# Unequal Global Convergence*

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**Abstract**

We study the spatial implications of structural transformation and economic growth using a novel dataset on the sub-national GDPs and employment by broad sectors of 687 regions in 34 countries. There has been a slowdown in the convergence rate between regions within countries since 1980. Moreover, the regional convergence process in most countries has stalled since 2010 despite residual spatial inequality. This decline in the rate of regional convergence is related to economic development, specifically to a structural transformation toward services. Globally, services employment exhibits a higher regional concentration than manufacturing and agriculture. Through the lens of a spatial model that features geographic mobility and agglomeration, we argue for a new role of structural change in spatial development. As an 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 understanding whether the rapid growth of developing countries is leaving individuals in some regions behind. However, answering these questions requires longitudinal data at the 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 relative to the poorer regions at least for the last 30 years. 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 study 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. Moreover, the rise of services is concentrated in a few regions within countries. Motivated by this empirical evidence, we develop a model of structural transformation and economic geography to study how the shift of the economy towards service reduces economic convergence within the country. The model puts forward a novel interplay between structural transformation and regional inequality: when regional

[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.

convergence declines, it further induces a push for structural transformation. This happens because the service sector has higher agglomeration economies than other sectors. Thus, when individuals move to cities with larger service sectors, agglomeration economies kick in, further increasing both regional inequality and structural transformation toward 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, and sectoral composition of employment.* Our starting point is the pioneer dataset of Gennaioli et al. (2014) which includes 83 countries and more than 1500 regions for GDP and education. 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 complement the GDP and education information by collecting data on sectoral employment by regions across countries over time from national statistical agencies and other sources. Differently from Gennaioli et al. (2014), the main sample we use for analysis 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, which 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 fall in regional convergence is present in 56% of the countries in our sample that represent more than 70% of the population of the sample itself. We test for heterogeneity of our result in terms of size, continent, and OECD status of countries. For no sub-sample in our data have we found any evidence of regional convergence after 1980.

We find that the change in within-country convergence rate is related to economic development and in particular, to the structural transformation of economies toward services. Even in the cross-section, countries with a higher share of services employment have a lower regional convergence rate. Further, we find that services employment is more spatially concentrated than manufacturing or agriculture. Moreover, the regional concentration of services employment has been increasing at a faster rate than manufacturing or agriculture. To be precise, we measure the regional concentration of a sector as the employment in the top decile region relative to the bottom decile region. For professional services, this ratio is 2.6 times higher today as compared to 1990. Compared to manufacturing and agriculture, the regional concentration of services employment is 20% higher in the cross-section and is 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 a standard economic geography model. 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. We verify that our representative country reproduces the $\beta$-convergence patterns as in the data over time. We calibrate the model using targeted moments on the sectoral dispersion over time and across geography. With the calibrated model, we test whether our model matches our main fact on the evolution of $\beta$-convergence over time, which it satisfactorily does. Our main exercise is to shut down the agglomeration force in service bringing them from 0.05 to 0. We find that $\beta$-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 $\beta$-convergence had not increased by as much as in the baseline, 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.

**Related Literature** Our paper contributes to a growing literature on structural transformation and economic geography. In particular, there is a recent set of papers studying the role of structural change in affecting regional inequality but all of them focus on specific countries. Caselli and Coleman (2001) and Eckert and Peters (2018) study how the structural transformation from agriculture to manufacturing increased regional convergence in the US. Hao et al. (2020) study the implications of structural change for regional convergence in China. Budi-Ors and Pijoan-Mas (2022) study regional implications of structural change to manufacturing and services in Spain. Finally, Fan et al. (2022) show how the service-led growth of India has created more inequality within the country and pushed for more growth. We contribute to this literature in two ways. First, we show that the role of structural transformation and in particular of services growth in impacting spatial inequality is a phenomenon that is present in various countries that are at different stages of development. This is consistent with the fact that different countries are deindustrializing at different stages of development Rodrik (2016). Second, we highlight that agglomeration economies in services provide further impetus to economic development and spatial inequality. Thus, our work points to a new dichotomy in the role of structural transformation for spatial development.

There is a large macro development literature on structural transformation and its aggregate implications summarized by Herrendorf et al. (2014). Recent work by Buera and Kaboski (2012) has studied the role of services, and Huneeus and Rogerson (2020a) studies the reasons behind premature deindustrialization. Our main contribution here is to add and study the spatial dimension and characterize the feedback effect of spatial inequality on structural transformation and aggregate economic growth.

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. Here, we contribute substantially to improving the dataset originally put together by Gennaioli et al. (2014). While Gennaioli et al. (2014) studies convergence between regions of the world in the cross-section, we focus on the evolution of within-country convergence. Moreover, we highlight the role of structural transformation in this process.

This paper is organized 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

The main dataset that we assemble for this study is on the GDP per capita, population, sectoral employment, and education at the first sub-national level (i.e. states or provinces) for 34 countries spanning 5 continents. There are two versions of our data. First, the balanced version is between 1980-2020, with the requirement that each country has one data point in each decade during this time period. We also have an unbalanced version that starts in 1950 but there are fewer countries between 1950-1980. In that time period, mostly the current rich nations collected data at the sub-national level.

Our starting point was the excellent dataset on sub-national GDP assembled by Gennaioli et al. (2012) spanning between 1950 and 2010. We updated it to the most recent possible year using new data from national statistical agencies and other publicly available sources like IPUMS and Eurostat. The details comparing our sample with the existing one are presented in table A.4. Then we add data on years of education, sectoral employment and GDP at the sub-national level. Our sample of countries is 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). Creating this dataset is a major contribution of our work and we hope that it'd be of use to other economists and social scientists.

Overall, the 34 countries in our sample account for 80% of the world GDP and 66% of the world population (see table A.1 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 A.3 and A.2. 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 A.2. 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 many other major countries in Asia.

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

[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.

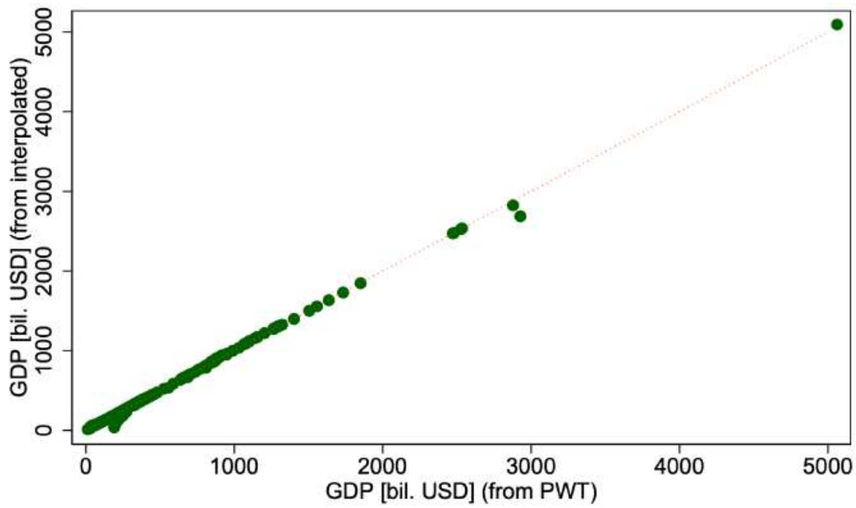
robustness of our results. Second, we purchased the dataset from *The Economist* which has longitudinal data on GDP and population for 923 cities in 77 countries between 2004 and 2020.

We also use various indicators at the country level for our analysis. This includes data on national GDP, employment and GDP shares of agriculture, manufacturing, and services from the World Development Indicators. We use data on years of schooling from Barro and Lee (2000) to capture the level of human capital in various countries. We use measures on Free Trade Agreements and global market access from CEPII and on roads from the Global Roads Inventory Project (GRIP) as a proxy for internal connectivity.

To measure political systems that can affect spatial patterns of economic growth within a country we use data on the democracy 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 use 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

In this section we document a set of novel empirical patterns that motivate our study. We are interested in studying the evolution of income disparities across regions within countries. For most of our analysis, we define regions to be states or provinces within countries. We make this choice for two reasons. First, states or provinces are the finest spatial units for which data on GDP, employment, and their sectoral allocation is collected consistently across a broad range of countries. Second, states are important political decision making units in most countries we study. Understanding their economic evolution has important implications for understanding not only the welfare of people but also the broad socio-political future of these countries. However, when possible we discuss robustness of our results with cities as our unit of analysis.

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

Economic growth over the last 30 years have been concentrated in a few regions of all countries. Thus, the poorer regions haven't been able to catch-up with the richer regions within countries. This has resulted in 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 between regions within a country using a standard convergence regression.

Our main specification to estimate the speed of convergence between regions of country $c$ at time $t$ follows from Baumol (1986):

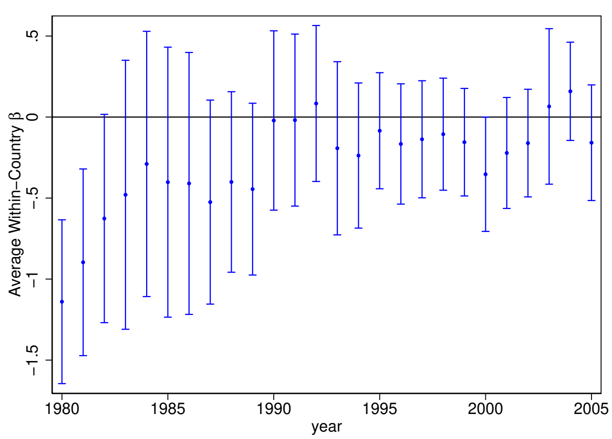
$$\frac{log(GDP_{r,t+10}) - log(GDP_{rt})}{10} = \alpha_c + \beta_{ct} log(GDP_{rt}) + \mathbf{X}'_{rt}\gamma + \varepsilon_{rt}, \tag{1}$$

where $r$ is a region (state or a province) within country $c$, $GDP_{rt}$ is the GDP per capita of region $r$ in country $c$ at time $t$, and $\mathbf{X}_{jt}$ is a vector of controls such as population and education. The dependent variable is the annual average growth in GDP per capita between $t$ and $t+10$. We weight the regression by population of each region at time $t$.

$\hat{\beta}_{ct} < 0$ implies that between years $t$ and $t+10$ the poorer regions of country $c$ grew faster than the richer regions and thus there was regional economic convergence within the country. Similarly, $\hat{\beta}_{ct} = 0$ implies lack of regional convergence and $\hat{\beta}_{ct} > 0$ implies regional divergence between years $t$ and $t+10$ within the country $c$.

In figure 2, we present results for the average country in our sample. To do so, we compute the average within-country $\beta_t$ for the countries in our sample as $\beta_t = \frac{\sum_c \beta_{ct}}{C}$ and plot it over time with 95% confidence intervals robust to heteroskedasticity. Thus, $\beta_t$ is the average within-country rate of convergence between years $t$ and $t+10$. Figure 2 shows a strong secular decline in the average within-country rate of convergence from about 1.5% in the 1980s to being statistically indistinguishable from zero in the 2000s.

Figure 2: Within-Country $\beta$ Over Time




Notes: This figure reports the average within-country $\beta$ convergence for the 34 countries in our sample between 1980 and 2015.

This result is in stark contrast to what we know about cross-country convergence over the same time period. Between 1980 and 2015, not only has there been an unconditional convergence between countries but also the rate of convergence has increased over time (Roy et al. (2016) and Patel et al. (2018)). Further, these results are robust to the exclusion of China and India. In B.4 of the Appendix, we reproduce results from Patel et al. (2018) for 83 major non-oil economies of the world and our sample of 34 countries. The contrast in magnitudes is also noteworthy. 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 are a mirror image of this pattern. 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, the average seems to be driven by rich and large countries. We explore the heterogeneity in within-country convergence next.

Table 1: The decline in within-country convergence

| | 1980 $\beta_c <$ 2007 $\beta_c$ |
|---|---|
| Share of countries | 56% |
| Share of GDP | 77.1% |
| Share of population | 69.0% |

Note: This table reports the summary statistics of within-country $\beta_c$ being lower in 2007 compared to 1980.

### 3.1.1 Heterogeneity in within-country Convergence

In order to understand which countries drive the fall in within-country $\beta$ convergence, we split the countries in various sub-groups by geography, size (population), and OECD status and describe the results graphically in appendix figure B.2. Detailed regression results are available in appendix table B.1. Overall, since 1980s we do not find any evidence for within-country convergence for any of these sub-samples.

### 3.1.2 Conditional Convergence

While our results show that there has been a decline in within-country convergence in the last 30 years, conditional convergence (à la Mankiw et al. (1992); Solow (1956)) could still be taking place. Figure 3 verifies that there has been a stall even in conditional convergence. Following Mankiw et al. (1992), we control for population growth in panel (a) and human capital or education in panel (b). Due to the unavailability of data on savings or investment at the regional level, it is impossible to verify convergence conditional on the savings rate.

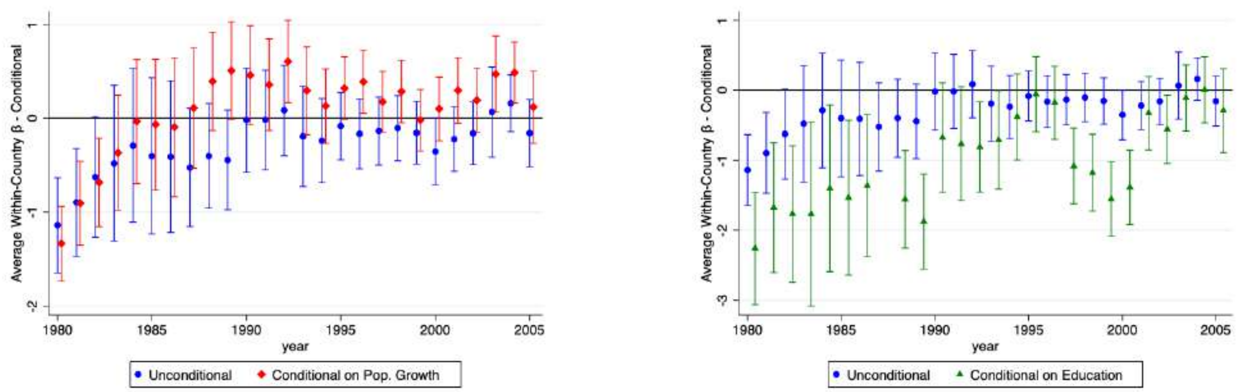



Figure 3: A Stall in Conditional Within-Country $\beta$ Over Time

### 3.1.3 Robustness

There could be several concerns with our analysis. First, our main result, i.e. a fall in within-country convergence, could be sensitive to the choice of state as the relevant "region". Second, our estimates may not be applicable for African countries–where we have limited data and especially because many African countries are at an early stage of development. Third, the lack of convergence in nominal GDP might mask convergence in real GDP if prices in poorer regions are substantially lower than in richer regions. We address these concerns in this section.

**Convergence between Cities:** Using data on GDP and the population of 923 cities in 77 countries, we show in figure 4 that between 2004 and 2020 there has been a lack of convergence even between cities within countries. This data comes from the Economist Intelligence Unit, and it even contains data on 19 African countries[3].

[3]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

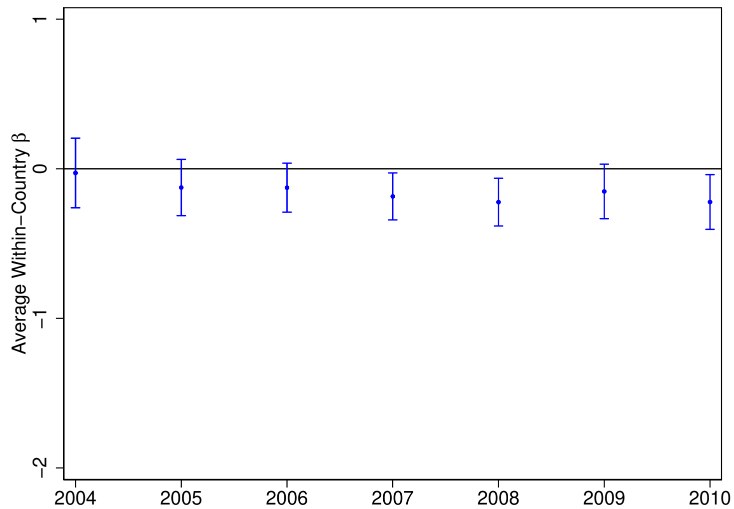



Figure 4: Within-country convergence between cities

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

**Convergence using Nighttime Lights as a Proxy for GDP:** As a second robustness exercise, we use nighttime light data as a proxy for GDP to complement our findings on fact 1. The main reason is that our principal dataset misses many important African countries. The nighttime light data comes from the Defense Meteorological Satellite Program (DMSP) and spans 1993 to 2018. We stopped our analysis in 2014 since the satellites change. It is well understood in the literature that a change in luminosity may result from the sensors of the new satellite may falsely be attributed to a change in GDP.

Figure 5 shows the change of the average within-country $\beta$-estimates between 1992 and 2013 for the world and in various continents. Since nightlights are just a proxy for GDP and their units do not have a natural economic interpretation, we normalize chose to normalize the $\beta$ in the initial year such that the graph can help us interpret changes in $\beta$ overtime. Overall we find that within-country $\beta$ estimates have increased, i.e. a fall in within-country convergence consistent with our headline result. For the world as a whole, the change is in the order of 1.3p.p. That the fall in regional convergence occurs first in Europe is also consistent with our main dataset. The trend in Africa is rather flat, i.e. there has been little change in the convergence rate in that continent.

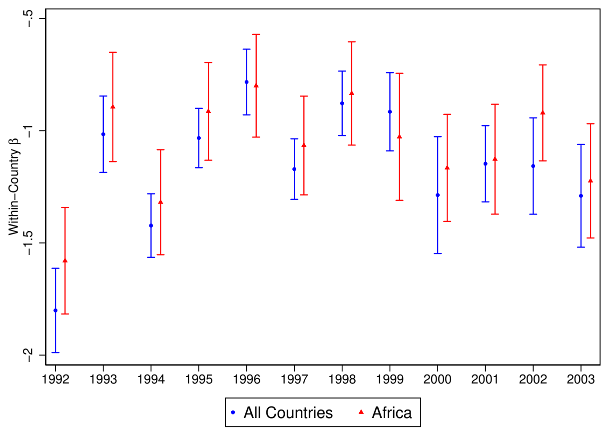



Figure 5: Within-country $\beta$ convergence with *Nightlights* Data

Note: This figure reports the within-country $\beta$ convergence for all the countries in the sample of the nightlights data with 10-year rolling windows.

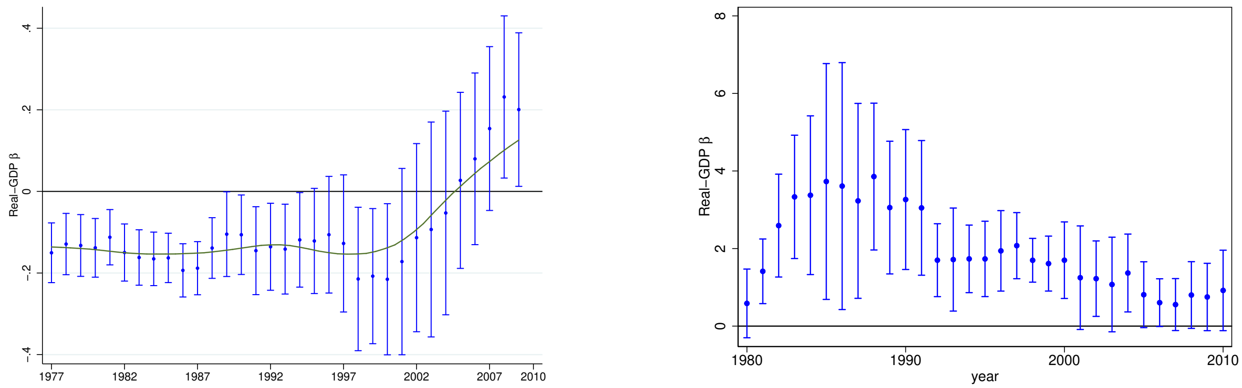
Both these robustness checks lend more credibility to our headline results. First, by showing that our results are not sensitive to the choice of regions and second, by including data from Africa in the "cites" GDP dataset and the nightlights data.

**Convergence in Real GDP:** A final concern could be that if prices are lower in poorer regions, an observed lack of convergence in nominal GDP may be misleading. Addressing this is much harder since regional price data or GDP deflators are hard to obtain for most countries. For now, we have obtained data on real GDP by states for the United States and India. In figure 6, we show that in the United States and India, there hasn't been any regional convergence since the 2000s even in real GDP. We are currently working on obtaining similar data for other countries.

## 3.2 Fact #2: Structural Transformation and Regional Convergence

What is the mechanism that is driving a global slowdown in regional convergence? In this section, we document that the stall in within-country convergence is associated with economic development and, in particular, the structural transformation of countries towards services. The left panel of figure 7 plots the non-parametric relationship between the within-country convergence rates, $\beta_{ct}$, against the level of GDP per capita, controlling for country fixed effects. In the right panel of figure 7, we replace GDP per capita with services employment share on the x-axis.

In figure 7, the solid green line estimates the change in convergence rates within countries

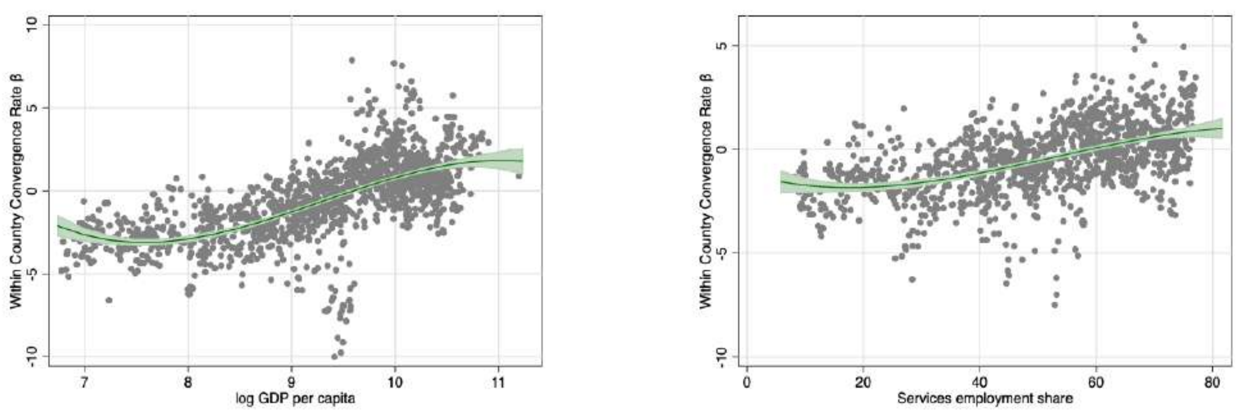



(a) United States

(b) India

Figure 6: Regional Convergence in Real GDP

Figure 7: Structural Transformation and Regional Convergence




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

as they become richer (left panel) or as employment gets concentrated in the services sector (right). Country fixed effects ensure that these relationships are estimated off the evolution of $\beta_{ct}$ within each country over its development path. Thus, the green line represents the relationship for the "average" country in our sample. We also plot the 95% heteroskedasticky robust confidence intervals estimated using the delta method.

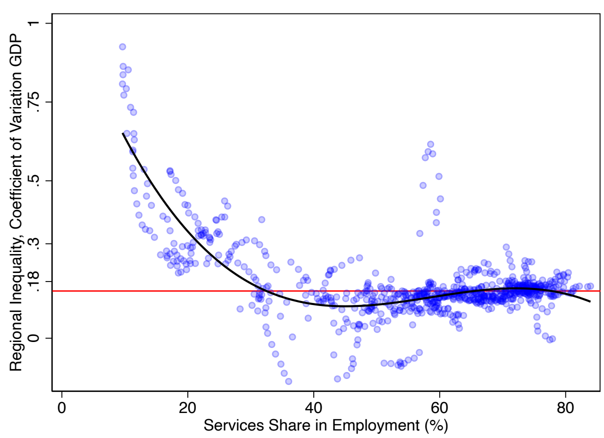
The left panel of figure 7 shows that, on average, as countries get richer, the convergence rates between their regions decline. The right panel shows that this decline is also related to growth being driven by an increased concentration of economic activity in the services sector away from manufacturing and agriculture. In fact, once the employment share in the service sector is greater than 60%, the average within-country convergence rate is positive ($\beta > 0$), implying divergence between regions within the country.

We run several robustness checks for this fact. Specifically, our main finding that within-country convergence rates, $\beta_{ct}$, decline with development and an increase in employment in the services sector are robust to estimating convergence rates either using the balanced or the unbalanced panel and using population-weighted or unweighted regressions (1).

### 3.2.1 Discussion

A potential concern with the analysis thus far could be that if spatial inequality falls with development in general, then there may not be any residual inequality left by the time countries reach the stage when a large fraction of their labor is employed in the services sector. Hence, a stall in the within-country convergence rate may be an outcome of the fact that there is no spatial disparity left to close. In figure 8, we indeed document a negative relationship between spatial inequality (measured by the coefficient of variation between the regions within a country) and the increase in service share from 20% to 40%. But we also find that spatial inequality stagnates at about 18%, and does not change for any further increase in services employment share. This implies that while regional income disparities are still present, the gap is not closing further.

Figure 8: A Fall and Stagnation of Inequality with Structural Transformation




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. The black line shows the evolution of the average country.

Third, could factors other than a structural transformation toward services drive the stagnation in within-country convergence? Indeed there may be many factors that drive or facilitate a structural transformation toward services like greater internal migration, lower internal transportation costs, trade, etc. These factors may even differ across different countries as the composition of services jobs differs. While important, our goal here is not to identify what factors cause a structural transformation toward services, but it is to understand the implications of the structural transformation process for regional inequality.

Nevertheless, in table 2, we first verify that it is the transformation of the economies toward services rather than manufacturing that is driving our main result. We regress the estimated within-country convergence rates, $\beta_{ct}$, on log GDP per capita or employment shares in broad sectors and a country dummy. Hence, the coefficient on a regressor measures the association between the evolution of convergence rates and that regressor within each country over time. Note that an increase in $\beta_{ct}$ implies a reduction in convergence rates. Cols 1 and 2 of table 2 show that the evolution of within-country convergence rates is related to the development of countries and structural transformation out of agriculture. Cols 3, 4, and 5 show however that it is the transformation out of agriculture into services rahter than manufacturing that reduces convergence rates.

Next in table 3, we verify that cross-country (or cross-sectional) differences in within-country convergence rates are not due to other factors like external trade agreements, the polity of countries, and their human capital endowment.

Table 2: Structural Transformation and Regional Convergence

| Dependent Variable: | Within-country $\beta_{ct}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| log GDP pc | 1.80 | | | |
| | $(0.40)^{***}$ | | | |
| Employment Shares | | | | |
| Agriculture | | -4.96 | | |
| | | $(1.74)^{***}$ | | |
| Manufacturing | | | -6.99 | -3.85 |
| | | | $(3.80)^{*}$ | (3.06) |
| Services | | | | 6.24 |
| | | | | $(1.55)^{***}$ |
| Country FE | ✓ | ✓ | ✓ | ✓ |
| N | 980 | 980 | 980 | 980 |
| $R^2$ | 0.30 | 0.32 | 0.30 | 0.37 |

Note: This table shows the regression estimates where the dependent variable in each column is the estimate of $\beta$-convergence for 10-year rolling window for each country in our sample using the unbalanced panel. Each specification includes country-fixed effects.

Table 3: 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)** |
| $\Delta$ 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) |
| $\Delta$ 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 |



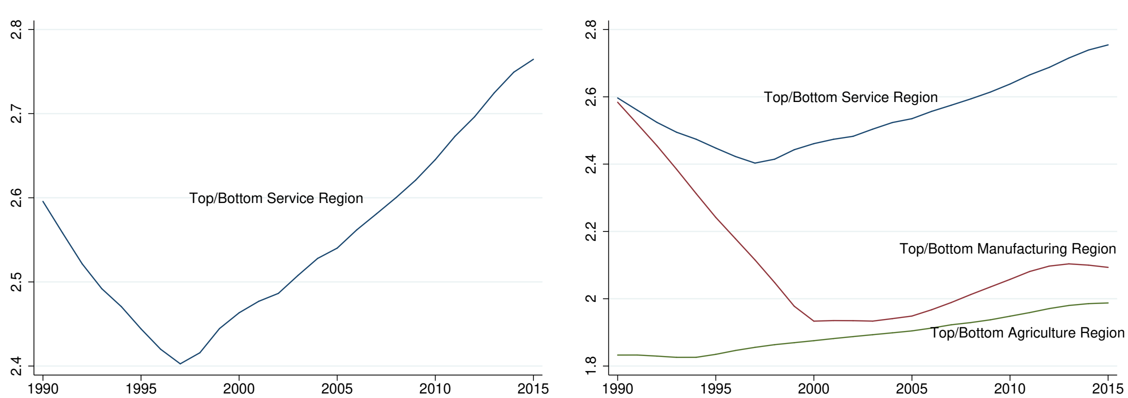
Note: This table shows the regression estimates where the dependent variable in each column is the estimate of $\beta$-convergence for 10-year rolling windows for each country in our sample. The unit of observation is country×year. Robust standard errors are reported in parenthesis.

## 3.3 Fact #3: The services economy is concentrated in a few regions

So far we have documented that in the last 30 years, there has been an average decline in within-country convergence rates and that process is related to a structural transformation of countries towards services. The third fact we document is that economic activity in services is highly concentrated in a few regions. The distribution of services activity across regions within a country is much more skewed than manufacturing or agriculture. This highlights a role for agglomeration economies, much more than in manufacturing or agriculture.

The left panel of figure 9 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. The right panel 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. Compared with manufacturing and services, we find that the concentration is higher in service both in levels and in its increase over time.

Figure 9: 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 toward services might affect 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 a 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 more inequality and more growth through the reallocation of workers to cities with high knowledge spillovers.

**Consumption**. In the model, there are $J$ regions and each of them is indexed by $j$. Workers decide where to locate in each period and have idiosyncratic taste shocks $\mu$ for regions originating from a Type-1 Extreme Value distribution. The parameter $\nu$ 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 composite 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:

$$C_j = C_{s,j}^{\gamma} C_{m,j}^{1-\gamma-\beta} (C_{a,j} - \bar{c_a})^{\beta} \tag{2}$$

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 functions 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:

$$Y_i = A_i N_i \tag{3}$$

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

$$A_{ijt} = e^{g_{it}} A_{ijt-1} \quad \text{for} \quad i = a, m \tag{4}$$

$$A_{sjt} = e^{g_{st}} A_{ijt-1} N_{sjt}^{\delta} \tag{5}$$

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:

$$C_{a,j} = \bar{c_a} + \frac{\beta(w_j)}{p_{a,j}} \tag{6}$$
$$C_{m,j} = (1 - \gamma - \beta)w_j \tag{7}$$
$$C_{s,j} = \frac{\gamma(w_j)}{p_{s,j}} \tag{8}$$

(ii) Location choice of the consumer:

$$\frac{N_j}{\bar{N}} = \frac{exp(\ln w_j - \gamma \ln p_{s,j} - \beta \ln p_{a,j})^{1/\nu}}{\sum_n exp(\ln(w_n) - \gamma \ln p_{s,n} - \beta \ln p_{a,n})^{1/\nu}} \tag{9}$$

(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:

$$\sum_i L_{i,j} = \bar{L}_j \tag{10}$$

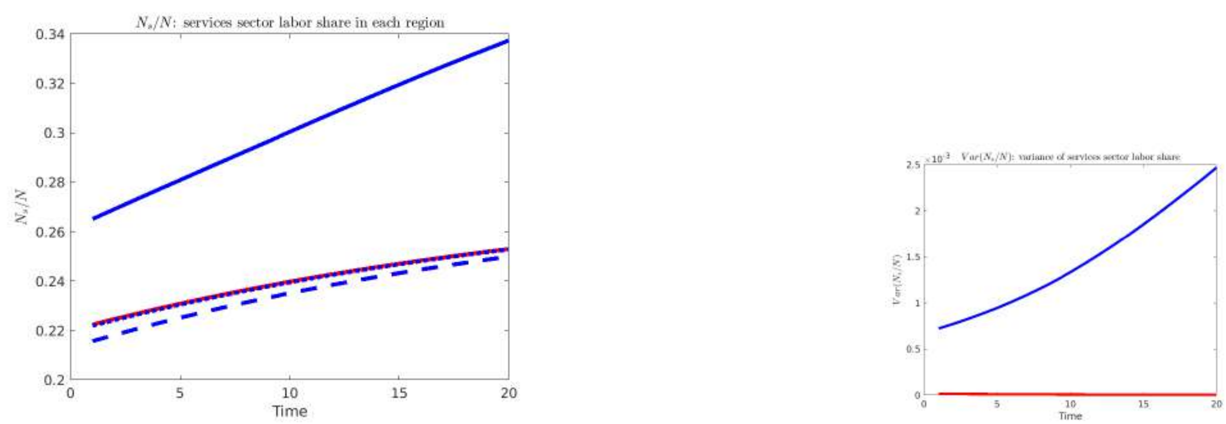
$$\sum_i N_{i,j} = N_j \tag{11}$$

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

$$C_{a,j} = A_{a,j} N_{a,j} \tag{13}$$

**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 10, 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.

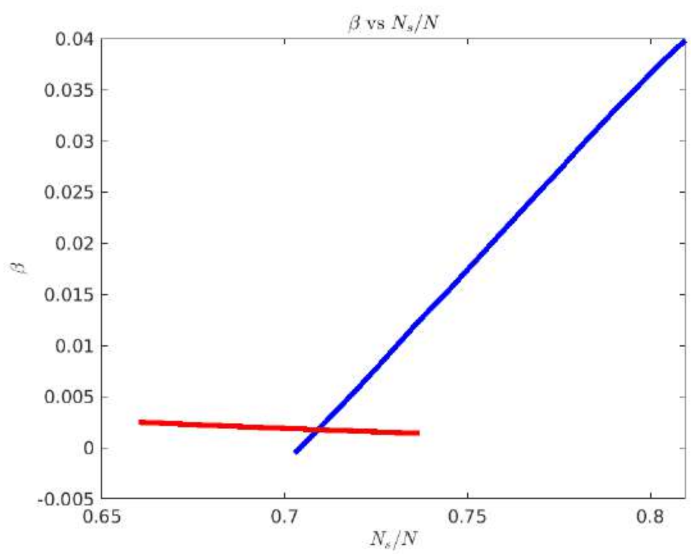
Figure 10: Model: Evolution of Service by City




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 $\delta$ is set to 0, otherwise, "no agglomeration".

Finally, we show whether our model replicates fact #2. Figure 11 reports the model generated estimates of average within-country $\beta$ convergence against service share. The blue lines represent the baseline model. The red line represents the estimates of the model when $\delta$ is set to 0, otherwise, "no agglomeration". We find that when service share in the economy goes up, within-country $\beta$ 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 $\beta$ convergence increases. This is consistent with Caselli and Coleman (2001) and corroborated by our other empirical evidence in section B.2.3.

Figure 11: Model: Structural Transformation and Regional Convergence




Note: This figure reports the model-generated estimates of average within-country $\beta$ convergence against service share. The blue lines represent the baseline model. The red line represent the estimates of the model when $\delta$ 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 $\beta$-convergence between 1980 and 2017 in the data. Table 4 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, $\delta$ 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 $\beta$-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 $\beta$ 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 $\beta$ 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 12 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 $\beta$-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 $\beta$-convergence and to assess the implications of regional convergence, or its lack thereof, we run a simple counterfactual in which we set agglomeration economies, $\delta$, to 0. Table 5 shows by how much $\beta$-convergence would be changed between 1980 and 2017 if agglomeration forces had been set to 0 rather than 0.05. We find that $\beta$-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

Table 4: 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 |
| $\delta$ | Agglomeration Service | ✓ | | 0.05 |
| $A_i$ | Initial Prod. by Sector | ✓ | | |
| Consumption | | | | |
| $\gamma$ | Service share | | ✓ | 0.8 |
| $\beta$ | Agr. share | | ✓ | 0.03 |
| $\nu$ | T1-EV variance | | ✓ | 1.1 |
| $c_a$ | Subsistance level of Agr. | ✓ | | 0.01 |

forces had been set to 0, and $\beta$-convergence had not increased by as much as in the baseline, 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.

# 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

Figure 12: Model Matching Data: $\beta$-convergence

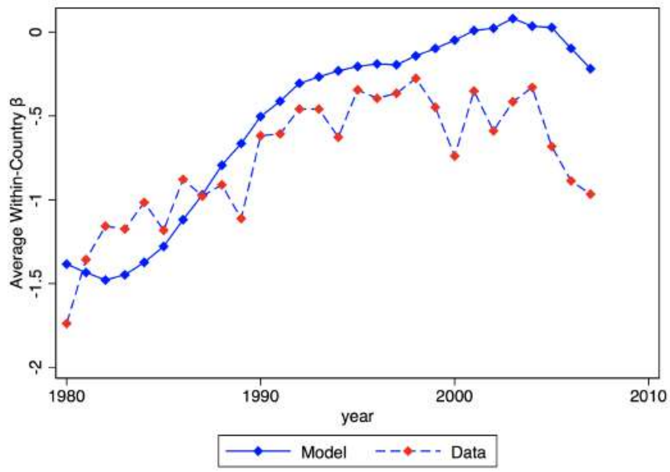



Table 5: Implications of $\beta$-convergence decline

| | Baseline | No agglomeration |
|---|---|---|
| $\%\Delta\beta$ 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 $\beta$-convergence and aggregte service share in the baseline model in column (1) compared to the case of no agglomeration, $\delta$ set to 0, in column (2).

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.

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# A Data

Table A.1: 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 A.2: 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 A.3: Representativeness of the Sample by Continents

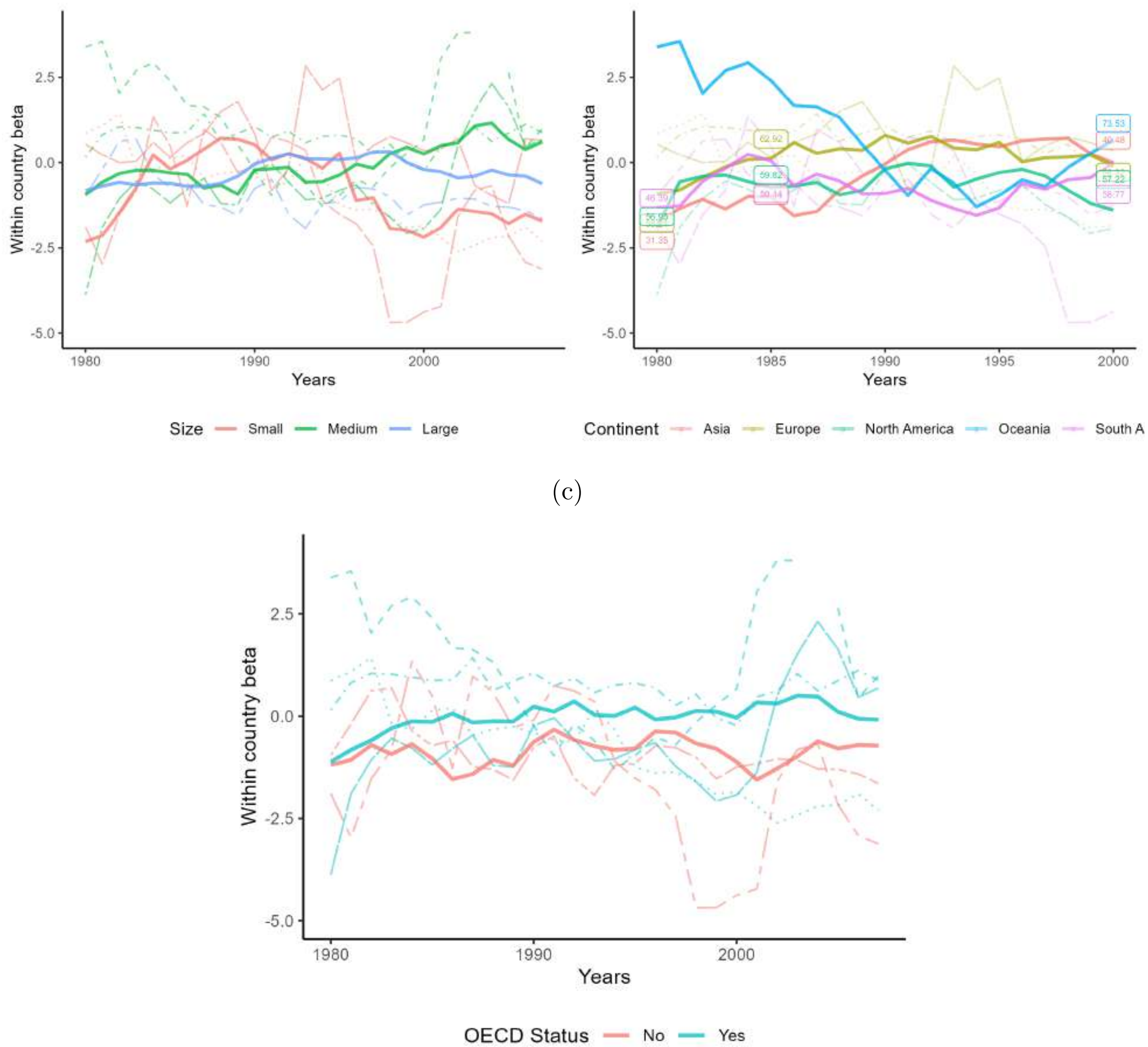
| | Share of Continent Population | Share of Continent GDP | Avg. GDP Growth Per Capita | Growth relative to World Avg | # Countries | Avg years of education |
|---|---|---|---|---|---|---|
| | | | Africa | | | |
| 1980-1990 | 0.148 | 0.253 | -3.83% | 0.95 | 3 | 3.66 |
| 1990-2000 | 0.144 | 0.270 | 0.20% | 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.

# B Heterogeneity in Estimates

Figure B.1: Within-country $\beta$ convergence: Heterogeneity

(a) (b)




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

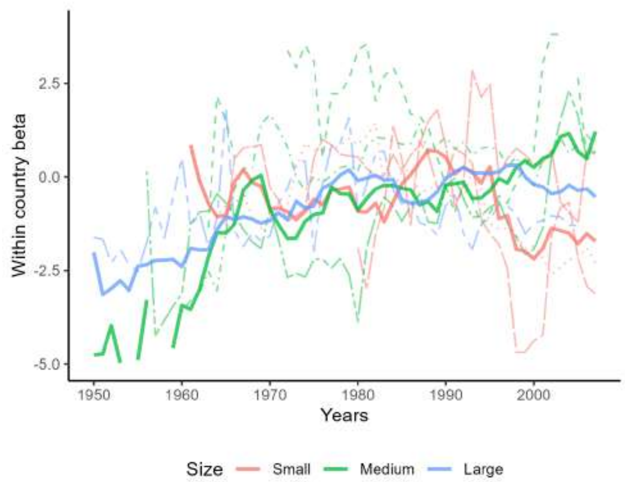
Table A.4: List of Countries and Sources

| 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 |

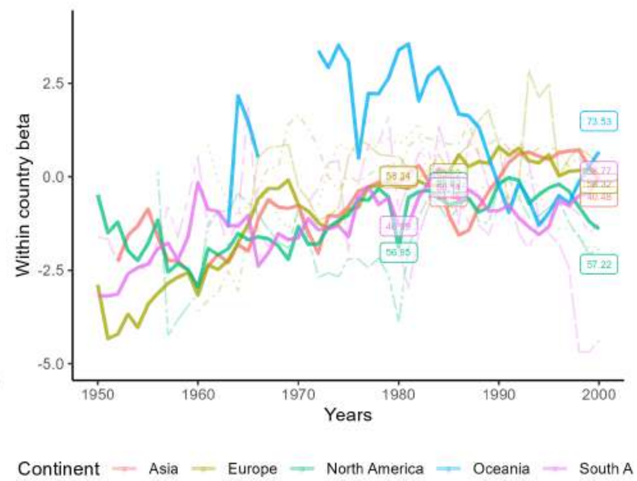
Note: This table reports the list of 34 countries in our sample in alphabetical order comparing the sample from Gennaioli et al. (2012) with others both for regional GDP and for years of schooling. GLLS stands for Gennaioli et al. (2014) and CGK stands for Chatterjee-Giannone-Kuno.

Figure B.2: (Unbalanced panel) Within-country $\beta$ convergence: Heterogeneity

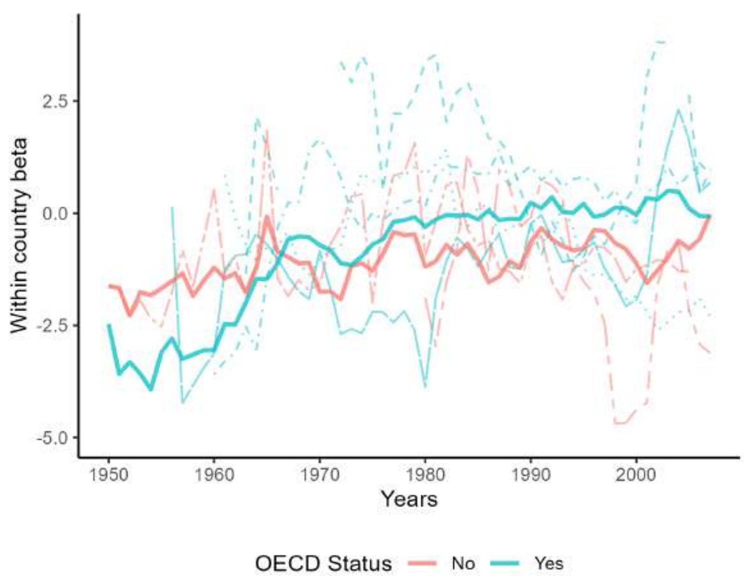
(a)




(b)




(c)




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

Table B.1: Heterogeneity in within-country $\beta$ estimates

| | | 1980-1990 | 1990-2000 | 2000-2010 | 2005-2015 | # Countries |
|---|---|---|---|---|---|---|
| Overall | | -0.51 | -0.13 | -0.15 | -0.23 | 34 |
| | | 0.96 | 0.97 | 1.01 | 0.97 | |
| Continent | AF | -2.80 | -2.15 | -2.31 | -2.34 | 3 |
| | | 1.26 | 1.16 | 1.22 | 1.22 | |
| | AS | -1.07 | 0.44 | -0.63 | -0.97 | 6 |
| | | 0.94 | 0.81 | 0.73 | 0.62 | |
| | EU | 0.03 | 0.36 | 0.00 | -0.06 | 16 |
| | | 0.97 | 0.97 | 0.98 | 0.98 | |
| | NA | -0.70 | -0.53 | -0.01 | 0.33 | 3 |
| | | 0.71 | 0.74 | 1.15 | 1.07 | |
| | OC | 1.99 | -0.42 | 2.56 | 1.36 | 1 |
| | | 1.28 | 1.36 | 1.51 | 1.48 | |
| | SA | -0.58 | -0.85 | 0.61 | 0.73 | 5 |
| | | 0.85 | 1.12 | 1.18 | 1.03 | |
| Size | Large | -0.58 | 0.11 | -0.37 | -0.46 | 13 |
| | | 0.75 | 0.74 | 0.65 | 0.60 | |
| | Medium | -0.50 | -0.12 | 0.65 | 0.56 | 15 |
| | | 1.11 | 1.16 | 1.25 | 1.23 | |
| | Small | -0.39 | -0.65 | -1.68 | -1.68 | 6 |
| | | 1.01 | 1.00 | 1.22 | 1.11 | |
| OECD Status | No | -1.04 | -0.66 | -0.97 | -0.74 | 10 |
| | | 1.00 | 1.01 | 1.04 | 1.00 | |
| | Yes | -0.29 | 0.10 | 0.19 | -0.01 | 24 |
| | | 0.94 | 0.96 | 1.00 | 0.96 | |

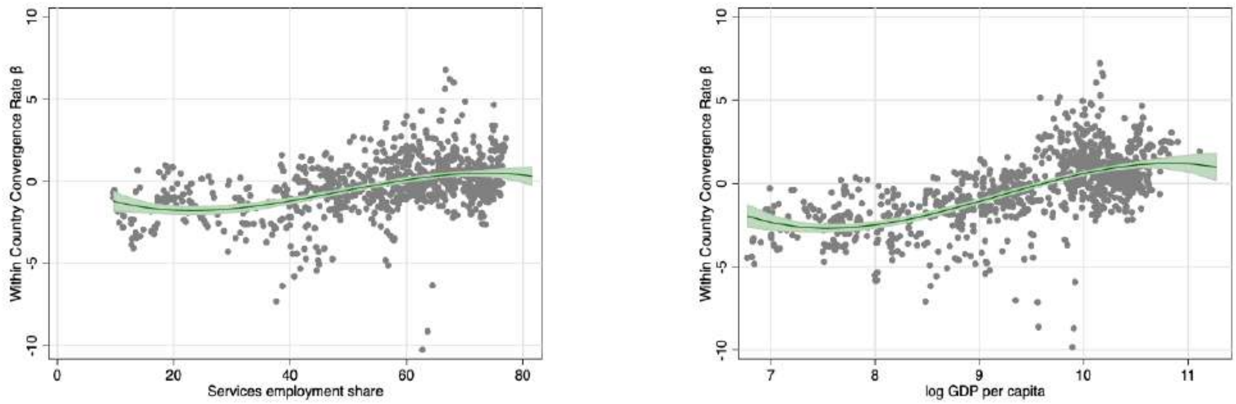
Note: This table reports the $\beta$ estimates for the within-country regression discussed in section 3. The sample is split in groups of countries by geography, size and OECD status. Standard errors are reported below the coefficient estimates.

Table B.2: Group status for 34 countries in the sample

| country | Continent | OECD | size |
|---|---|---|---|
| Kenya | AF | No | Medium |
| South Africa | AF | No | Medium |
| Tanzania | AF | No | Medium |
| China | AS | No | Large |
| India | AS | No | Large |
| Indonesia | AS | No | Large |
| Malaysia | AS | No | Medium |
| Japan | AS | Yes | Large |
| South Korea | AS | Yes | Large |
| France | EU | Yes | Large |
| Germany, West | EU | Yes | Large |
| Italy | EU | Yes | Large |
| Turkey | EU | Yes | Large |
| United Kingdom | EU | Yes | Large |
| Belgium | EU | Yes | Medium |
| Greece | EU | Yes | Medium |
| Hungary | EU | Yes | Medium |
| Netherlands | EU | Yes | Medium |
| Portugal | EU | Yes | Medium |
| Spain | EU | Yes | Medium |
| Austria | EU | Yes | Small |
| Denmark | EU | Yes | Small |
| Norway | EU | Yes | Small |
| Sweden | EU | Yes | Small |
| Switzerland | EU | Yes | Small |
| Mexico | NA | Yes | Large |
| United States | NA | Yes | Large |
| Canada | NA | Yes | Medium |
| Australia | OC | Yes | Medium |
| Brazil | SA | No | Large |
| Peru | SA | No | Medium |
| Bolivia | SA | No | Small |
| Chile | SA | Yes | Medium |
| Colombia | SA | Yes | Medium |

## B.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 7. 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.



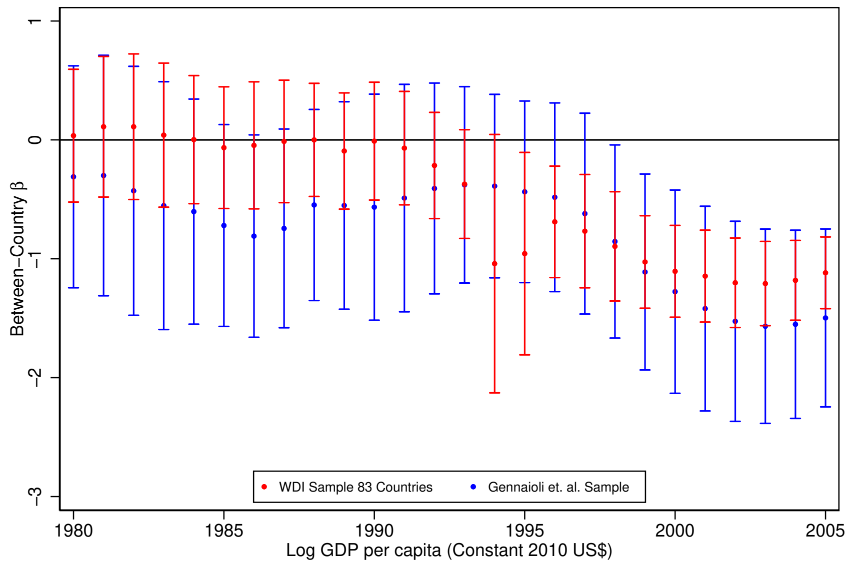

Notes: Population weighted beta vs services employment share (left) and log GDP per capita (right) for balanced panel. Estimates are residualized off country fixed effects. Green line shows the evolution of the average country.

## B.2 Other Results

We report below two other findings related to $\beta$-convergence across countries to complement the main fact of the decline of $\beta$-convergence within-country. We then report an observation about the relationship between economic growth and inequality within country and across 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 $\beta$-convergence within-country. We confirm the hypothesis above that structural transformation has the largest role overall.

### B.2.1 $\beta$ Cross-country Convergence increased over time

Figure B.4: $\beta$ Cross-Country Convergence




Each point is the regression coefficient of an unweighted regression of growth in GDP p.c. between t and t+10 on log GDP p.c. at t.
Bars represent 95% confidence intervals with robust standard errors.

### B.2.2 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 B.3. Regional inequality is captured by our $\beta$ 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 $\beta$ estimates and Gini coefficients. The $\beta$ 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 $\beta$ 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 $\beta$ 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 $\beta$) 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 B.3: Growth and Inequality

| | Δ GDP | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Within-country $\beta$ | .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 $\beta$ convergence conditional on several observables in different specifications. Standard errors are clustered at country level.

### B.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 and Peters (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 and Peters (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 B.4 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 $\beta$ 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 B.4: Testing for Complementary Hypotheses

| | Within country $\beta$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| $\Delta$ 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) |
| $\Delta$ Agr. Product. | | | -20.31 | | | | | -19.62 |
| | | | (10.58)* | | | | | (12.65) |
| $\Delta$ 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) |
| $\Delta$ 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 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.