UNEQUAL GLOBAL CONVERGENCE*

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Abstract

We assemble and harmonize a new time-consistent dataset on the sub-national GDP and employment by broad sectors of 687 regions in 34 countries across 5 continents. Once we validate our data we show that, in the last three decades, growth within countries has been highly spatially concentrated. Specifically, we document a sharp slowdown in the convergence rate between regions within countries since 1980. By 2010, the regional convergence process in most countries has stalled despite residual spatial inequality. Second, this decline in the rate of regional convergence is related to economic development, specifically to a structural transformation toward services. Third, service share exhibits higher regional concentration compared to manufacturing and agriculture. Next, we argue a new role of structural change for spatial development through the lens of a spatial model that features geographic mobility and agglomeration. Estimates from the model suggest that as the economy transforms toward services, economic activity becomes spatially concentrated, and regional convergence declines. This, in turn, accelerates global economic inequality and structural transformation toward services.

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1 Introduction

It is well known that in the last half-century, countries that were initially poorer have witnessed faster economic growth than richer countries. That is, there has been cross-country convergence. While macro-development research has focused on understanding cross-country disparities in income levels, little is known about the spatial nature and consequences of the shrinking income differences. Consider India's economic growth and its catch-up with the advanced economies. India's GDP today is slightly more than that of the United Kingdom, its former colonizer. Was this growth broad based or driven by a few regions within India? Did poorer states of India catch-up with the richer states or grow farther apart? What role did structural change play? Gathering evidence to answer these questions is paramount to understand whether the rapid growth of developing countries is leaving individuals in some regions behind. However, answering these questions requires longitudinal data at regional level over time harmonized across countries, which are often sparse.

Against this background, in this paper, we make advances by assembling and validating a novel longitudinal dataset at a sub-national level for 674 regions within 34 countries across 5 continents between 1980–2015. We identify two striking empirical regularities. First, we document that the faster growth of countries masks a global stall in within-country convergence. Specifically, richer regions within countries have grown faster and the catch-up rate of the poorer regions has declined. While an increase in spatial income disparities is well-known in the US (e.g., Glaeser and Gyourko 2006, Ganong and Shoag 2017, Giannone 2017), this is the first evidence that a stall in regional convergence is a global feature of the data, happening across a broad set of countries across continents. We document this phenomenon for a set of countries that account for 80% of the world's.[1] Second, we turn to studying the drivers of regional inequality. We find that this global decline of regional convergence is associated with economic development. As a country develops and the share of services employment rises, the rate of within-country convergence falls. Motivated by this empirical evidence, we develop a model of structural transformation and economic geography that shows how the shift of the economy towards service reduces economic convergence within the country. Thus, highlighting how structural transformation might increase inequality through space increasing economic growth at the same time. The model puts forward a novel interplay

[1]As supporting evidence we also find that economic growth is positively associated with regional inequality but negatively associated with individual inequality (as measured by the GINI coefficient and its growth). This second fact highlights how inequality across space has a role above and beyond individual level inequality.

between structural transformation and regional inequality: when regional convergence declines, it induces a push for structural transformation. This happens because the service sector has higher agglomeration economies. Thus, when individuals move to cities with larger service sectors, agglomeration economies kick in exacerbating both regional inequality and structural transformation towards services.

The paper is divided into two parts. In the first part, we describe the data and the empirical evidence. *One of the main contributions of this paper is to provide social scientists with a time-consistent dataset for regions within countries to conduct analysis with information on GDP, education, sectoral GDP and employment.* Our starting point is the pioneer dataset of Gennaioli et al. (2014) which includes 83 countries and more than 1500 regions. We complement it in the following ways. First, we augment the regional data on GDP and education for the last available year and we also search for other countries that might have not been included in their dataset. Second, to include also Sub-Saharian Africa, we purchased and analyzed regional data by city from *The Economist*. Third, we collect a new set of regional data on sectoral GDP and employment. Differently from Gennaioli et al. (2014), our sample has only 34 countries due to our time-consistency requirements between 1980 and 2015. We validate our sample against other data and find that it is representative of approximately 80% of the world GDP and 66% of the world population. It is, however, less representative of Africa, that is why we corroborate the findings with *The Economist* dataset. Once we validate our data, we estimate within-country convergence for each country in our sample over time. Overall, we find that for the average country in our sample, within-country convergence between 1980 and 1990 is larger than within-country convergence between 2005 and 2015. Even more, interestingly, we find that in the latest period, within-country convergence is close to zero. This result is driven by 56% of the country in our sample that represents more 70% of the population of the sample itself. We test for heterogeneity in terms of size, continent and income status and find that income status has an interesting level of heterogeneity with OECD countries diverging faster than non-OECD countries. Aware of this result, we dig more into how sectoral changes in services and income levels are related to the within-country convergence development. The results are salient. Countries that in 1980 had higher sectoral shares had lower level of within-country convergence. This points to the direction of structural transformation towards services being an important factor in explaining this stark change in the data of the last half-century. Finally, to dig further on the role of space for sectoral reallocation, we describe how sectors are concentrated geographically over time. We find that service share, in particular, professional services are 2.6 times higher nowadays in locations where they started higher in 1990. Compared to manufacturing and agriculture, the concentration is 20% higher in the cross-section and also increasing faster over time.

In the second part, we interpret our mechanism through the lenses of a simple model of structural transformation nested with economic geography. The model embeds both convergence forces as well as divergence forces. Regional convergence forces are added through the productivity growth of agriculture being higher than the others. Divergence forces, in contrast, are included through endogenous agglomeration economies in services. The model features three sectors: agriculture, manufacturing, and services. The three sectors use only labor as the only input to keep it as simple as possible. The productivity of each sector grows at different rates with the service sectors growing faster and agriculture the slowest. In line with classic structural transformation models, there is a subsistence level of agricultural goods. This, as highlighted by Caselli and Coleman (2001), serves as a source of regional convergence when agricultural productivity growth goes up. The service sector instead features agglomeration economies that foster its productivity and concentration in some sectors, especially when workers can freely move across regions.

We calibrate the model to the "representative" country that we build from our sample dividing the regions into low, medium and high GDP. With the calibrated model, we test what happens to the relationship between within-country convergence and service sectoral share and find a positive relationship as in the data. Thus, the model supports our empirical results. The main reason is that thanks to the agglomeration economies, along with the structural transformation towards services, service shares concentrated further in richer regions exacerbating both structural transformation and the stall of regional convergence.

Related Literature Our paper contributes to several pieces of literature on structural transformation and economic geography. We contribute by studying the role of structural transformation on regional inequality. Hence, we add to Caselli and Coleman (2001) and Eckert et al. (2018) who quantitatively study how the structural transformation from agriculture to manufacturing increased regional convergence in the US. In our work, besides corroborating this hypothesis, we provide new evidence that a shift from manufacturing to services might have decreased regional convergence globally. Since the latter result is inconsistent with existing theories of structural change, we develop a model of structural change that can account for the decline in within-country convergence when service sectoral shares increase.

This points to a new dichotomy in the role of structural transformation for spatial development. Recently, Fan et al. (2022) show how service-led growth of India has created more inequality within the country and pushed for more growth. Overall, our paper is consistent with these hypotheses with supporting evidence at a global scale and identifies a simple overarching theory that rationalizes the facts.

Our work is also related to the recent and growing literature about the role of structural transformation summarized by Herrendorf et al. (2014) with a large focus on services on the aggregate economy as in Buera and Kaboski (2012), Huneeus and Rogerson (2020a). To this explanation of how structural transformation towards services affected the economy, we add the geographic component which highlights how the concentration of the key economies in a few locations might change the nature of economic growth across the world. Our main contribution is, indeed, to highlight a feedback effect of spatial inequality on structural transformation: when the inequality within-country grows and regional convergence declines, structural transformation towards services speeds up.

This paper also relates to the empirical literature that studies convergence within and across countries (e.g., Sala-i Martin 1996, Blanchard et al. 1992, Gennaioli et al. 2014, Ganong and Shoag 2017, Guriev and Vakulenko 2012) pioneered with the seminal work of Barro and i Martin 1992. Our starting point for the dataset is based on Gennaioli et al. (2014) that documents patterns of regional convergence across regions of the world between 1950 and 2010. We build on and augment their data for the most recent years while also adding detailed information on sectoral and education data at sub-regional data. We also add data from *The Economist* to account for the missing sample such as Africa. While Gennaioli et al. (2014) studies cross sectional patterns, we focus on the evolution of regional convergence. Thus, we also need a time-consistent sample of countries which leave us with 34 countries and 674 regions.

This paper develops as follows. Section 2 reports the datasets used for the analysis. Section 3 reports the stylized facts we encounter in the data. Section 4 develops a model of structural transformation and economic geography to explain the patterns in the data. Section 5 concludes and highlights the work we are currently pursuing.

2 Data

One key purpose of this paper is to provide a time-consistent dataset of key variables at the regional level across the world that economists and other social scientists can use to conduct research. In this respect, we construct a time series of sub-national key economics variables (GDP, education and sectoral employment and GDP) for a wide range of countries. Our starting point is the excellent dataset on sub-national GDP assembled by Gennaioli et al. (2012) spanning between 1950 and 2010. We update it to the most recent possible year, select only those countries that had at least one data point in each decade and complement it with other data sources that we manually search. The details comparing our sample with the existing one are presented in table 5. As table 5 shows, we complement also years of education, sectoral employment and GDP at sub-regional level. Our sample consists of 34 countries. This is significantly lower than the sample of 83 countries in Gennaioli et al. (2012) because we require a balanced panel of countries that have data at least once in each decade between 1980-2020. This leaves us with 678 sub-national regions of the world, as compared to 1503 sub-national regions in Gennaioli et al. (2012). Nevertheless, we will also release the broader dataset unbalanced over time.

Overall, the 34 countries in our sample account for 80% of the world GDP and 66% of the world population (see table 6 for details).[2] The coverage is biased towards high and middle-income countries, primarily because we miss data on many African countries as shown in tables 8 and 7. Thus, while our sample accounts for over 90% of the population and GDP of high-income countries and over 50% of the population and GDP of middle-income countries, we capture about 29% of the population and 24% of the GDP of low-income countries (see table 7. Similarly, our coverage is the best for the Americas and Europe. Since our sample has India, China, Japan, South Korea and Malaysia, we account for about 41% of the Asian GDP but we miss all other countries on that continent. This includes Vietnam, Thailand, Indonesia, and Philippines which have seen robust economic growth in the last three decades.

That we do not cover much of Africa is another concern, but this is not peculiar to our dataset. Even national accounts data of many African countries in the WDI is spotty. To address these concerns we proceed in two ways. First, we use night lights data to test the robustness of our results. More details about coverage of nightlights data and estimates of regional convergence are reported in appendix 6.3. Second, we purchased the dataset from

[2] In our sample, there were two regions (Northern Ireland of the United Kingdom and Northern Sri Lanka) for which no years of education data were available.

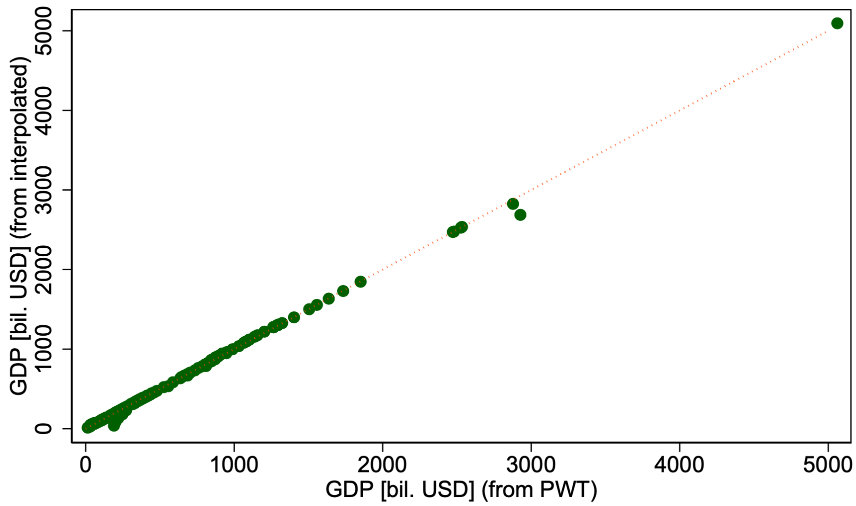
The Economist which has longitudinal data at city level between 2004 and 2020. More details about the coverage and the list of countries are given in the same Appendix.

In order to shed light on the determinants of regional inequality, we use various indicators. We supplement this data with data on national GDP, shares of agriculture, manufacturing, and services in GDP from the World Development Indicators. We use years of schooling from Barro and Lee (2000) to capture the level of human capital. We use measures on FTAs and global market access from CEPII to control for the openness of economies and on roads from the Global Roads Inventory Project (GRIP) to control for internal connectivity.

Since political systems can effect spatial patterns of economic growth within a country, we control for the level of democracy using the score from the Political-IV project. As tropical countries have had poor long-term economic performance for various reasons (Sachs (2001), Acemoglu et al. (2001)), we control for long-run measures of institutions and technology like type of climate, distance to the coast, and ruggedness from Nunn and Puga (2012).

GDP Data Validation We interpolate our dataset on GDP under the condition that the regions have at least one data point per decade. Our interpolation proceeds in the following way. First, we regress each year-region's regional GDP per capita on a constant, year, and national GDP per capita (obtained from PWT9.1). Using the OLS estimates, we fill in missing values using predicted values. Similarly, we fill in missing values for regional population using prediction based on national population data from PWT9.1. We also fill in missing values for regional population using prediction based on national population data from WDI. Since we have many missing values even at national level, we then linearly extrapolate using these predicted values. Figure 1 shows the results of the interpolation exercise on our main GDP variable. Overall, our estimates are very close to the 45-degree line.

Figure 1: Validation of GDP data: Interpolation



3 A Novel Set of Facts about Global Convergence

We begin by documenting two new facts about the spatial dimension of global economic growth in the last four decades and contrast it with known facts about cross-country convergence. First, we document that the speed of convergence between different regions within countries has gone down from 1.5% to close to zero between 1980 and 2015. This is in stark contrast to the well-known fact of a secular increase in the rate of convergence between countries (see Roy et al. (2016) for example). Second, we document that the global slowdown in within-country convergence is related to a structural transformation of countries from manufacturing to services.

3.1 Fact #1: A stall in the convergence within countries 1980–2015

There has been a stall in the rate of convergence between regions within countries between 1980 and 2015. To document this, we estimate the rate of convergence in the economic growth regions within a country from a standard convergence regression. Our main specification to estimate the speed of convergence follows from Baumol (1986):

$$\frac{log(GDP_{jt}) - log(GDP_{j\tau})}{(t-\tau)} = \alpha + \beta log(GDP_{j\tau}) + \gamma \mathbf{X}_{jt} + \varepsilon_{jt}$$

where j can be a country or a region within a country, t is the final year of the analysis and τ is the initial year. GDP_{jt} is the GDP per capita in region or country j at time τ. The dependent variable is the annual average GDP per capita growth between τ and t. $\mathbf{X}_{jt}$ is a vector of controls such as population, education and capital. All the regressions are weighted by initial population size. If the estimates of β are negative and statistically significant, then, we interpret it as *catch-up* and the convergence rate is exactly β. If they are positive and statistically significant, there is divergence or lack of *catch-up*. All the standard errors are robust to correct for heteroskedasticity in the data. From now on, we are going to refer to "within-country β" for the specifications that we estimate within a country where each observation is a region. And, we are going to refer to "cross-country β" for the specifications that we estimate across countries where each observation is a country, later on.

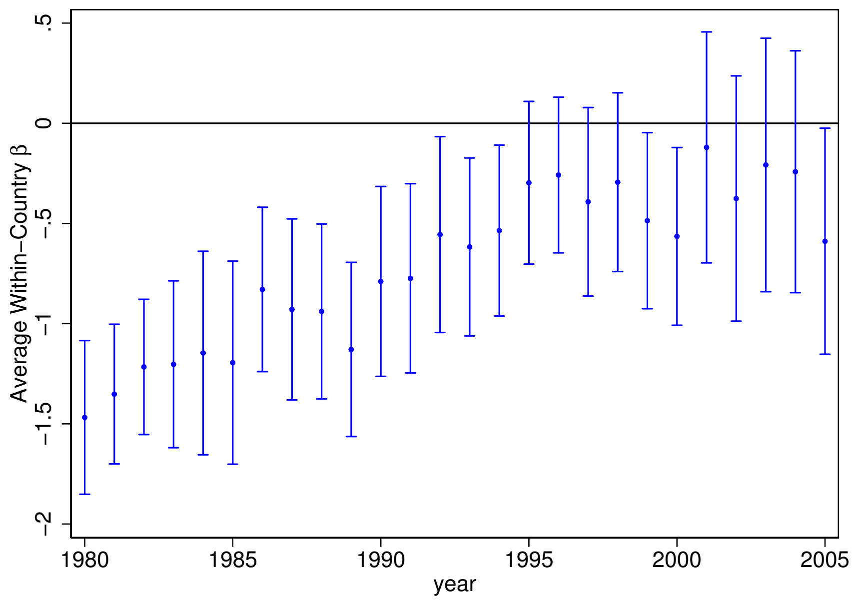
For each country-year, we regress the annual growth in per-capita GDP of its regions over the next ten years on the log of the level of initial per-capita GDP. The regression coefficient is the rate of convergence between regions of that country. We average these rates for the 34 countries in our sample to obtain the average within-country convergence rate for the world. Standard errors are obtained using "delta-method". The averaged within-country convergence rates plotted in figure 2 show that it decreased from about 1.5% in the 1980s to being statistically indistinguishable from zero in the 2000s and a slight negative sign in 2005.

This is in stark contrast to what we know about cross-country convergence in figure 2 of the Appendix section. As has been noted by Roy et al. (2016) and Patel et al. (2018), there has been an unconditional convergence between countries since 1990s and the rate of convergence has been increasing over time. Further, these results are robust to the exclusion of China and India. This can be seen in the appendix figure 2 where we reproduce figure 1 from Patel et al. (2018) for 83 major non-oil economies of the world and our sample of 34 countries.

Note also the contrast in the magnitudes. The rate of convergence between countries in the 1980s was zero. Convergence started in the mid-90s with the rate increasing to 1–1.5% in the 2000s. The within-country convergence patterns mirror this. While in the 1980s the within-country convergence rates were between 1-1.5%, they fell almost to zero in the 2000s and kept in that range in 2015.

Overall, as we show in table 1, we find that the estimates of beta convergence decreased for 19 our the 34 countries between 1980 and 2017, which is 56% of our sample. This sample represents approximately 77% of the GDP and 69% of the population. Thus, it seems to be more skewed towards rich and large countries.

Figure 2: Within-Country β Over Time



Note: This figure reports the average within-country β convergence for the 34 countries in our sample between 1980 and 2015. The confidence intervals around the estimates are calculated with the deltha-method.

Table 1: The Decline in within-country β convergence

	1980 β < 2007 β
Share of countries	56%
Share of GDP	77.1%
Share of population	69.0%

Note: This table reports the summary statistics of within-country β convergence being lower in 2017 vs 2015. The definition of within-country β convergence is the one reported in 3.1.

Heterogeneity In order to understand what caused the slow-down in within-country β convergence, we split the sample in groups by geography, size and OECD status and describe the results graphically in figure 1. Detailed regression results are available in appendix table 1.

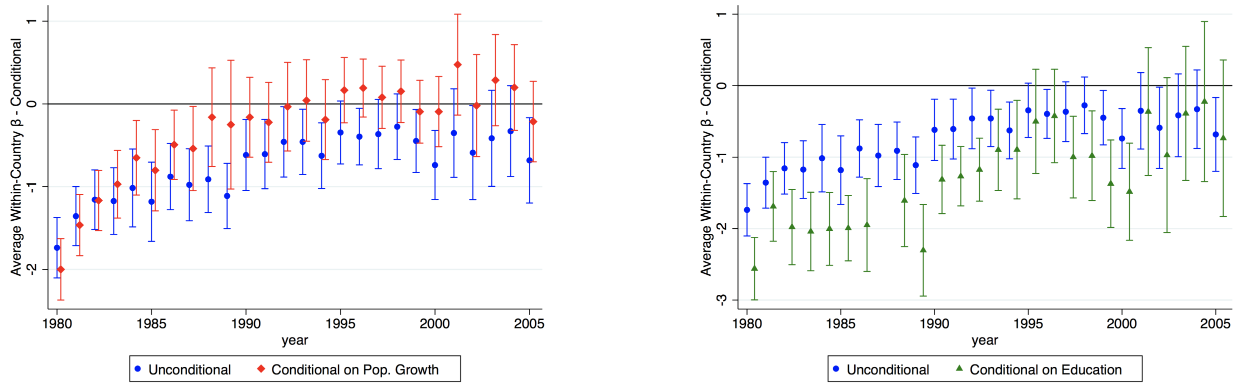
During 1980-1990, within-country convergence was highest in North America and in Asia but it was overall negative. During 2000-2010, however, within-country β convergence stall across continents and the effect kept being there also until 2015. We continue by splitting the countries by size. We define small countries those which population is below the 33rd percentile, large those with population over the time span taken in consideration is above the 67th percentile and middle size those in between. Within-country convergence rates were twice as much among large economies as compared to medium and smaller economies during 1980-1990. During 2000-2010 the regions within larger economies continued to converge at the rate of 1.15%, convergence stalled in the medium size countries. The regions within smaller economies are the ones where convergence rates dropped the most in the whole sample. Finally, to account for economic initial conditions, we split the sample in countries that belonged or not to OECD. We find that convergence rates dropped the most in non-OECD countries, Specifically, for non-OECD countries there convergence rates are statistically indistinguishable from zero.

Conditional Convergence While we observe the decline of absolute convergence in the last 40 years, it might be the case that conditional convergence on key predictors of economic growth might replicate more convergence in the data as predicted by the Solow model. The key variables to corroborate conditional convergence are education, population, population growth and savings/investment. Our dataset allows us to control both for education and population at regional level within the country. However, we do not have data for savings/investment among the regions of the countries within our sample. Thus, we cannot control for the latter. Figure 3 shows the same regression analysis as the one in figure 2 controlling respectively for population growth on the left panel and years of education on the right panel. We find that when controlling for population growth, the within-country estimate of β convergence does not flatten out over time, if anything, it becomes even more positive. When we control for education at regional level, we find that regional convergence increases at the beginning of the sample for the average country but it does not explain the decline we observe towards the end of the sample.

3.2 Fact #2: Structural Transformation and Regional Convergence

Next we document that this slowdown in within-country convergence is associated with the structural transformation of economies towards services. On the left panel of figure 4

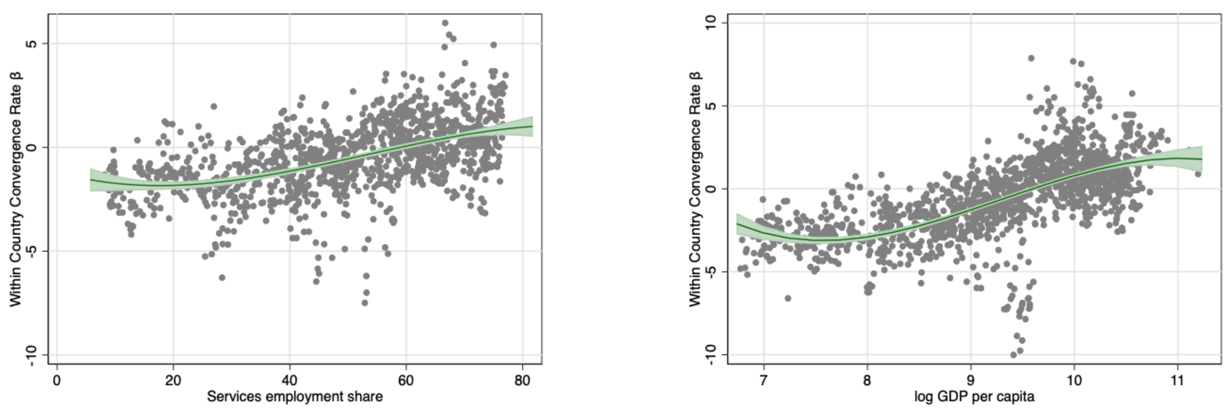
Figure 3: A Stall in Conditional Within-Country β Over Time



Note: This figure reports the average β within-country after conditioning for population growth (left) and education (right) for all the countries in our sample.

we non-parametrically plot the relationship between the within-country β convergence rates against the level of GDP per capita, residualizing for country fixed effects. On the right panel of figure 4 we plot services employment share on the x-axis instead of GDP per capita.

Figure 4: Structural Transformation and Regional Convergence



Notes: Population weighted beta vs services employment share (left) and log GDP per capita (right) for unbalanced panel. Estimates are residualized off country fixed effects. Green line shows the evolution of the average country. Confidence intervals are plotted around the estimated.

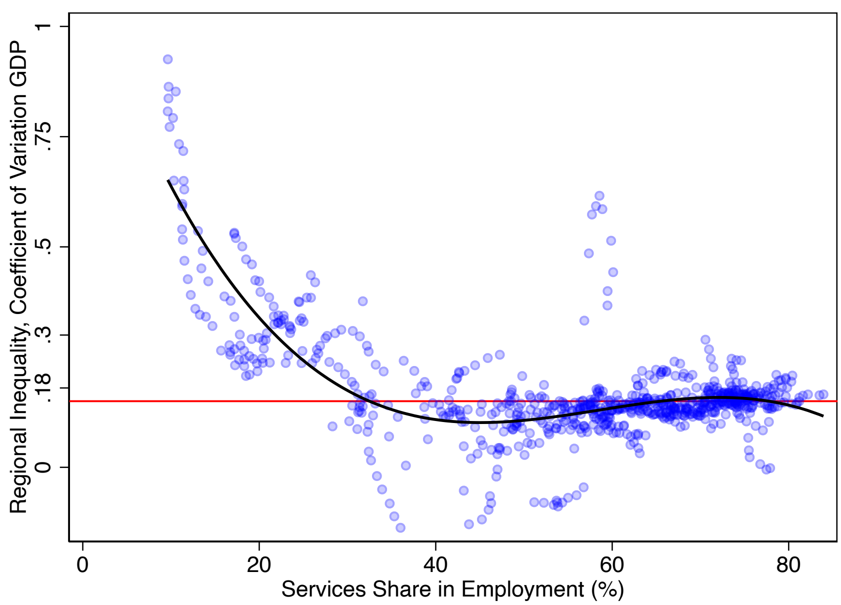
The solid green line estimates the change in convergence rates within countries as they become richer (right panel of figure 4) or as employment gets concentrated in the services sector (left panel of figure 4). Country fixed effects ensure that these relationships are estimated off the evolution of β within each country over its development path. We also plot the confidence intervals around the average estimates estimated with the delta-method. We do find that, in the average country, the relationship between regional convergence and sectoral shares reverts when service share goes above 40%.

While the left panel of figure 4 shows that on average as countries get richer, the convergence rates between their regions decline, figure 4 shows that this decline is also related to growth being driven by an increased concentration of economic activity toward services away from manufacturing and agriculture.

We do run several robustness tests for this fact. Specifically, we weigh for population size and take into account the presence of a balanced vs unbalanced sample. Overall, as we document in all the different versions of fact 2 in 7.1, the results are qualitatively unchanged.

Overall, these two facts might lead to the conclusion that over the course of economic development, regional inequality has ended. Thus, there is no need anymore for the economy to converge even further. In figure 5, we document a negative relationship between the increase in service share from 20% to 40% that stagnates afterwards. Overall, the average level of regional inequality has stagnated at 18%, yet, regional inequality has ended. This implies that while disparities are still present, and even increasing when analyzing the data at further proximity, the gap is not closing further.

Figure 5: A Fall and Stagnation of Inequality with Structural Trasnformation



Note: This figure plots the coefficient of variation of GDP by country plotted against service share in the economy. Estimates are residualized off country fixed effects. Black line shows the evolution of the average country.

Finally, table 2 shows how β-convergence within countries vary over time by determinants that go above and beyond service share. The idea is to observe which other factors that we shut down in figure 4 might be important in explaining regional convergence differences across countries. We find that service productivity growth has the main explanatory power above and beyond service share suggesting that when economy face a larger service productivity growth, regional convergence is lower even after controlling for other factors that might affect regional convergence such as education, trade openness, migration rates and political factors. These factors by themselves do not have add much explanatory power.

Table 2: Determinants of Regional Convergence

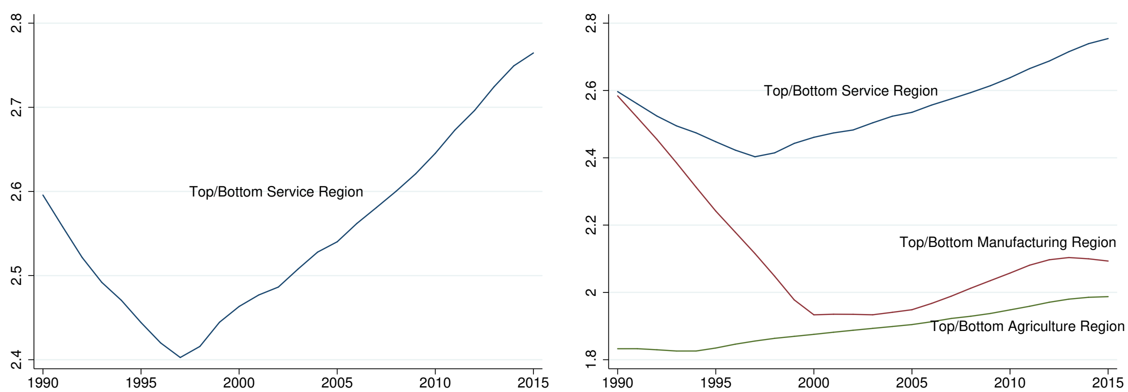
	(1)	(2)	(3)	(4)	(5)
Service Share	0.0539	0.0596	0.0696	0.0836	0.1036
	(0.0563)	(0.0576)	(0.0546)	(0.0455)*	(0.0400)**
Δ Serv. Product.	58.1721	57.7615	62.7862	56.2782	65.8885
	(17.1730)***	(16.7112)***	(19.3753)***	(13.1700)***	(10.1276)***
Roads/Cap. (km)		-9.5731	-3.7698	6.0459	8.6554
		(15.4056)	(14.9946)	(16.2952)	(15.1441)
Avg. FTAs			1.1752	1.7897	2.2101
			(1.2591)	(1.7238)	(1.6152)
Years of Education				-0.0786	-0.1271
				(0.1904)	(0.1989)
Δ Years of Educ.				3.1583	-8.7005
				(31.4909)	(30.9531)
Political Score					-0.0962
					(0.0654)
Year FE Yes	Yes	Yes	Yes	Yes	
R^2	0.2013	0.2155	0.2191	0.3213	0.3442

Note: This table shows the regression estimates where the dependent variable in each column is the estimate of β-convergence for 10-year rolling window for each country in our sample. We also add controls for other factors in the economy such as agricultural share, manufacturing share and initial GDP per capita.

3.3 Fact #3: An Increase in Concentration of Service Shares

We document that service share got more regionally concentrated over time. We compare also the concentration of service relative to the concentration in other sectors such as manufacturing and agriculture and find that it is higher in levels and in trends in service compared to the others. On the left panel, Figure 6 shows the evolution over time of the ratio of service share between the region that was in the 1st decile of service share in 1990 compared to the region that was in the 10th decile of service share in 1990. On the right panel, it compares the evolution of the concentration in the service share sector with the same in manufacturing and agriculture. The figures show that the concentration in service has been between 2.4 and 2.8 between 1990 and 2015 with a positive trend after 1997. Comparing with manufacturing and service, we find that the concentration is higher in service both in levels and over time.

Figure 6: Regional Concentration in Service Sector



Note: This figure plots the ratio of the service share between the regions at the top decile of service share in 1990 and the regions at the bottom decile of service share in 1990 on the left graph. On the right graph, it compares the same statistic for the service sector, manufacturing and agriculture sector.

4 A Model of Structural Change and Geography

The facts described above highlight how structural transformation towards services might be affecting regional convergence. We provide a simple framework that rationalizes this striking pattern of the data combining a traditional model of structural transformation with economic geography. While simple, the model captures the key forces that the literature has emphasized as the drivers of structural change. Our objective is to show that such simple model embedded with standard economic geography forces can rationalize the patterns of regional convergence for different countries but also to show how the structural transformation towards service induced both more inequality and more growth through the reallocation of workers to cities with high knowledge spillovers.

Consumption. In the model there are J regions where each of them is j. Workers decide where to locate in each period and have idiosyncratic taste shocks μ for regions originating from a Type-1 Extreme Value distribution. The parameter ν scales the variance of the idiosyncratic shocks. Note that households choose to relocate to the labor market that delivers the highest utility net of costs. A representative agent in each region j gets utility from the consumption of a final good C, which is a composit of three goods in the economy. We allow for non-homotheticity in agriculture by having a subsistence level $\bar{c_a}$. This implies that the new direct utility function will be dependent on:

$$C_j = C_{s,j}^{\gamma} C_{m,j}^{1-\gamma-\beta} (C_{a,j} - \bar{c_a})^{\beta} \tag{1}$$

Households choose a location to maximize their utility:

$$U_{i,j} = \max_{j'} \max_{C} \ln C_{j'} + \nu \mu_{i,j'}$$

$$\text{s.t.} \qquad C_{s,j} p_{s,j} + C_{m,j} + C_{a,j} p_{a,j} = w_j,$$

where N_j is the total number of workers in each location j. Using the properties of T1EV shocks, we can write the population share $N_j/\bar{N}$ in close-form such that

$$\frac{N_j}{\bar{N}} = \frac{exp(\ln w_j - \gamma \ln p_{s,j} - \beta \ln p_{a,j})^{1/\nu}}{\sum_n exp(\ln w_n - \gamma \ln p_{s,n} - \beta \ln p_{a,n})^{1/\nu}}$$

Production In each of these regions there are three sectors: agriculture a, manufacturing m and service s. The three sectors produce labor as only input and have linear production function in labor as in Huneeus and Rogerson (2020b). However, due to our assumption of endogenous knowledge spillover in services, the returns to scale in service are higher. This assumption is justified by empirical evidence. For instance, Moretti (2021) finds that high-tech sectors tend to concentrate in a few places identifying strong agglomeration externalities. Markets are competitive, the price of labor is w, the price of a is p_a and the price of s is p_s and the price of m is the numeraire.

The production function for sector $i = a, m, s$ is linear in labor:

$$Y_i = A_i N_i \tag{2}$$

The *key* component is the productivity process for each sector, which follows the following formulation:

$$A_{ijt} = e^{g_{it}} A_{ijt-1} \quad \text{for} \quad i = a, m \tag{3}$$

$$A_{sjt} = e^{g_{st}} A_{ijt-1} N_{sjt}^{\delta} \tag{4}$$

where $A_{i10} > A_{i20}$ for any sector i where the growth in agriculture $g_{at} > g_{mt} > g_{st}$.

4.1 Equilibrium

We define the competitive equilibrium of this model as follows. For each period t is characterized by a set of allocations $\{\{C_{i,j}, N_j, N_{i,j}\}_i^I\}_j^J$, a set of prices $\{\{p_{s,j}, p_{a,j}, w_j\}_i^I\}_j^J$ such that given $\{\{A_{i,j,0}\}_i^I\}_j^J$, a set of normalizing parameters such that $p_{m,j} = p_j$ and $\sum_j N_j = \bar{N}$, the following conditions hold:

(i) Given idiosyncratic preferences, workers choose their location and consumption to maximize the utility satisfying equations:

$$C_{a,j} = \bar{c_a} + \frac{\beta(w_j)}{p_{a,j}} \tag{5}$$

$$C_{m,j} = (1 - \gamma - \beta) w_j \tag{6}$$

$$C_{s,j} = \frac{\gamma(w_j)}{p_{s,j}} \tag{7}$$

(ii) Location choice of the consumer:

$$\frac{N_j}{\bar{N}} = \frac{exp(\ln w_j - \gamma \ln p_{s,j} - \beta \ln p_{a,j})^{1/\nu}}{\sum_n exp(\ln(w_n) - \gamma \ln p_{s,n} - \beta \ln p_{a,n})^{1/\nu}} \tag{8}$$

(iii) Profit maximization of the firm in each sector i:

$$w_j = p_{i,j} A_{i,j} L_{i,j}$$

(iv) Market clearing conditions for labor, service and agricultural goods:

$$\sum_i L_{i,j} = \bar{L}_j \tag{9}$$

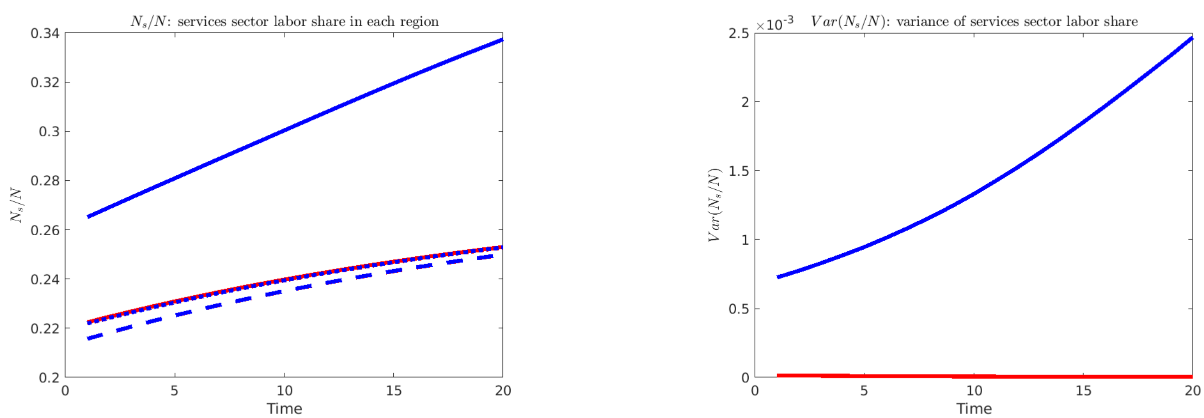
$$\sum_i N_{i,j} = N_j \tag{10}$$

$$C_{s,j} = A_{s,j} N_{s,j} \tag{11}$$

$$C_{a,j} = A_{a,j} N_{a,j} \tag{12}$$

Qualitative Predictions: Understanding the Mechanism Using the model-generated estimates of service share by region over time, we show how the model matches the structural transformation towards services and its heterogeneity by region over time. Specifically, in figure 7, we report the baseline estimates of service share by region in blue. Service share increases in all regions but it increases at a faster rate where the initial level of service share is higher. In fact, on the right panel, we observe that the variance of service share increases over time. However, when we set the agglomeration forces to 0, represented by the red line, we find that while service share increases, there are no differences across regions and at the same time, the overall rate at which it increases is lower.

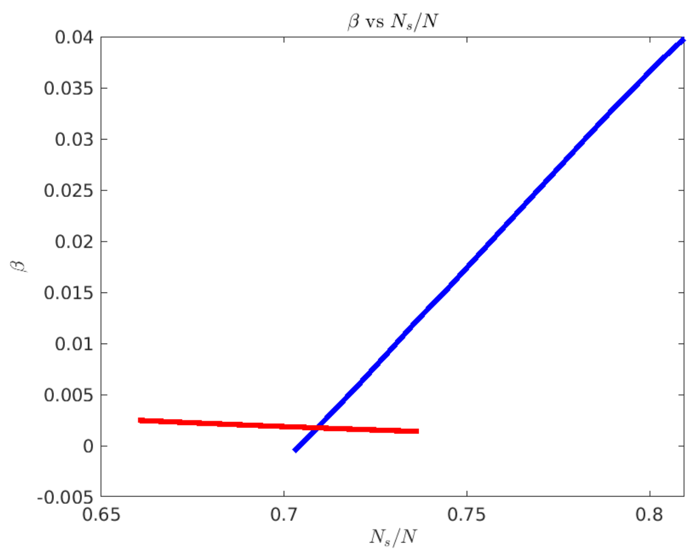
Figure 7: Model: Evolution of Service by City



Note: The left panel reports the model generated estimates of service share by region (low, medium and high) over time. The right panel reports the estimates of the variance of service share over time. The blue lines represent the baseline model. The red line represent the estimates of the model when δ is set to 0, otherwise, “no agglomeration”.

Finally, we show whether our model replicates fact #2. Figure 8 reports the model generated estimates of average within-country β convergence against service share. The blue lines represent the baseline model. The red line represents the estimates of the model when δ is set to 0, otherwise, "no agglomeration". We find that when service share in the economy goes up, within-country β convergence goes up as well as in the data. This happens because, through the higher agglomeration economies of the service sectors, workers will sort in larger regions to take further advantage of the spillovers, thus, increasing the gap with the other regions. At the same time, due to the competitive market, the concentration of workers in already populated regions will push income down but the agglomeration forces will go in the other direction and push for divergence. As also shown in table **??**, when the economy moves towards manufacturing, thus g_a goes up, within-country β convergence increases. This is consistent with Caselli and Coleman (2001) and corroborated by our other empirical evidence in section 7.2.3.

Figure 8: Model: Structural Transformation and Regional Convergence



Note: This figure reports the model generated estimates of average within-country β convergence against service share. The blue lines represent the baseline model. The red line represent the estimates of the model when δ is set to 0, otherwise, "no agglomeration".

4.2 Calibration

We calibrate the model to the "representative" country of our sample. To do so, we start from our estimates of GDP per capita over time. From those, we create regions J, which will correspond to 3 in this case (low, medium and high) over time starting in 1980 onward.

We check that our rapresentative country replicates the empirical feature of β-convergence between 1980 and 2017 in the data. Table 3 reports our parameters. We divide them in those calibrated internally matching moments and those that we read from the literature and existing papers. Specifically, we target the elasticity of the knowledge spillover, δ to the share of service sector in the initial period. We use moments on the sectoral shares to pin down growth rates for each sector productivity growth g_i. We similarly calibrate A_{i0} using moments of the initial β-convergence in 1980-1990.

Regarding the consumption side of the economy, we read the consumption shares of services and agriculture from consumption data at national level. Instead, we internally calibrate the subsistence level of agriculture, $\bar{c_a}$, targeting the initial level of agriculture.

Our calibration is still preliminary. We are currently working on improving the fit of the model and to be able to conduct quantitative counterfactuals closer to the data. The current simulation is an exercise to understand the mechanism of the model. We solve the model numerically and with estimated real GDP measures by region, we estimate β within-country convergence generated by the model same as estimated in the data. Using these estimates, then, we validate the mechanism by showing how the model performs in terms of within-country β convergence when service sectoral share increases as shown in table reftab:simulation.

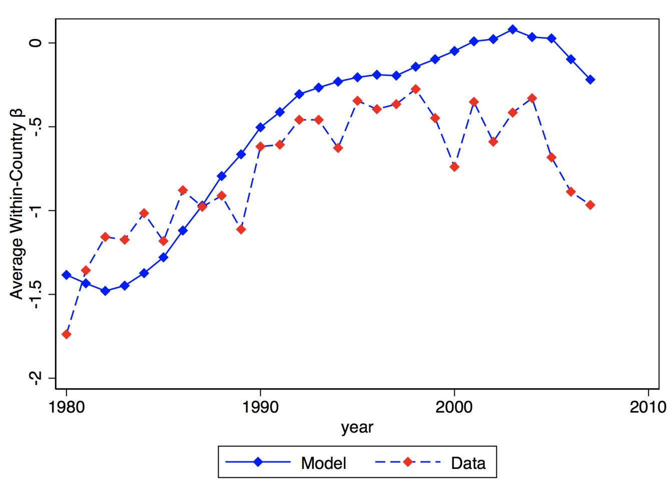
Model Matching Data Despite the simplicity of the model, we are able to match the patterns of regional convergence over time for the representative country. Figure 9 reports the evolution of the beta convergence estimates both in the model and in the data. Overall, we find that the model matches the convergence patterns well for the "representative" country. Notice that we match the β-convergence in 1980-1990 and let the model free for the later periods.

In order to understand what are the implications of our mechanism to assess the β-convergence and to assess the implications of regional convergence, or its lack thereof, we run a simple counterfactual in which we set agglomeration economies, δ, to 0. Table 4 shows by how much β-convergence would be changed between 1980 and 2017 if agglomeration forces had been set to 0 rather than 0.05. We find that β-convergence would have declined by one-third less approximately. At the same time, the variance in the service sector in 2017 would have been close to 0 while in the baseline model is 10%. At the same time, a final aggregate implication we would like to highlight of this simple mechanism is that if agglomeration forces had been set to 0, and β-convergence had not increased by as much as in the baseline,

Table 3: Calibration

		Targeted Moment	Literature	Value
Production				
g_a	Pro. Growth Agr.	✓		0.04
g_m	Pro. Growth Man.	✓		0.02
g_s	Pro. Growth Serv.	✓		0.01
δ	Agglomeration Service	✓		0.05
A_i	Initial Prod. by Sector	✓		
Consumption				
γ	Service share		✓	0.8
β	Agr. share		✓	0.03
ν	T1-EV variance		✓	1.1
c_a	Subsistance level of Agr.	✓		0.01

Figure 9: Model Matching Data: β-convergence



we would have observed a lower structural transformation towards a service economy. This final result highlights a trade-off between regional disparities and faster aggregate structural transformation.

Table 4: Implications of β-convergence decline

	Baseline High	No agglomeration Low
$\%\Delta\beta$ convergence 1980-2017	0.78	0.53
Variance of service share 2017	0.1	0.02
$\%\Delta$ services share 1980-2017	0.29	0.26

Note: This table shows the performance of the baseline model in terms of change in β-convergence and aggregte service share in the baseline model in column (1) compared to the case of no agglomeration, δ set to 0, in column (2).

5 Conclusions

We assembled and validated a longitudinal dataset for 34 countries and 678 between 1980 and 2015, and we provide the first evidence that, globally, regional convergence is decreasing over time in the average country. This goes in stark contrast with existing results showing that poorer countries around the world are catching up at a faster rate than they used to. Thus, we conclude that globally, convergence has been extremely unequal.

With the aim to understand why this is the case, our second core contribution is to show empirically that the structural shift towards service has a relevant explanatory power in this phenomenon. The latter result shows a very different role of structural transformation on reducing disparities than the one formerly known. In fact, if it was well-known that structural transformation from agriculture to manufacturing was a push for more convergence, we find that structural transformation towards services is a push for less regional convergence.

This set of evidence provides the ground to ask what are the implications on the decline of regional convergence on global growth. Specifically, if regional convergence had not increased in the average country, would we observe less or more growth this days? To provide an answer to this question, we develop a new framework with structural transformation and economic geography. The model highlights how the nature of structural transformation towards service might impact regional differences and, in turn, affect economic growth.

In current work we are finalizing the collection of sub-regional sectoral data to corroborate further our evidence of the mechanism.

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6 Appendix

6.1 Data: Countries in Our Sample

6.2 Data: Representativeness of Our Sample

Table 6: Representativeness of the Sample

Period	Share of World Population	Share of World GDP	Avg Growth GDP p.c.	Growth relative to World Avg	# Countries	Avg years of education
1980-1990	0.675	0.856	1.93%	1.60	34	6.49
1990-2000	0.662	0.794	2.82%	1.54	34	7.80
2000-2010	0.647	0.779	3.74%	1.04	34	9.03
2010-2020	0.642	0.773	2.30%	1.33	34	9.67
All Years	0.656	0.802	2.80%	1.13	34	8.16

Note: This table reports the main summary statistics such as share continent population, share of continent GDP, average GDP Growth per capita, GDP growth relative to the world average, # of countries and average years of education of our sample over the decades.

Table 5: List of Countries and Sources

Country	Data on GDP - GLLS*	Data on GDP - CGK*	(Source - CGK*)	Data on years of schooling - GLLS*	Data on years of schooling - CGK*	(Source - CGK*)
	Sample Period			Sample Period		
Australia	1953, 1976, 1989-2010	2011-2017	National Statistical Agency	1966, 2006		
Austria	1961-1992, 1995-2010	2011-2017	National Statistical Agency	1964, 1971, 1981, 1991, 2001, 2009	2011	IPUMS
Belgium	1960-1968, 1995-2010	2011-2017	Eurostat	1961, 2001		
Bolivia	1980-1986, 1988-2010		National Statistical Agency	1976, 1992, 2001		
Brazil	1950-1966, 1970, 1975, 1980, 1985-2010	2011-2015	National Statistical Agency	1950, 1960, 1970, 1980, 1991, 2000, 2010	2010	IPUMS
Canada	1956, 1961-2010	2011-2017	National Statistical Agency	1961, 1971, 1981, 1991, 2001, 2006	2010	IPUMS
Chile	1960-2010	2011-2017	Central Bank of Chile	1960, 1970, 1982, 1992, 2002		
China	1952-2010	2011-2017	National Statistical Agency	1982, 1990, 2000, 2010		
Colombia	1950, 1960-2010	2011-2017	National Statistical Agency	1964, 1973, 1985, 1993, 2005		
Denmark	1970-1991, 1993-2010	2011-2017	National Statistical Agency	1970, 2006	2008-2019	National Statistical Agency
France	1950, 1960, 1962-1969, 1977-2010	2015, 2016, 2017	Eurostat	1962, 1968, 1975, 1982, 1990, 1999, 2006	2011	IPUMS
Germany, West	1950, 1960, 1970-2010	2011-2017	National Statistical Agency	1970, 1971, 1981, 1987, 2009	2011	National Statistical Agency
Greece	1970, 1974, 1977-2010	2011-2017	Eurostat	1971, 1981, 1991, 2001	2011	IPUMS
Hungary	1975, 1994-2010	2011-2017	Eurostat	1970, 2005	2016	National Statistical Agency
India	1980-1993, 1999-2010	2011-2017	National Statistical Agency	1971, 2001		
Indonesia	1971, 1983, 1996, 2004-2010	2011-2017	National Statistical Agency	1971, 1976, 1980, 1985, 1990, 1995, 2000, 2005, 2010		
Italy	1950, 1977-2009	2011-2017	Eurostat	1951, 1961, 1971, 1981, 1991, 2001	2011	IPUMS
Japan	1955-1965, 1975-2009	2010-2016	National Statistical Agency	1960, 2000, 2010		
Kenya	1962, 2005	2013-2017	National Statistical Agency	1962, 1989, 1999, 2009		
Korea, Rep.	1985-2010	2011-2017	National Statistical Agency	1970, 1975, 1980, 1985, 1990, 1995, 2000, 2005, 2010		
Malaysia	1970, 1975, 1980, 1990, 1995, 2000, 2005-2010	2011-2015	National Statistical Agency	1970, 1980, 1991, 2000	2010	
Mexico	1950, 1960, 1970, 1975, 1980, 1993-2010	2011-2017	National Statistical Agency	1950, 1960, 1970, 1990, 1995, 2000, 2005, 2010		
Netherlands	1960, 1965, 1995-2010	2011-2017	Eurostat	2001		
Norway	1973, 1976, 1980, 1995, 1997-2010	2011-2017	Eurostat	1960, 2010	2019	National Statistical Agency
Peru	1970-1995, 2001-2010	2011-2017	National Statistical Agency	1961, 1993, 2007		
Portugal	1977-2010	2011-2017	Eurostat	1960, 1981, 1991, 2001, 2011	2011	IPUMS
South Africa	1970, 1975, 1980-1989, 1995-2010	2011-2016	National Statistical Agency	1970, 1996, 2001, 2007		
Spain	1981-2008, 2010	2011-2017	National Statistical Agency	1981, 1991, 2001	2011	IPUMS
Sweden	1985-2010	2011-2017	Eurostat	1985, 2010		
Switzerland	1965, 1970, 1975, 1978,1980-1995, 1998-2005, 2008-2010	2011-2017	National Statistical Agency	1970, 1980, 1990, 2000, 2010		
Tanzania	1980, 1985, 1990, 1994, 2000-2010	2011-2016	National Statistical Agency	1978, 1988, 2002	2012	IPUMS
Turkey	1975-2001	2004-2017		1965, 1985, 1990, 2000		
United Kingdom	1950, 1960, 1970, 1995-2010	2011-2017	Eurostat	1951, 1991, 2001		
United States	1950-2010	2011-2017	National Statistical Agency	1960, 1970, 1980, 1990, 2000, 2005	2010, 2015	IPUMS

Note: This table reports the list of 34 countries in our sample in alphabetical order comparing the sample from Gennaioli et al. (2012) with others both for regional GDP and for years of schooling. GLLS stands for Gennaioli et al. (2014) and CGK stands for Chatterjee-Giannone-Kuno.

Table 7: Representativeness of the Sample by Income Groups

	Share of Continent Population	Share of Continent GDP	Avg. GDP Growth Per Capita	Growth relative to World Avg	# Countries	Avg years of education
			High Income			
1980-1990	0.922	0.948	2.12%	1.03	16	9.24
1990-2000	0.897	0.922	2.65%	1.02	16	10.04
2000-2010	0.887	0.898	2.14%	1.16	16	10.81
2010-2020	0.916	0.916	1.62%	1.14	16	10.52
All Years	0.905	0.921	2.24%	1.03	16	10.22
			Middle Income			
1980-1990	0.554	0.561	6.27%	5.28	5	5.39
1990-2000	0.541	0.651	4.48%	0.94	5	6.99
2000-2010	0.535	0.595	4.04%	0.78	5	8.40
2010-2020	0.568	0.598	0.46%	-2.93	5	8.84
All Years	0.549	0.601	3.50%	1.01	5	7.41
			Low Income			
1980-1990	0.707	0.732	0.70%	0.58	13	4.24
1990-2000	0.693	0.752	2.63%	0.81	13	5.34
2000-2010	0.675	0.762	5.51%	0.89	13	6.48
2010-2020	0.663	0.778	3.50%	1.05	13	7.38
All Years	0.686	0.755	3.29%	0.86	13	5.49

Note: This table reports the main summary statistics such as share continent population, share of continent GDP, average GDP Growth per capita, GDP growth relative to the world average, # of countries and average years of education of our sample by income group and over the decades in our sample. We divided countries in high income (more than 67th percentile), middle income (between 67th and 33th percentile) and low income (33th percentile and less).

Table 8: Representativeness of the Sample by Continents

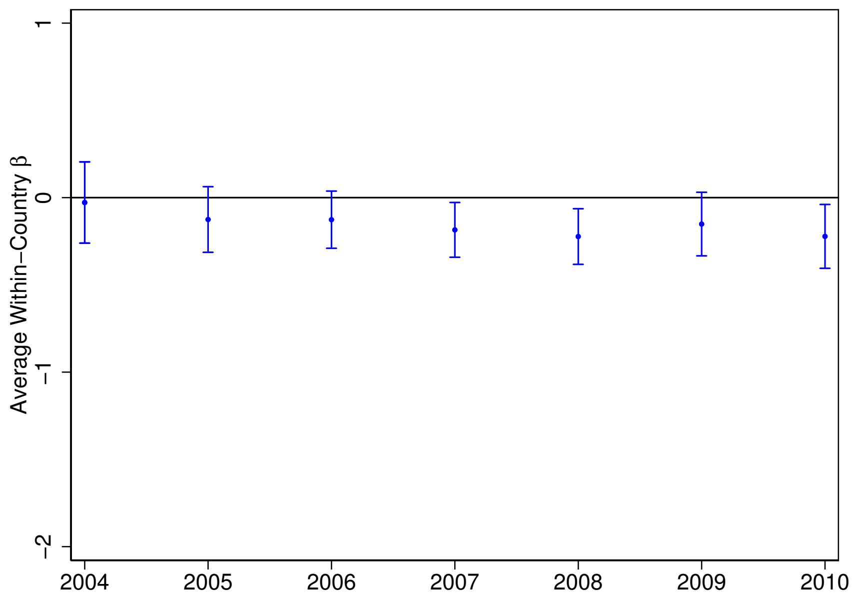
	Share of Continent Population	Share of Continent GDP	Avg. GDP Growth Per Capita	Growth relative to World Avg	# Countries	Avg years of education
			Africa			
1980-1990	0.148	0.253	-3.83%	0.95	3	3.66
1990-2000	0.144	0.270	0.20%	0.29	3	4.21
2000-2010	0.139	0.225	4.68%	0.84	3	5.82
2010-2020	0.135	0.179	2.58%	13.08	3	5.67
All Years	0.142	0.235	1.74%	1.16	3	4.61
			Asia			
1980-1990	0.795	0.743	4.02%	2.09	6	5.94
1990-2000	0.772	0.757	3.74%	1.14	6	7.01
2000-2010	0.759	0.737	4.84%	0.87	6	8.88
2010-2020	0.756	0.742	3.16%	1.10	6	8.36
All Years	0.771	0.745	4.00%	1.01	6	7.48
			Europe			
1980-1990	0.833	0.955	2.11%	1.20	16	7.61
1990-2000	0.522	0.733	2.52%	2.18	16	8.67
2000-2010	0.544	0.735	3.34%	0.85	16	9.71
2010-2020	0.559	0.678	2.32%	1.24	16	10.06
All Years	0.617	0.780	2.59%	1.26	16	9.08
			North America			
1980-1990	0.888	0.983	1.11%	0.55	3	9.27
1990-2000	0.880	0.982	1.76%	0.88	3	10.36
2000-2010	0.873	0.978	1.35%	1.19	3	10.41
2010-2020	0.941	1.071	1.90%	1.23	3	10.26
All Years	0.893	1.000	1.65%	1.04	3	10.09
			Oceania			
1980-1990	0.807	0.867	2.23%	0.97	1	
1990-2000	0.803	0.861	3.04%	1.01	1	11.42
2000-2010	0.804	0.864	2.02%	1.01	1	12.41
2010-2020	0.811	0.865	1.33%	0.92	1	
All Years	0.806	0.864	2.19%	0.98	1	11.92
			South America			
1980-1990	0.761	0.744	0.48%	0.63	5	4.71
1990-2000	0.761	0.735	4.21%	0.89	5	5.65
2000-2010	0.760	0.731	5.59%	1.14	5	6.76
2010-2020	0.819	0.818	1.19%	-2.64	5	7.01
All Years	0.773	0.754	3.09%	1.04	5	5.68

Note: This table reports the main summary statistics such as share continent population, share of continent GDP, average GDP Growth per capita, GDP growth relative to the world average, # of countries and average years of education of our sample by continent and over the decades in our sample.

6.3 Robustness for Fact #1: Adding Africa

Our sample while representative of the overall economy lacks information about Sub-Saharan Africa. We complement this data with two data sources and estimate β within-country convergence over time. Figure 10 reports the estimates from the Economist data which has GDP data for cities between 2004-2020.[3] Although at a different level of aggregation, our results confirm that the for the countries in *The Economist* sample, which include 19 African countries, the estimates of the within-country β convergence between 2004 and 2020 are consistently around 0 suggesting that even when we include more countries from Africa, we confirm that in the last 15 years of the sample, poorer regions/cities within countries are not moving closer to richer regions/cities.

Figure 10: Within-countryβ with *The Economist* Dataset



Note: This figure reports the estimates of within-country β convergence between 2004 and 2020 using 10-year rolling windows for each country in the sample. The unit of analysis is a city.

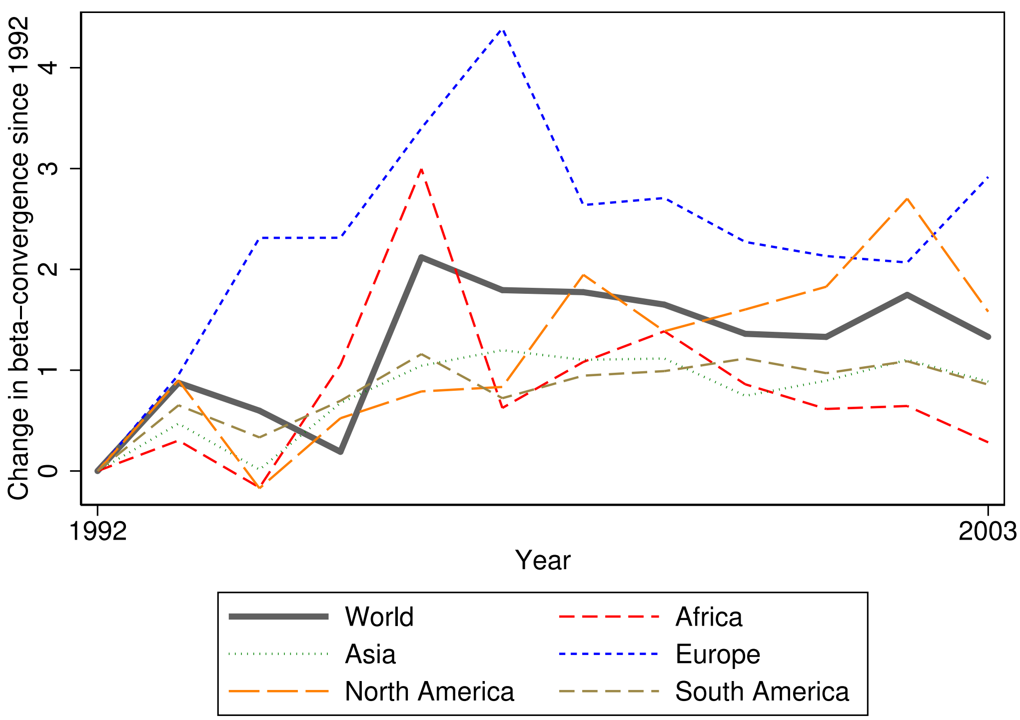
As a further robustness exercise, we use nightlights data to complement our findings on fact 1. The main reason is that our principal dataset is skewed towards richer countries since it is hard to collect information on poorer ones such African countries going back in time. Therefore, we overcome this issue by calculating the β-estimates using nightlights data. The

[3] *The Economist* dataset includes data for the following countries: Angola, Benin, Burkina Faso, Cameroon, Congo-Brazzaville, Congo-Kinshasa, Cote d'Ivoire, Ghana, Kenya, Malawi, Mozambique, Nigeria, Senegal, Somalia, South Africa, Sudan, Tanzania, Zambia and Zimbabwe

data span from 1993 to 2018 but we stop it in 2014 when the satellite changed and might affect the estimates. Figure 11 shows the change of the β-estimates between 1993 and 2014. We also split them by continent to highlight that the reduction in the speed of convergence appear also among African countries. The dataset covers 222 countries around the world and most of the African countries.

We restimate fact # 1 using this dataset for a larger set of countries. Figure 11 reports the change in within-country β estimates for 10-year rolling windows using as baseline 1993-2003. Overall we find that within-country β estimates become more positive highlighting less regional convergence in nightlights as the thick black line shows. Specifically, the change is in the order of 1.3p.p. In order to control whether this is an aggregate phenomenon or it is only happening in some sets of countries, we group the estimates by continent. We observe that Africa is the continent with lower decrease in regional convergence over the course of the 24 years take into consideration. Yet, there is a decrease of approximately 0.5p.p. Thus, we conclude that this is not a phenomenon specific to a set of country only but it is quite genralizable.

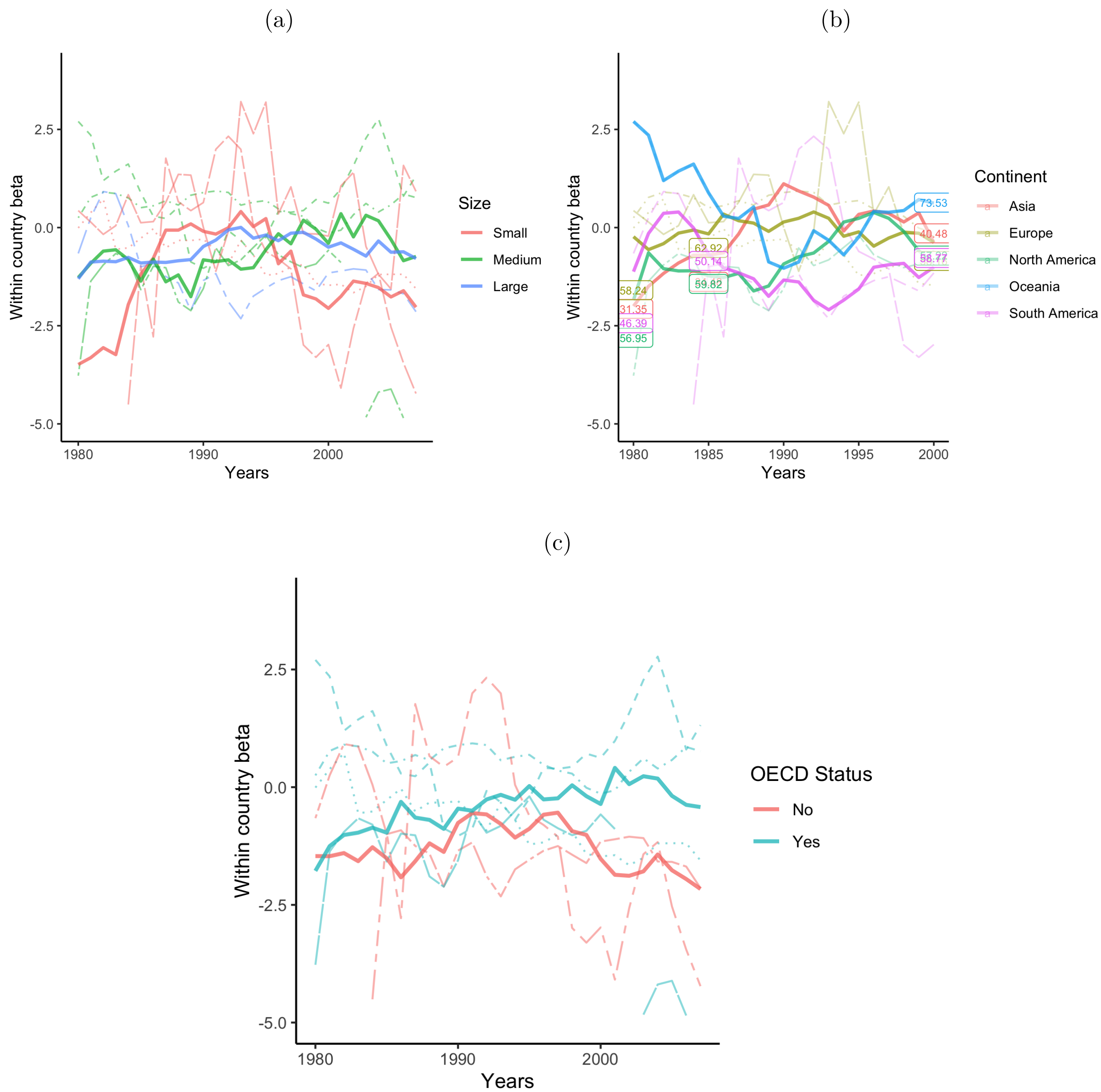
Figure 11: Within-country β convergence with *Nightlights* Data



Note: This figure reports the within-country β convergence for all the country in the sample of the nightlights data with 10-year rolling windows. The estimates have been normalized to 0 to make cross-continent continent easier to visualize.

7 Heterogeneity in Estimates

Figure 1: Within-country β convergence: Heterogeneity



Note: This figure reports the average within-country β convergence by groups of countries divided by size on the top left, continent in the top right and by OECD on the bottom.

Table 1: Heterogeneity in within-country β estimates

		1980-1990	1990-2000	2000-2010	2005-2015	# countries
Overall		-1.46	-0.79	-.57	-.58	31
		0.19	0.24	0.23	.28	
Continent	Africa	-0.74	-7.72	-3.6	-3.77	2
		1.31	1.48	0.65	.59	
	North America	-2.41	-1.16	-0.77	-1.99	2
		0.58	0.45	0.751	2.32	
	Asia	-2.43	-0.84	0.04	-0.93	5
		0.33	.56	0.55	.26	
	Europe	-1.53	0.32	-0.59	.195	13
		0.25	0.40	0.40	0.51	
	South America	-2.51	-1.21	-0.58	-1.19	5
		0.719	0.49	0.59	.63	
Size	Small	-1.55	0.27	-0.53	-.20	14
		0.33	0.39	0.43	.52	
	Medium	-1.05	-2.37	-0.91	-1.02	10
		0.34	0.42	0.28	0.51	
	Large	-0.98	-0.32	-0.43	-0.88	5
		0.30	0.25	0.31	0.19	
OECD Status	No	-1.83	0.01	-0.47	-.12	16
		0.23	0.41	0.36	.57	
	Yes	-1.10	-1.24	-.56	-.96	14
		0.32	0.29	0.29	.24	

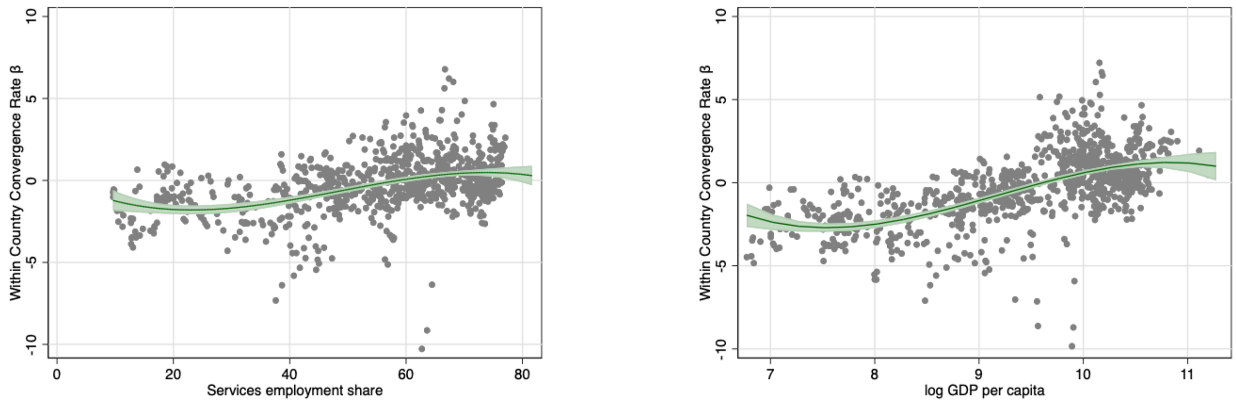
Note: This table reports the β estimates for the within-country regression discussed in section 3. The sample is split in groups of countries by geography, size and OECD status. Standard errors are reported below the coefficient estimates.

7.1 Fact #2: Robustness

In this section, we report robustness exercises for fact #2. Specifically, we change specifications to keep a balanced panel and without weights by population size as in figure 4. In all these different scenarios, we find that the results are very similar suggesting that changing specifications does not alter the results discussed in the main text.

7.2 Other Facts

We report below two facts related to β-convergence across countries to complement the main fact of the decline of β-convergence within-country. We then report an observation about the relationship between economic growth and inequality within country and across

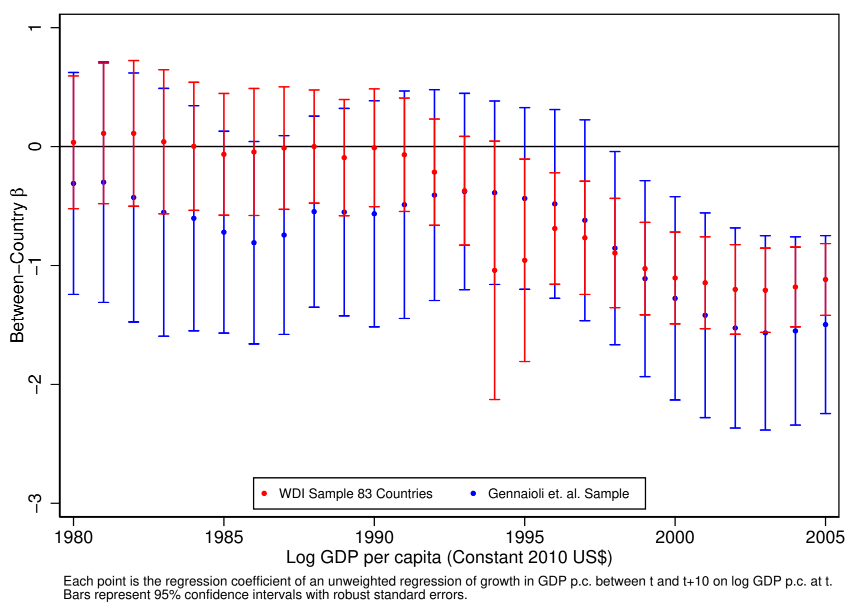


Notes: Population weighted beta vs services employment share (left) and log GDP per capita (right) for balanced panel. Estimates are residualized off country fixed effects. Green line shows the evolution of the average country.

individuals to highlight the different roles of regional and individual inequality on economic growth. Finally we complement our fact # 2 with a "growth-style" regression in which we assess the role of alternative forces on the change in β-convergence within-country. We confirm the hypothesis above that structural transformation has the largest role overall.

7.2.1 Fact #4: β Cross-country Convergence increased over time

Figure 2: β Cross-Country Convergence



7.2.2 Fact #4: National economic growth is positively correlated with spatial income inequality but negatively correlated with individual income inequality

We document how economic growth correlates with inequality at individual and at regional level reporting results in table 2. Regional inequality is captured by our β estimates from fact 1. Individual inequality is measured with Gini coefficients and Gini growth. In column 1 we correlate GDP growth over 10 years at country level with the beta estimates. We control for year fixed effects and we cluster the standard errors at country level. We find that the coefficient is positive but it is not statistically significant. In column 2 we regress GDP growth on initial Gini coefficient. Similarly to column 1, we find a positive coefficient but no statistical significance. In column 3 we regress GDP growth on both β estimates and Gini coefficients. The β estimates report a coefficients very close to 0 and not statistically significant. Instead, the Gini coefficient is positively correlated and statistically significant at 90%. In column 4, to take into account both changes in individual inequality and differences in initial level of GDP, we find that the estimate on the Gini coefficient becomes negative as well as the sign on the growth of Gini coefficient. In the remaining columns we had controls for potential drivers of economic growth that might also be correlated with regional and individual inequality measures.

We start from democracy indicators to account for how institutions might drive growth. We then add controls for education years to proxy for human capital levels. Then, we complement the analysis by adding proxies for structural transformation such as agricultural share and agricultural productivity growth. To account for geography we include controls such as roads per capita and total road. We then account for trade openness of the country by adding a measure of foreign trade agreement. In each of these specifications we notice that the coefficient on β stays positive and in the order between 0.04 and 0.12 but it is not statistically significant. Instead, the coefficient on Gini is negative, ranging between -.02 and -.09 and statistically significant in most of the cases. Finally, in the last column we add all the controls described before. This allows to control for co-founders that could drive the relationship between inequality and economic growth.

We find that the coefficient estimate on Within-country β is equal to .22 and statistically significant at 99%. This is in stark contrast with the estimate on both the Gini coefficient the Gini coefficient growth that are respectively equal to -.08 and -32.63 and both statistically significant at 99%. Therefore, we conclude that while regional inequality (higher β) is positively correlated with economic growth, individual inequality and individual inequality growth are negatively correlated with GDP growth.

This result is important since it highlights a different role of space in affecting growth Within-country convergence is negatively related to a country's growth in agricultural productivity. This is presumably because the latter is a strong predictor of structural transformation as documented by Huneeus and Rogerson (2020a). Hence, once we control for the growth in agricultural productivity, the relationship between economic growth and the change in within-country regional inequality doubles.

Table 2: Growth and Inequality

	Δ GDP									
Within-country β	.023		-.001	.04	.04	.12	.09	.04	.04	.22
	.81		.99	0.74	0.10	.08	.10	.10	.10	0.02
Gini		.03	.04	-.02	-.02	-.03	-.09	-.03	-.02	-.08
		.08	.02	.01	.01	.01	.03	.01	-.02	0.00
Gini Growth				-16.95	-17.04	4.91	-48.75	-24.90	-17.95	-32.63
				16.63	16.96	15.01	18.59	14.46	16.09	0.20
ln(Initial GDP)				-1.08	-1.08	-1.32	-2.41	-1.11	-1.06	-2.10
				.00	.19	.27	.51	.25	.22	0.00
N	795	905	536	536	536	406	341	536	536	217
R^2	.06	.10	.09	.34	0.34	0.36	.56	0.35	0.34	.59
Controls:										
Democracy					X					
Education						X				
Structural Change							X			
Geography								X		
Trade Openness									X	
All										X
Time FE	X	X	X	X	X	X	X	X	X	X

Note: This table reports the estimates of running a regression of GDP growth levels on within-country β convergence conditional on several observables in different specifications. Standard errors are clustered at country level.

7.2.3 Understanding the Drivers of Regional Inequality

Fact 2 highlights the correlation between a shift towards service and regional convergence. To provide supportive evidence to this fact and test for alternative hypothesis, we run a horse race among several potential candidates. We find some hypotheses consistent with existing literature but we also highlight a new for role of structural transformation in shaping regional convergence in both directions. Specifically, in accordance with Caselli and Coleman (2001) and Eckert et al. (2018), we find that structural transformation from agriculture to manufacturing pushes for regional convergence. We confirm the new result that structural transformation towards service reduces regional convergence. The literature on regional inequality has pointed out to several explanations for regional convergence.

As previously mentioned, Caselli and Coleman (2001) and Eckert et al. (2018) highlight the role of structural transformation as a driver of regional convergence in the US. To take into account such force we include agricultural productivity growth as well as share of manufacturing in the economy and he include the role of service productivity growth to capture the transition to modern economy.

offered an explanation suggesting that open access to trade. Market access as well as free trade agreements capture aim at capturing this story in our specification. Another factor that might drive the low speed of convergence is land restrictions such as geographical factors as shown by Ganong and Shoag (2017). To capture land unavailability we include several measures such as ruggedness, % of land in desert, distance from the coast and % of fertile soil.

Differential increase and return in human capital might be one of the explanations as well as in Giannone (2017). We include average years of education as well as change in average years of education to capture human capital. Table 3 reports the estimates of the horse race. The dependent variable in each of these specifications is the speed of convergence $\hat{\beta}$ estimated with a 10-year interval at country level for each decade between 1980 and 2020. The results of column (1) suggest a positive but non statistically significant correlation between speed of convergence and GDP per capita growth. Once we adjust for initial GDP in column (2) we find a positive correlation between initial GDP and speed of convergence suggesting that countries with richer countries experience a lower speed of convergence (or more regional inequality). To account for our main story of structural transformation we include controls for change in agricultural productivity as well changes in service productivity. The first is negatively correlated with β convergence. We interpret this result suggesting that an increase in agricultural productivity growth will increase regional convergence. Simultaneously, an increase in service productivity growth will decrease regional convergence.

When including political scores in column (4), we find that while the coefficient is positive it is not statistically significant. In column (5), we add controls for average years of education and their respective growth over 10 years. We find these coefficients are negatively correlated with higher speed of convergence but are not statistically significant either.

In column (6), we include variables that capture internal geographical differences as well as internal mobility. We find that more roads per capita are positively correlated with higher regional convergence. We also find that higher percentage of land covered in desert is correlated with lower regional convergence. Column 7 accounts for a story of trade openness. However, while we find a positive coefficient we do find statistical significance. Column (8) accounts for the final horse race among all the potential channels and allows to control for access to trade and overall market access suggests that more foreign trade agreements are positively correlated with slower convergence speed. Once all these determinants are considered jointly, we find that faster service productivity growth, higher political score index, a higher percentage of land covered in desert and more access to trade are all explanatory variables that predict slower speed of convergence. Simultaneously, structural change and distance from the coast are correlated with faster speed of convergence. When we run a variance decomposition exercise, we find that structural transformation is the biggest contributor by a large margin that explain the variation in speed of convergence across countries and over time.

Table 3: Testing for Complementary Hypotheses

	Within country β							
Δ GDP	0.03	0.09	0.06	0.07	0.15	0.17	0.09	0.32
	(0.12)	(0.12)	(0.33)	(0.12)	(0.13)	(0.12)	(0.12)	(0.19)
Initial GDP		0.59	0.31	0.37	0.63	0.76	0.46	-0.77
		(0.25)**	(0.47)	(0.32)	(0.28)**	(0.44)*	(0.29)	(0.51)
Δ Agr. Product.			-20.31					-19.62
			(10.58)*					(12.65)
Δ Serv. Product.			61.92					27.47
			(21.96)***					(14.03)*
Political Score				0.06				0.21
				(0.05)				(0.10)**
Years of Education					-0.157			0.12
					(0.16)			(0.25)
Δ Years of Educ.					-35.18			-1.82
					(31.52)			(31.16)
Roads/Cap. (km)						-1.67		-8.95
						(17.74)		(20.55)
Ruggedness						0.04		0.160
						(0.25)		(0.14)
% Desert						0.08		0.21
						(0.05)*		(0.04)***
Dist. from Coast						-0.45		-1.97
						(0.60)		(1.03)*
% Fertile Soil,						0.021		-0.03
						(0.02)		(0.01)**
% Tropical						0.01		0.02
						(0.01)		(0.01)*
Avg. FTAs							1.22	6.35
							(1.72)	(1.79)***
Market Access								0.00
								(0.00)
Year FE	X	X	X	X	X	X	X	X
N	795	795	375	769	619	748	769	228
R^2	0.0172	0.0746	0.2171	0.0827	0.0853	0.1141	0.0756	0.5168

Note: This table reports the estimates of 3.1 conditional on several observables. Standard errors are clustered at country level. The ***, **, and * represent statistical significance at the 0.001, 0.005, and 0.01 levels respectively.