financial market infrastructure and trade barriers emerge as robust predictors of faster regional convergence.

Next, we investigate the role of regional human capital in promoting regional convergence. We find no evidence that the rate of convergence (as opposed to regional growth rate per se) varies with regional education. The results in the last column of Panel A show that while regional education has a large impact on the growth rate of GDP per capita, the interaction term between regional education and GDP per capita is insignificant (and remains insignificant in Panel B).

"Appendix 4" investigates the role of several potential deep determinants of limited capital mobility, including: (a) the size of the agricultural sector, (b) soil quality, and (c) fertility rates. The share of agriculture in output plays a large role in accounting for resource misallocation in developing countries (Duarte and Restuccia 2010). We have limited data on the regional composition of output but have census data on employment for 3,556 region-years. In the growth regressions, the interaction between the share of employment in agriculture and regional GDP per capita is negative but insignificant. Land ownership—or more precisely, the distribution of land ownership—plays a large role in political economy explanations of resource misallocation. Galor et al. (2009) find support for the hypothesis that landowners have an incentive to suppress human capital formation in the US data during 1900-40. Unfortunately, we do not have direct data on land ownership. Instead, we use data on soil quality as a proxy for land ownership since soil quality is arguably inversely related to ownership concentration. We do not find evidence that soil quality, measured following Michalopoulos (2012), or its variance affects the speed of convergence. Finally, we consider the role of

[12] Results are qualitatively similar for the index of capital controls (i.e. 7.40 percentage points faster growth when GDP per capita is 20 % below the steady state and the index of capital controls is one standard deviations above its average) and the index of banking regulation (i.e. 14.0 percentage point faster growth when GDP per capita is 20 % below the steady state and the index of banking regulation is one standard deviations above its average).

regional differences in fertility rates, since the negative correlation between fertility rates and regional GDP per capita may slow the speed of convergence in per capita GDP. We find that the interaction between fertility rates and the initial level of regional GDP per capita is positive but insignificant.

4.4 Direct evidence on regional labor mobility

Having documented that proxies for mobility barriers are indeed correlated with slower regional convergence, we now trace out directly the patterns of mobility of human capital and labor by looking at migration. We have no data on the mobility of physical capital. To get a rough estimate of the magnitude of human capital mobility between regions, we use census data. Data on a region's population born in a different region is available for 33 countries. For 26 countries we also have data on the residents of a region who arrived in the previous 5 years from a different region. These data enable us to compare human capital of natives and residents.

Table 8 presents results on migration using the most recently available census data. Consistent with common wisdom, a very high fraction (41 %) of the residents of an average US region are migrants. Only the Kyrgyz Republic beats the US in internal mobility (80 vs. 41 %). For the sample as a whole, 21 % of the residents of an average region are migrants. Migration is low in Egypt (8 %), Nepal (5 %), and Pakistan (5 %). It is high in Kyrgyz Republic, US, and Chile. Consistent with Gennaioli et al. (2013), migrants are typically more skilled. On average, workers that choose to emigrate from a region have 1.02 more years of schooling than the natives from those regions. The outflow of migrants thus tends to lower the human capital of the sending region. The effect of migration on the human capital of the receiving region is ambiguous. All else equal, the inflow of migrants tends to increase the human capital of the receiving region. This effect, however, relies on the sending and receiving regions having similar levels of human capital—an assumption likely to be violated if migration flows form poor regions to rich ones. In the data, migration has a very small effect on a region's human capital. For example, residents of poor regions in Brazil (in the bottom quartile of regional GDP per capita) have 0.10 more years of education than the natives of such regions. In contrast, residents of rich regions in Brazil (in the top quartile of regional GDP per capita) have 0.18 less years of schooling than the natives of such regions.

Figure 4 illustrates the relationship between the spread in the human capital of residents and natives and (log) regional GDP per capita after controlling for country and year fixed effects. For the overall sample, migration lowers the number of years of education of residents of both poor regions (by 0.17 years) and rich regions (by 0.19 years) relative to the human capital of natives of those regions. The fact that the impact of migration on human capital is so small is consistent with our basic evidence of slow convergence.

Table 9A presents simple regressions of the determinants of in-migration into each region. In-migration is lower into densely populated regions, which might reflect housing costs. Total in-migration into a region also increases with the region's relative income, as does the fraction of college educated workers that are in-migrants. However, the responsiveness of total in-migration to relative per capita GDP is fairly muted: in-migration adds 17 percentage points to the population of a region with twice the per capita GDP of the national level. Focusing on migrants that arrived in the region in the previous 5 years ("flow of migrants") helps calibrate the magnitude of the elasticity of migration with respect to GDP per capita: the flow of migrants adds roughly 1 percentage points to the population of a region with twice per capita GDP of the national level (results not reported). In Panel 9B we run a finer test, considering how the flow of in-migration is related to the previously used measures of a

Table 8 Internal migration and changes in human capital

Country	Census year	% Immi-grants	$HK_{Natives}$−$HK_{emigrants}$	$HK_{residents}$−$HK_{natives}$			
				1st *quartile GDP pc*	2nd *quartile GDP pc*	3rd *quartile GDP pc*	4th *quartile GDP pc*
Panel A: Migration increases HK in both low and high income regions							
Argentina	2001	24	−0.03	0.30	0.32	0.02	0.17
Nepal	2001	5	−2.40	0.06	−0.16	−0.15	0.17
Pakistan	1973	5	−2.95	0.08	0.11	−1.64	0.10
United States	2010	41	−0.43	0.04	0.05	−0.01	0.09
Panel B: Migration increases (lowers) HK in low (high) income regions							
Brazil	2010	16	−0.16	0.10	0.03	0.09	−0.18
Chile	2002	29	−0.77	0.09	−0.10	−0.57	−0.60
Kyrgyz Republic	1999	80	−0.10	0.44	−0.23	−0.34	−1.12
Mexico	2010	23	−0.18	0.05	0.08	−0.18	−0.08
Spain	2001	21	−0.23	0.20	0.04	0.15	−0.53
Panel C: Migration increases (lowers) HK in high (low) income regions							
Canada	2001	22	−0.55	−0.14	0.05	−0.11	0.13
France	1999	28	−1.28	−0.24	−0.16	−0.11	0.01
Ireland	2006	21	−1.24	−0.22	−0.18	−0.18	0.27
Malaysia	2000	18	−1.98	−0.35	−0.52	−0.41	0.05
Slovenia	2002	13	−0.73	−0.25	−0.13	−0.13	0.07
Tanzania	2002	16	−1.29	−0.22	−0.28	−0.22	0.06
Panel D: Migration lowers HK in both low and high income regions							
Bolivia	2001	24	−1.31	−0.13	−0.05	−0.34	−1.30
Colombia	2005	23	−0.66	−0.28	−0.35	−0.20	−0.44
Ecuador	2001	26	−0.80	−0.30	−0.67	−0.34	−0.12
Egypt, Arab Rep.	2006	8	−0.54	−0.02	−0.05	−0.08	−0.31
El Salvador	2007	15	−0.86	−0.35	−0.45	−0.37	−0.02
Indonesia	2010	18	−2.15	−0.14	−0.26	−0.03	−0.13
Kenya	1999	27	−1.76	−0.27	−0.33	0.46	−0.30
Mongolia	2000	17	−1.33	−0.53	−0.54	−0.60	−0.31
Nicaragua	2005	13	−0.47	−0.39	−0.10	−0.20	−0.01
Panama	2000	20	−0.76	−0.79	−0.29	−0.51	−0.65
Peru	2007	21	−1.20	−0.80	−0.57	−0.44	−0.65
Philippines	1990	12	−1.00	−0.26	−0.21	−0.03	−0.11
Romania	2002	17	−1.29	−0.35	−0.17	−0.07	−0.02
South Africa	2007	10	−1.20	−0.09	−0.08	0.01	−0.01
Thailand	2000	18	−1.61	−0.37	−0.30	−0.38	−0.05
Turkey	2000	20	−1.18	−0.11	−0.33	−0.32	−0.23
Uruguay	1996	22	−0.27	−0.05	−0.10	−0.18	−0.17
Venezuela	1990	27	−0.69	−0.23	0.02	−0.18	−0.26
Average		21	−1.02	−0.17	−0.19	−0.23	−0.19

[a] Significant at the 1 % level; [b] significant at the 5 % level; and [c] significant at the 10 % level

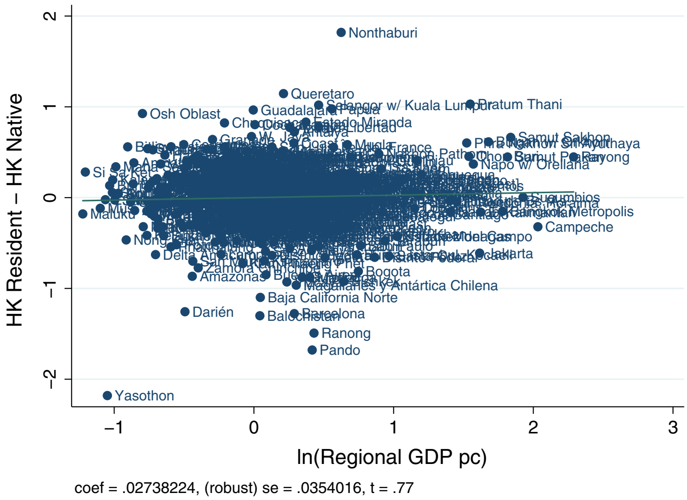

Fig. 4 Migration and Changes in Human Capital

country's market infrastructure. In-migration is higher in countries having less regulated financial and goods markets, consistent with the idea that better market infrastructure fosters human capital mobility. Consistent with Lucas's hypothesis, in-migration increases with the level of education of the region. These preliminary results are consistent with our finding of slow convergence: human capital does not move too fast. Of course, the movement of physical capital might be faster.

4.5 Region fixed effects

Before interpreting the results of our regional growth regressions in light of our model, we briefly discuss their robustness with respect to the inclusion of regional fixed effects. In a regional context, this is akin to introducing a region-specific constants b_i, consistent with Eq. (7). Barro (2012) urges against the use of such estimates because of the strong bias toward faster estimated convergence in short panels (see Nickell 1981). As previously noted, we agree with Barro, but show the results for completeness.

Table 10 presents the results. The regional convergence rate ranges from 3.43 % when we do not control for national GDP per capita (see column 1 Table 10A) to roughly 10 % when we do (see columns 2–4). The estimated national convergence rates now range from 3 to 4.6 % (see columns 1–4 in Table 10B). Our regional convergence results are of the same order of magnitude as the 10 % annual cross-country convergence rate estimated by Caselli et al. (1996) for growth using instrumental variables, but in all likelihood overestimate the speed of convergence. The coefficient on national income also rises sharply (see Panel A), indicating large spillovers from national income to regional growth. These estimated convergence rates seem implausibly high, and inconsistent with the evidence of persistent regional inequality. At 11 % annual convergence rates, the regional disparities that we observe in the data would quickly become small (assuming that productivity differences across regions are modest). Correspondingly, at these much higher, but likely biased, parameter estimates regional mobility is higher. The estimates suggested by column (3) of Panel A, for example, imply $\alpha = .96$ and $\tau = 0.92$. In Sect. 5 we evaluate the implication of these parameter values for mobility.

Table 9 Determinants of migration

	Dependent variable	
	Immigration/population	Immigration college educated/college educated
Panel A: Stock of immigrants—OLS Regressions		
ln(density)	−0.0116[c]	−0.0217[a]
	(0.0062)	(0.0076)
Temperature	−0.0026	−0.0036
	(0.0020)	(0.0023)
ln(Reg GDP pc/country GDP pc)	0.1780[a]	0.1198[a]
	(0.0258)	(0.0270)
Constant	0.3574[a]	0.5591[a]
	(0.0656)	(0.0616)
Observations	2,235	2,230
Adjusted R^2	26%	14%
Fixed effect	Country	Country

Table 9 continued

	Control variable							
	None	Ln(GDP pc)	Financial regulation	Trade	Labor	Transf/Gov	Gov/GDP	Years Educ (Regional)
Panel B: Flow of Immigrants in the previous 5 years—Regressions with country-fixed-effects								
ln(density)	−0.0013	−0.0015	−0.0021[b]	−0.0018[a]	−0.0031[a]	−0.0004	−0.0001	−0.0019[c]
	(0.0009)	(0.0010)	(0.0008)	(0.0006)	(0.0009)	(0.0031)	(0.0025)	(0.0010)
Temperature	0.0001	0.0002	−0.0000	−0.0000	−0.0001	0.0006	0.0004	0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0012)	(0.0009)	(0.0002)
ln(Reg GDP pc/Ctry GDP pc)	0.0132[a]	0.0135[a]	0.0107[a]	0.0107[a]	0.0114[a]	0.0176[c]	0.0154[c]	0.0100[a]
	(0.0042)	(0.0042)	(0.0030)	(0.0027)	(0.0029)	(0.0098)	(0.0077)	(0.0035)
Control variable		0.0139[a]	0.0102[c]	0.0091	0.0164	−0.0071	−0.0017	0.0029[a]
		(0.0048)	(0.0057)	(0.0074)	(0.0219)	(0.0055)	(0.0153)	(0.0009)
Constant	0.0250[a]	−0.1020[b]	0.0206[a]	0.0185[a]	0.0238	0.0278	0.0213	0.0026
	(0.0047)	(0.0413)	(0.0050)	(0.0048)	(0.0159)	(0.0238)	(0.0161)	(0.0075)
Observations	1,333	1,333	1,018	1,172	615	378	481	1,333
Adjusted R^2	59 %	60 %	44 %	39 %	48 %	63 %	64 %	60 %
Fixed effect	Country	Country	Country	Country	Country	Country	Country	Country

[a] Significant at the 1 % level; [b] significant at the 5 % level; and [c] significant at the 10 % level

Table 10 Robustness

	(1)	(2)	(3)	(4)
Panel A: Regional fixed effects; Driscoll–Kraay standard errors				
Ln(GDP pc Region)	−0.0343[a]	−0.0935[a]	−0.1039[a]	−0.1029[a]
	(0.0048)	(0.0084)	(0.0100)	(0.0106)
Ln(GDP pc country)		0.0740[a]	0.0670[a]	0.0403[a]
		(0.0091)	(0.0115)	(0.0104)
Ln(Population density)	0.0245[a]	0.0110[a]	0.0059	−0.0126
	(0.0042)	(0.0039)	(0.0088)	(0.0084)
Years of education			0.0048[c]	0.0013
			(0.0028)	(0.0022)
Constant	0.2293[a]	0.1400[a]	0.2825[a]	0.5304[a]
	(0.0309)	(0.0238)	(0.0713)	(0.1167)
Observations	7,951	7,951	6,824	6,824
Number regions	1,528	1,528	1,505	1,505
Within R^2	11 %	21 %	23 %	36 %
Fixed effects	Region	Region	Region	Region and year
Panel B: National GDP; Country fixed effects				
Ln(GDP pc Ctry)	−0.0293[a]	−0.0301[a]	−0.0456[a]	−0.0432[a]
	(0.0053)	(0.0052)	(0.0049)	(0.0050)
Ln(GDP pc World)	0.0134[b]	0.0064	-0.0141	
	(0.0065)	(0.0108)	(0.0100)	
Years education		0.0013	−0.0016	−0.0037[c]
		(0.0016)	(0.0018)	(0.0020)
1/(life expectancy at birth)			−0.8026	−1.0569
			(1.2028)	(1.2522)
Fertility			−0.0341[a]	−0.0337[a]
			(0.0084)	(0.0083)
Law and order			0.0161[c]	0.0141
			(0.0095)	(0.0107)
Investment-to-GDP ratio			0.0815[a]	0.0838[a]
			(0.0192)	(0.0199)
Government-consumption-to-GDP ratio			−0.1627[a]	−0.1355[a]
			(0.0451)	(0.0463)
Openness			0.0267[a]	0.0228[a]
			(0.0060)	(0.0063)
(Change in terms of trade) × openness			0.0343	0.0270
			(0.0258)	(0.0253)
Democracy			0.0116[b]	0.0072
			(0.0056)	(0.0051)
Democracy squared			−0.0009[b]	−0.0006[c]
			(0.0004)	(0.0003)
Inflation			−0.0035[a]	−0.0032[a]
			(0.0007)	(0.0007)

Table 10 continued

	(1)	(2)	(3)	(4)
Constant	0.1536[a]	0.2112[a]	0.5535[a]	0.4334[a]
	(0.0424)	(0.0756)	(0.0917)	(0.0431)
Observations	868	868	868	868
Adjusted R^2	12 %	12 %	28 %	32 %
Countries	89	89	89	89
Within R2	12 %	12 %	29 %	33 %
Between R2	14 %	13 %	1 %	2 %
Fixed effects	Country	Country	Country	Country and Year

[a] Significant at the 1% level; [b] significant at the 5 % level; and [c] significant at the 10 % level

In sum, the results in this section indicate that the speed of regional convergence is not substantially faster than that of national convergence. This puzzling phenomenon is unlikely to be due to differences in standards of living across regions. Our analysis points to a different possibility, namely the presence of sub-national barriers to the mobility of human and physical capital across regions. In particular, the data point to the importance of poorly developed financial markets as one of the factors slowing down mobility.

5 Taking stock

Our baseline estimates—summarized by the estimates in Table 5—imply values for the structural parameters α and τ that point to significant limits to regional mobility. While the value of α is reasonable, placed in a narrow range between 0.95 (in column 8) and 0.99 (columns 1, 2, 3, and 4), the values of τ are puzzlingly large, located in a narrow range between 0.98 (in column 2) and 1.03 (column 8). We now investigate the implication of these findings for: (i) the elasticity of migration to return differentials, (ii) the country-level variation in mobility frictions, and thus (iii) country-level variation in regional inequality.

Equation (10) provides a direct way to map α and τ into an estimate for the elasticity of migration to return differentials. The latter is in fact given by $(1-\tau)/(1-\alpha)$. For $\alpha = .989$, if $\tau = .991$ the elasticity of capital migration (or, equivalently, employment) equals 0.85. Because in our regressions we measure average growth over 5-year intervals, the value 0.85 should be interpreted as the yearly elasticity of migration over a 5-year period of persistent return differentials.

Across countries, Ortega and Peri (2009) find an elasticity of migration of roughly 0.7 to 1-year changes in destination country income, while Barro and Sala-I-Martin (1991) surprisingly find a number close to zero within the United States. Braun (1993) extends Barro and Sala-i-Martin results to a sample of regions within 6 wealthy countries, and finds an even lower elasticity of migration than in the US in five of them, and comparable in one (Japan). These estimates, which compute the elasticity of the number of migrants, are not directly comparable to our elasticity, which pertains to migration in (combined) capital. Still, our results on migration in Table 5 are indicative of a low elasticity, and in particular suggest a migration elasticity of combined capital within countries in the same ballpark of the migration elasticity across countries documented by Ortega and Peri (2009). This result is robust to the fixed effect estimation in Table 10. At the implied parameter values $\alpha = 0.96$ and $\tau = 0.93$, the elasticity of migration is equal to 1.75 (i.e. 0.35 annual), which is somewhat above the elasticity obtained with OLS. One caveat in interpreting these findings is that the elasticity of factor mobility implied by Eq. (10) is very sensitive to the value of τ. If in our benchmark calibration τ drops from 0.99 to 0.95 elasticity rises from 0.85 to 4.72. Given the scant evidence on the elasticity of migration of capital, these numbers should be viewed as preliminary.

We now use the analysis of Sect. 4.3 to shed light on the role of different institutional determinants of limited factor mobility. With all the usual caveats attached to cross-country regressions, in Table 7 finance emerges as a key factor that explains differences in factor mobility costs. The estimate of the role of finance in Panel A is again consistent with a value of α that is close to 0.99 but it further implies that β, the parameter shaping the gradient of mobility costs with respect to our financial market indicator, is roughly equal to 0.02 (indeed, estimates for the finance-income interaction imply $\alpha\beta = .0198$). Thus, the elasticity of capital mobility to return differentials should be equal to 0 in a country with fully repressed financial markets ($d_c = 0$) and to 2 in a country financial markets are fully liberalized ($d_c = 1$).

We conclude by illustrating the implications of our findings for the impact of financial frictions on the speed of regional convergence and on the steady state level of regional inequality. Our estimates indicate that fully liberalizing financial markets increases the convergence rate by 1.97 percentage points. Financial development can play an important role in the process of regional convergence. At the same time, financial development alone cannot break the shackles of the iron law: the maximum convergence rate equals 2.8 % (≈0.0076+0.0197), and has a modest impact on the number of years that it takes for the per capita GDP of a poor region to catch up to the national average. In sum, the mobility attained with fully liberalized financial markets is still far from ensuring fast regional convergence.

Can finance account for cross country patterns of regional income disparities? For $\alpha = 0.99$ and $\beta = 0.02$, Eq. (9) implies that the variance of log regional GDP in a country with repressed financial markets ($d_c = 0$) is 2.95 times larger than in a country with fully liberalized financial markets (d_c= 1). Unlike in the case of the speed of convergence, variation in financial liberalization exerts a large impact on the dispersion of regional GDP. The average variance of log GDP per capita is 19 % among the 20 poorest countries and 8 % among the 20 richest ones. The average d_c for the poorest 20 countries in our sample is .34; that for the richest 20 is .70, implying that the dispersion of regional GDP pc in the former is 1.3 times larger than that in the latter. The model can thus explain roughly 50 % of the 2.37-fold difference in measures of regional income dispersion.[13]

To conclude, we examine how the mapping between the structural parameters and the estimated coefficients changes when we relax the assumptions that capital depreciates fully in one period ($\delta = 1$) and that population growth is zero ($n = 0$). As we show in "Appendix 2", in the more general case with population growth rate n and depreciation rate δ, the speed of convergence equals $(\delta + n) \cdot (1 - \alpha\tau)$ and the coefficient on national per capita GDP is $(\delta + n) \cdot \alpha \cdot (1 - \tau)$. In this case, backing out α and τ from estimated coefficients requires making an explicit assumption on $\delta + n$. Note that our main estimating equation (7) holds exactly when $\delta + n$ equals 1. In the more general case, the convergence coefficients are based on a log-linear approximation around the steady state. We assume that the *annual* growth rate

[13] We also explored the convergence of the standard deviation of GDP per capita ("sigma convergence"). To that end, we computed the change in the within-country standard deviation of regional GDP per capita between the first and last cross-section of each country and regressed it on the following country-level variables: (1) the (log) initial GDP per capita, (2) the growth of GDP per capita, (3) initial years of schooling, (4) change in schooling, (5) government consumption as a percent of GDP, and (6) government transfers and subsidies as a percent of total government expenditure. In unreported univariate OLS regressions, years of schooling—with a positive coefficient—is the only significant regressor.

of population is 2 % (i.e., roughly equal to the average growth rate of the world population during the period 1960–2010) and that the *annual* depreciation rate is 6 % in line with the depreciation of physical capital (e.g. see Caselli 2005). Next, we combine the assumption that $\delta + n$ equals 8 % with the coefficients from estimating the empirical analog of our preferred specification (i.e. column 3 of Table 5) for the average annual convergence rate of regional GDP per capita. These estimates imply that relaxing the assumption that $\delta + n = 1$ does not lead to regional convergence rates that are meaningfully faster than the benchmark case of no mobility. For $\alpha = 0.87$ and $\tau = 1$, the convergence rate is 1 %. Accordingly, our finding of substantial limits to within country factor mobility is robust to allowing for conventional value of population growth and the depreciation rate of the capital stock.

6 Conclusion

Our analysis of growth and convergence in 1,528 regions of 83 countries allows for some tentative conclusions. First, regional growth is shaped by some of the same key factors as national growth, namely geography and human capital. Second, our estimated annual rate of regional convergence of 2 % per year is similar to Barro's "iron law" of 2 %. These regional convergence estimates are perhaps 1 % per year higher than what we estimate for countries, but still raise a key puzzle of why the flow of capital between regions of a country is so slow. Third, regional growth and convergence are faster in richer countries, consistent with the prediction of our neoclassical model that the national supply of capital benefits regional investment and growth. Fourth, capital market regulation is among the national factors correlated with the speed of regional convergence: countries with better regulation exhibit faster convergence. This finding is again consistent with the notion that frictions within countries limit capital flows and convergence. The facts on persistent regional inequality and slow convergence thus line up with each other, but they do leave open the puzzle of why resource flows within countries are typically so slow.

The paper raises the puzzle of slow convergence between subnational regions, but does not provide a resolution of this puzzle. For that, we need more detailed evidence on such issues as (1) technological diffusion between regions of a country, (2) the importance of capital accumulation (human and physical) within a region versus capital movements across regions, (3) patterns of migration within countries, (4) the contribution of changes in sector allocation (i.e. away from agriculture) and urbanization to regional development, and (5) the role of productive externalities in sustaining per capita income dispersion. Although we do not yet have sufficient comparable data on these issues for many countries, perhaps individual country studies can supplement our comparative evidence.

Appendix 1

Proof of Proposition 1 At time t+1, the employment of capital in region i is equal to $h_{i,t+1} = v_{t+1} \cdot \left(\hat{h}_{i,t+1}\right)^{\tau} \left(\hat{A}_i \cdot h_{t+1}\right)^{1-\tau}$. By replacing in this expression the capital endowment $\hat{h}_{i,t+1} \equiv sy_{i,t} = sA_i h_{i,t}^{\alpha}$, and the aggregate capital shock $h_{t+1} = s \int A_i h_{i,t}^{\alpha} di$, we obtain that the growth of employed capital in region i is equal to:

$$\frac{h_{i,t+1}}{h_{i,t}} = v_{t+1} \cdot h_{i,t}^{\alpha\tau-1} \cdot (sA_i)^{\tau} \left(\hat{A}_i \cdot s \cdot \int A_i h_{i,t}^{\alpha} di\right)^{1-\tau},$$

which is Eq. (5) in the text. □

A steady state in the economy is a configuration of regional employment $\left(h_i^*\right)_i$ and an entailed aggregate capital employment $h^* = s \int_i^A \left(h_i^*\right)^{\alpha} di$ such that the steady state capital h_r^* in any region r is:

$$1 = v^* \cdot \left(h_r^*\right)^{\alpha\tau - 1} \cdot (sA_r)^{\tau} \left(\hat{A}_r \cdot s \cdot \int A_i \left(h_i^*\right)^{\alpha} di\right)^{1-\tau},$$

where v^* is the normalization factor in the steady state. This can be rewritten as:

$$\left(h_r^*\right)^{1-\alpha\tau} = A_r^{\tau-(1-\alpha)(1-\tau)} \cdot v^* \cdot s \cdot \left(\frac{\int A_i \left(h_i^*\right)^{\alpha} di}{\int A_i^{1-\alpha} di}\right)^{1-\tau}. \tag{14}$$

There is always an equilibrium in which $h_i^* = 0$ for all regions i. Once we rule out this possibility, the equilibrium is interior and unique. In fact, Eq. (14) can be written as $h_r^* = A_r^{\frac{\tau-(1-\alpha)(1-\tau)}{1-\alpha\tau}} \cdot C$, where C is a positive constant which takes the same value for all depending on the entire profile of regional capital employment levels. Because the capital employed in a region does not affect (has a negligible impact on) the aggregate constant C, there is a unique value of h_r^* fulfilling the condition. By plugging the value of h_r^* into the expressions for v^* and $\int A_i \left(h_i^*\right)^{\alpha} di$, one can find that for $\alpha < 1$ and $\tau < 1$, there is a unique value of C that is consistent with equilibrium.

Finally, given the fact that $y_{i,t+1}/y_{i,t} = \left(h_{i,t+1}/h_{i,t}\right)^{\alpha}$, the economy approaches the interior steady state according to Eq. (5) in the text.

Appendix 2: Convergence coefficients for generic values of depreciation and population growth

Our main analysis assumes a zero rate of population growth ($n = 0$) and full depreciation ($\delta = 1$). Focusing on this case allowed us to obtain an exact closed form for our main estimating equation. We now perform a log-linear approximation to derive convergence coefficients when n and δ are generic.

In region i, the growth of per capita GDP between periods t and $t + 1$ is equal to $ln(y_{i,t+1}/y_{i,t})$ which, by the assumed production function, is equal to $\alpha ln\left(\frac{h_{i,t+1}}{h_{i,t}}\right) \cong \alpha\left(\frac{h_{i,t+1}}{h_{i,t}} - 1\right)$. There is a direct link between a region's income growth and the growth of the region's per capita capital employment.

Let us therefore find the law of motion for $h_{i,t}$ for generic values of n and δ. Denote by $\hat{H}_{i,t}$ the capital endowment of region i at time t, and by $H_{i,t}$ the same region's employment of capital. The law of motion for $\hat{H}_{i,t}$ then fulfills:

$$\hat{H}_{i,t+1} = sA_i H_{i,t}^{\alpha} L_{i,t}^{1-\alpha} + (1-\delta) \cdot \hat{H}_{i,t}.$$

The capital stock next period is equal to undepreciated capital $(1-\delta) \cdot \hat{H}_{i,t}$ plus this period's savings $sA_i H_{i,t}^{\alpha} L_{i,t}^{1-\alpha}$. To express the equation in per capita terms, we devide both sides of the above equation by the region's population $L_{i,t}$ at time t and obtain:

$$\frac{\hat{H}_{i,t+1}}{L_{i,t}} \equiv \frac{\hat{H}_{i,t+1}}{L_{i,t+1}} \cdot \frac{L_{i,t+1}}{L_{i,t}} \equiv \hat{h}_{i,t+1}(1+n)$$
$$= sAh_{i,t}^{\alpha} + (1-\delta) \cdot \hat{h}_{i,t}.$$

The law of motion of the region's per capita capital endowment can be approximated as:

$$\hat{h}_{i,t+1} \cong sA_i h_{i,t}^{\alpha} + (1-\delta-n)\,\hat{h}_{i,t}. \tag{15}$$

To solve for regional GDP growth, we need to transform the above equation into a law of motion for regional capital employment $h_{i,t}$. To do so, we can exploit our migration equation (4) to write:

$$\hat{h}_{i,t} = \left(h_{i,t}\right)^{\frac{1}{\tau}} \cdot \left(\hat{A}_i \cdot h_t\right)^{-\frac{1-\tau}{\tau}} \cdot \left(v_t\right)^{-\frac{1}{\tau}}.$$

By plugging the above equation into (15) we then obtain, after some algebra, the following equation:

$$\frac{h_{i,t+1}}{h_{i,t}} - 1 \cong \left[sA_i h_{i,t}^{\frac{\alpha\tau-1}{\tau}} \cdot (v_t)^{\frac{1}{\tau}} \cdot \left(\hat{A}_i \cdot h_t\right)^{\frac{1-\tau}{\tau}} + (1-\delta-n)\right]^{\tau} \cdot \left[\frac{h_{t+1}}{h_t}\right]^{1-\tau} \cdot \left[\frac{v_t}{v_{t+1}}\right] - 1.$$

By noting that the aggregate capital stock grows at the rate $(h_{t+1}/h_t) = s\,(y_t/h_t) + (1-n-\delta)$, we can rewrite the above law of motion as:

$$\frac{h_{i,t+1}}{h_{i,t}} - 1 \cong \left[sA_i h_{i,t}^{\frac{\alpha\tau-1}{\tau}} \cdot (v_t)^{\frac{1}{\tau}} \cdot \left(\hat{A}_i \cdot h_t\right)^{\frac{1-\tau}{\tau}} + (1-\delta-n)\right]^{\tau}$$
$$\times \left[s\,(y_t/h_t) + (1-n-\delta)\right]^{1-\tau} \cdot \left[\frac{v_t}{v_{t+1}}\right] - 1.$$

A steady state is identified by the condition $h_{i,t+1} = h_{i,t} = h_{i,SS}$ and thus $h_{t+1} = h_t = h_{SS}$. Because in the steady state there is no migration, and the human capital endowment of a region is also equal to its ideal employment level, we also have that $v_{t+1} = v_t = 1$. As a result, the steady state is identified by the following conditions:

$$sA_i h_{i,SS}^{\frac{\alpha\tau-1}{\tau}} \cdot \left(\hat{A}_i \cdot h_{SS}\right)^{\frac{1-\tau}{\tau}} = (\delta+n),$$
$$s\,(y_{SS}/h_{SS}) \equiv s\left(\int A_i h_{i,SS}^{\alpha}/h_{SS}\right) = (n+\delta).$$

If we log-linearize with respect to regional employment $h_{i,t}$ and national output y_t the right hand side of the law of motion of $h_{i,t}$ around the steady state above, we find that for any $\tau > 0$ we can write the following approximation:

$$\frac{h_{i,t+1}}{h_{i,t}} - 1 \cong -(\delta+n)\cdot(1-\alpha\tau)\cdot\ln\left(\frac{h_{i,t}}{h_{i,SS}}\right) + (\delta+n)\cdot(1-\tau)\cdot\ln\left(\frac{y_t}{y_{SS}}\right).$$

By exploiting the fact that $ln\left(\frac{y_{i,t+1}}{y_{i,t}}\right) \cong \left(\frac{y_{i,t+1}}{y_{i,t}} - 1\right) \cong \alpha \cdot \left(\frac{h_{i,t+1}}{h_{i,t}} - 1\right)$, we can then write:

$$\frac{y_{i,t+1} - y_{i,t}}{y_{i,t}} \cong -(\delta+n)\cdot(1-\alpha\tau)\cdot\ln\left(\frac{y_{i,t}}{y_{i,SS}}\right) + (\delta+n)\cdot\alpha\cdot(1-\tau)\cdot\ln\left(\frac{y_t}{y_{SS}}\right).$$

As a result, the speed of convergence is equal to $(\delta+n)\cdot(1-\alpha\tau)$ and regional growth increases in country level income with coefficient $(\delta+n)\cdot\alpha\cdot(1-\tau)$. These coefficient boil down to those obtained under the exact formulas of our model when $(\delta+n) = 1$ (and thus when, as assumed in the model, $\delta = 1$ and $n = 0$). When, on the other hand, $(\delta+n) \neq 1$, the mapping between our estimates and the economy's "deep" parameters will be different, entailing different values for α and τ.

Appendix 3

See the Appendix Table 11.

Table 11 Description of the variables

Variable	Description
I. Regional variables	
Regional GDP pc	Gross domestic product per capita in the region (in constant 2005 PPP dollars). For each country, we scale regional GDP per capita so that their population-weighted sum equals the value of Gross Domestic Product reported in Penn World Tables or, when unavailable, World Development Indicators. Similarly, for each country, we adjust the regional population values so that their sum equals the country-level analog in World Development Indicators. See the online data appendix for sources and time periods
Years of education	The average years of schooling from primary school onwards for the population aged 15 years or older. To make levels of educational attainment comparable across countries, we translate educational statistics into the International Standard Classification of Education (ISCED) standard and use UNESCO data on the duration of school levels in each country for the year for which we have educational attainment data. Eurostat aggregates data for ISCED levels 0–2 and we assign such observations an ISCED level 1. Following Barro and Lee (1993): (1) we assign zero years of schooling to ISCED level 0 (i.e., pre-primary); (2) we assign zero years of additional schooling to (a) ISCED level 4 (i.e., vocational), and (b) ISCED level 6 (i.e. post-graduate); and (3) we assign 4 years of additional schooling to ISCED level 5 (i.e. graduate). Since regional data is not available for all countries, unlike Barro and Lee (1993), we assign zero years of additional schooling: (a) to all incomplete levels; and (b) to ISCED level 2 (i.e. lower secondary). Thus, the average years of schooling in a region is calculated as: (1) the product of the fraction of people whose highest attainment level is ISCED 1 or 2 and the duration of ISCED 1; plus (2) the product of the fraction of people whose highest attainment level is ISCED 3 or 4 and the cumulative duration of ISCED 3; plus (3) the product of the fraction of people whose highest attainment level is ISCED 5 or 6 and the sum of the cumulative duration of ISCED 3 plus 4 years. At the country level, we calculate this variable as the population-weighted average of the regional values. See the online data appendix for sources and time periods
Area	The area of a region, in square kilometers. To obtain area, we put the regions into an equal area projection and calculated the area in ArcGIS
Population density	Population per regional area (in square kilometers). The area of a region is based on an equal area projection and calculated using ArcGIS. Source: National statistical agencies for population
Latitude	The latitude of the centroid of each region calculated in ArcGIS
Distance to the coast	Average distance to the coast in kilometers. To calculate the average distance to the coast, we put the regions into an equal distance projection, and then generate a raster file with the distance to the coast in each cell using coastline data from Natural Earth. Then, we sum the distances to the coast of all the cells falling within a region and divide by the number of cells in that region. Source: Natural Earth: http://www.naturalearthdata.com/downloads/110m-physical-vectors/110m-coastline/
Capital is in region	Dummy equal to 1 if the region contains a national capital, 0 otherwise. Source: ESRI World Cities: http://www.esri.com/data/data-maps

Table 11 continued

Variable	Description
Oil and gas production	Cumulative oil, gas and liquid natural gas production from the time production began to 2000. For onshore oil and gas, we calculated the production by region by allocating oil production to regions based on the fraction of the petroleum assessment areas within the region. We removed offshore assessment areas that are closer at all points to countries not included in the dataset than to countries included. Offshore assessment areas that are in the area of countries within the dataset and countries not in the dataset are clipped at a distance of 100 km from the regions in the dataset. The assessment fields were then converted to a raster layer containing the cumulative production values in each cell, and the cells were allocated to regions based on the closest region. Oil and liquid natural gas were collected in millions of barrels. Gas was collected in billions of cubic feet and divided by 6 to convert to millions of barrels of oil equivalents. Source: USGS World Petroleum Assessment Data: http://energy.usgs.gov/OilGas/AssessmentsData/WorldPetroleumAssessment/tabid/558/Agg2421_SelectTab/4/Default.aspx
Malaria index	The "malaria ecology" index of Kiszewski et al. (2004) which takes into account both climactic factors and the dominant vector species to give an overall measure of the component of malaria variation that is exogenous to human intervention. The index is calculated for grid squares of one half degree longitude by one half degree latitude. Regional averages are calculated via ArcGIS. http://irps.ucsd.edu/faculty/faculty-directory/gordon-c-mccord.htm
Soil quality	Index of land suitability for agriculture, based on geographic and other environmental factors. Regional averages are calculated via ArcGIS. Source: Ramankutty, N., J.A. Foley, J. Norman, and K. McSweeney (2001); http://atlas.sage.wisc.edu/
Night-time lights intensity	Average annual intensity of light detections in a cloud-free night-time sky. Regional averages calculated via ArcGIS. Source: National Oceanic and Atmospheric Administration at the National Geophysical Data Center; http://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html
Fertility	Number of newly born children within a census year per female population aged 15 years or older. Source: IPUMS census microdata
Human capital stock of residents	Average years of schooling of the population aged 15 years or older currently residing in a given region. Source: IPUMS census microdata
Human capital stock of natives	Average years of schooling of the population aged 15 years or older born in a given region. Source: IPUMS census microdata
Immigration flow	Population aged 15 years or older moving into a given region within 5 years of a given census. Source: IPUMS census microdata
Agricultural employment	Population aged 15 years or older employed in agriculture. Source: IPUMS census microdata
% households using piped water	Share of households which use piped water within their housing. Source: DHS microdata

Table 11 continued

Variable	Description
% households using flush toilet	Share of households with flush toilet within their housing. Source: DHS microdata
% households with electricity	Share of households with electricity within their housing. Source: DHS microdata
% households possessing a radio	Share of households which posses a radio. Source: DHS microdata
% households possessing a television	Share of households which posses a television. Source: DHS microdata
% households possessing a refrigerator	Share of households with a refrigerator within their living property. Source: DHS microdata
% households possessing a private car	Share of households which own a private car. Source: DHS microdata
Housing cost index	Average regional housing cost, relative to the country-level housing cost, using the following variables in order of preference: total housing cost, total housing and utility costs, dwelling value, actual rent, imputed rent. Following Ganong and Shoag (2013), total housing cost is calculated by using 5 % of property value if a given household's housing is owned, or 100 % of annual rent (or housing and utility costs, depending on a given country-sample data availability) if housing is rented. Source: LIS microdata
Regional price deflator	Regional price deflator is calculated by assuming that non-tradable goods (proxied by housing for the purpose of calculating price-levels), are 30 % of household expenditure, while tradable goods are assumed to be 70 % of hosehold expenditure. Tradable goods are assumed to have identical prices across all regions within a given country. Regional price deflator is then defined as a ratio of regional housing prices and country-level housing prices, to the power of 0.3. Source: LIS microdata
Price-adjusted GDP per capita	Ratio of regional GDP per capita and the regional price deflator. Source: Own calculations
II. Country-level Variables	
GDP pc, Country	Gross domestic product per capita of the country (in constant 2005 PPP dollars). Source: Penn World Tables and World Bank World Development Indicators
Life expectancy at birth	Country-level life expectancy at birth for a given year. Source: World Bank World Development Indicators
Law and order	Country-level index of law and order, based on socio-economic and legal measures, converted from seven categories to a 0–1 scale. Source: Political Risk Services, International Country Risk Guide
Openness	Sum of exports and imports as a share of GDP. Source: Penn World Tables
Government Consumption/GDP	Total government consumption as a share of GDP. Source: Penn World Tables
Investment/GDP	Total Investment as a share of GDP. Source: Penn World Tables

Table 11 continued

Variable	Description
Government transfers and subsidies/total government consumption	Sum of government transfers and subsidies as a share of total government consumption. Source: Penn World Tables
Change in terms of trade	Five-year growth rate of export prices relative to import prices. Source: International Monetary Fund, International Financial Statistics, and World Development Indicators
Democracy	Polity2 index of democracy, converted from a −10 to +10 scale to a 0–1 scale. Source: Polity IV
Inflation	Annual country-level price inflation. Source: International Monetary Fund, International Financial Statistics, and World Development Indicators
English legal origin	Dummy variable which equals 1 if a given country's legal system has English legal origin, and zero otherwise. Source: La Porta et al. (2008)
Finance	Average of six sub-indices of financial regulation. Five of them relate to banking: (i) interest rate controls, such as floors or ceilings; (ii) credit controls; (iii) competition restrictions; (iv) the degree of state ownership; and (v) the quality of banking supervision and regulation. The sixth sub-index relates to securities markets and covers policies to develop domestic bond and equity markets. Each sub-index is coded from zero (fully repressed) to three (fully liberalized). Source: Abiad et al. (2008)
Trade tariffs	Average tariff rate. Index normalized to be between zero and unity: zero means the tariff rates are 60 percent or higher, while unity means the tariff rates are zero. Source: Spilimbergo and Che (2012)
Labor	Highest level of the tax wedge. Variable ranges from 0 to 1. Source: Aleksynska and Schindler (2011) as used by Spilimbergo and Che (2012)
Transf/Gov	The normalized value of transfers and subsidies as a percent of government expenses. We normalize the variable using its maximum and minimum sample values. Source: World Bank World Development Indicators
Gov/GDP	Normalized value of government expenditure as a percent of gross domestic product. We normalize the variable using its maximum and minimum sample values. Source: World Development Indicators

Appendix 4

See the Appendix Table 12

Table 12 Fertility, land quality, employment in agriculture

	(1)	(2)	(3)	(4)
Ln(GDP pc region)	−0.0285[c]	−0.0211[a]	−0.0199[a]	−0.0203[b]
	(0.0151)	(0.0048)	(0.0047)	(0.0085)
Ln(GDP pc country)	0.0070	0.0090[b]	0.0089[b]	0.0033
	(0.0046)	(0.0037)	(0.0038)	(0.0030)
Latitude	0.0003[b]	0.0002	0.0002	0.0004[a]
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Inverse distance to coast	0.0539	0.0532[a]	0.0795[a]	0.0469[b]
	(0.0330)	(0.0166)	(0.0292)	(0.0223)
Malaria ecology	0.0012	0.0004	0.0005	0.0019[c]
	(0.0008)	(0.0006)	(0.0005)	(0.0011)
Ln(Cum oil and gas prod)	0.0462	0.2043[a]	0.1807[a]	0.0371
	(0.1311)	(0.0409)	(0.0455)	(0.1200)
Ln(Population density)	0.0010	0.0011	0.0008	0.0005
	(0.0009)	(0.0008)	(0.0007)	(0.0009)
Capital is in region	0.0041	0.0061	0.0079[a]	0.0030
	(0.0043)	(0.0039)	(0.0030)	(0.0027)
Years of education	0.0027	0.0018	0.0020[c]	0.0014
	(0.0017)	(0.0011)	(0.0012)	(0.0018)
Fertility	−0.1044			
	(0.0981)			
Fertility × Ln(GDP pc region)	0.0120			
	(0.0108)			
Soil quality		−0.0307		
		(0.0246)		
Soil quality × Ln(GDP pc region)		0.0030		
		(0.0026)		
Variance of soil quality			−0.2311	
			(0.1700)	
Variance of soil quality × Ln(GDP pc region)			0.0243	
			(0.0181)	
Agricultural employment				−0.0091
				(0.0833)
Agricultural employment × Ln(GDP pc region)				−0.0016
				(0.0101)
Constant	0.1827[b]	0.1082[b]	0.0954[b]	0.1579[a]
	(0.0916)	(0.0423)	(0.0402)	(0.0522)

Table 12 continued

	(1)	(2)	(3)	(4)
Observations	2,796	6,728	6,299	3,556
Regions	715	1,480	1,378	753
R^2	9 %	7 %	7 %	10 %
Fixed effects	None	None	None	None
Estimation	OLS	OLS	OLS	OLS
Instrument	NA	NA	NA	NA

[a] Significant at the 1 % level; [b] significant at the 5 % level; and [c] significant at the 10 % level

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