UNEQUAL GLOBAL CONVERGENCE

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Abstract

Economic growth in the last half-century has led to a convergence between rich and poor nations. Using a sample of 31 countries and 555 regions in 5 continents, we study the convergence of regions within countries between 1980 and 2015 and establish two new facts. First, we find a stall in regional convergence within countries, i.e., a decline in the catch-up rate of poorer regions. Second, aggregate economic growth is positively correlated with regional inequality but negatively correlated with individual-level inequality. Next, we show that while an increase in agricultural productivity leads to convergence between regions, an increase in services productivity increases spatial inequality. This highlights a new dichotomy in the role of structural transformation for spatial development.

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1 Introduction

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?

To deepen our understanding about these questions, we build on the data set first complied by Gennaioli et al. (2012) and put together GDP data at a sub-national level for 555 regions within 31 countries across 5 continents between 1980–2015. This allows us to establish two novel empirical regularities. First, we find that the faster growth of countries is accompanied with a 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 for the US (e.g., Glaeser and Gyourko (2006), Ganong and Shoag (2017), Giannone (2017)), to the best of our knowledge, this is the first evidence that a stall in regional convergence is happening at a broader leve. Speficially, we document it for a set of countries that account for 64% of the world's GDP. Second, we 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 indiviudal level inequality.

Having established these facts, we turn to studying the drivers of regional inequality. We find that growth in agricultural productivity and development of roads are associated with a decrease in regional inequality (or greater regional convergence). On the other hand, growth in services productivity and international integration increases regional inequality (or stalls regional convergence). As the growth in agricultural productivity largely accounts for cross-country differences in premature de-industrialization (Huneeus and Rogerson (2020)), this points to a new dichotomy in the role of structural transformation for spatial development.

Related Literature This paper related 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). The closest paper is Gennaioli et al. (2014) that document 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 Gennaioli et al. (2014) studies cross sectional patterns, we focus on the evolution of spatial inequality. Thus, we also need a time-consistent sample of countries that leave us with 555 regions.

We also contribute by studying the role of strucutral transformation for regional inequality. Hence, we add to Caselli and Coleman (2001) and to Eckert et al. (2018) who quantitatively study how structural transformation from agriculture to manufacturing increased regional convergence. In our work, we provide evidence supporting this hypothesis but we complement it with new evidence that a shift from manufacturing to services might have decreased regional convergence.

Since the latter result is inconsistent with existing theories of structural change, in a future version we aim to develop a model of structural change that can account for across- and within-country convergence patterns.

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 uncovers what are the determinants of regional convergence and the lack there off. Section 5 concludes and highlights the work we are currently pursuing.

2 Data

The main data we use is a time-series on sub-national GDPs. For this we build on the excellent dataset on sub-national GDP that was constructed by Gennaioli et al. (2012) spanning between 1950 and 2010. We update it to the most recent year possible. The details comparing our sample with the existing one are presented in table A.1. As table A.1 shows, we compliment also years of education at sub-regional level. We supplement this data with data on national GDP, shares of agriculture, manufacturing, and services in GDP from the World Development Indicators.

In order to shed light on the determinants of regional inequality we use various 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).

Our sample consists of 31 countries. This is significantly lower than the sample of 82 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 555 sub-national regions of the world, as compared to 1503 sub-national regions in Gennaioli et al. (2012).

Overall, the 31 countries in our sample account for 64% of the world GDP and 38% of the world population (see table B.1 for details). The coverage is biased towards high and middle income countries, primarily because we miss data on many African countries as show in tables B.2 and B.3. 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 B.3. 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 in that continent. This includes Vietnam, Thailand, Indonesia, and Phillipines that 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 use night lights data to test robustness of our results. More details about coverage of nightlights data and estimates of regional convergence are reported in appendix D.

3 Two Novel Facts about Spatial Inequality and Economic Growth

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 speed of convergence between different regions within countries has gone down from 1.5% to being 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 in the last four decades countries that have grown more are those where initial individual income inequality was lower but spatial inequality increased over time.

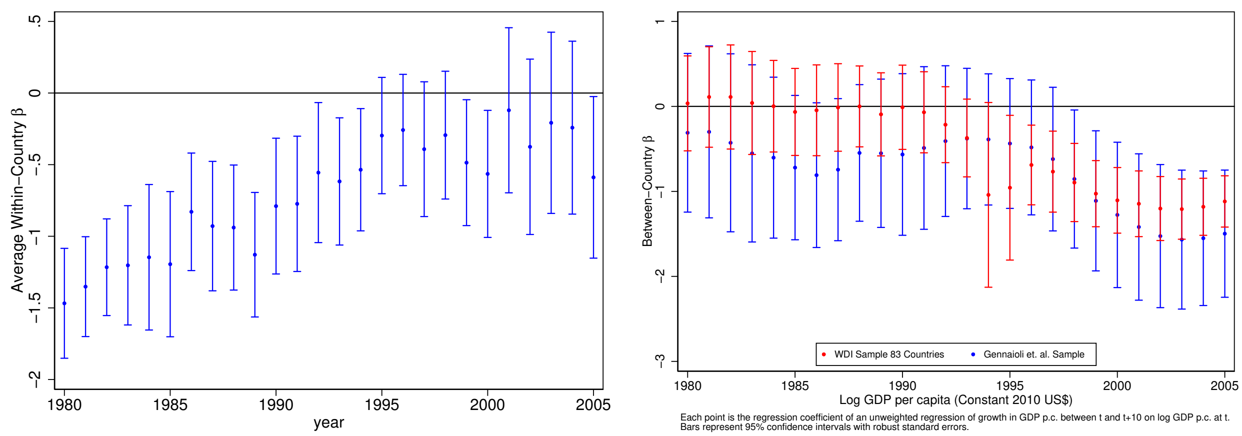
3.1 Fact #1: A stall in convergence of regions within countries 1980–2015

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):

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

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. 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 $\beta_{\text{within country}}$ for the specifications that we estimate within a country where each observation is a region. And, we are going to refer to $\beta_{\text{cross country}}$ for the specifications that we estimate across countries where each observation is a country.

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 31 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 1a 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.



(a) Within Country

(b) Cross Country

Figure 1: β-Convergence Cross-Country vs Within-Country Over Time

This is in stark contrast to what we know about cross-country convergence. 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 figure 1b where we reproduce figure 1 from Patel et al. (2018) for 83 major non-oil economies of the world and our sample of 31 countries. As before, the rate of convergence in any year between countries is obtained by regressing the annual growth in per-capita GDP over the next decade on the initial log GDP per-capita of the 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%, it fell almost to zero in the 2000s and kept in that range in 2015.

In case any specific subset of countries might be driving our finding, we split counties in groups by geography, size and OECD status. Table C.1 reports the detailed regression results over time.

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 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.

3.2 Fact #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 1. 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 compliment 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 betweeb 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 β within-country 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 (2020). 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 1: Growth and Inequality

	Δ GDP									
β within-country	.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

4 Understanding the Drivers of Regional Inequality

To understand what are the factors driving the different speeds of convergence across countries and over time, 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 find a 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 2 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 srvice 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 2: The Determinants of Regional Inequality

	β within country							
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

5 Conclusions and Current Work

We provide the first evidence that the patterns of regional convergence is decreasing over time in the average country of a sample of 31 countries and 555 between 1980 and 2015. This goes in opposite directions to results showing that poorer countries around the world are catching up at a faster rate than they used to. Our second core contribution is to show empirically that the structural shift towards service might have large 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 are currently working on a model with regions and structural transformation from agriculture and manufacturing towards service.

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Appendices

A Updated Sample

Table A.1: Summary of Data Collected

Country	Sub-national GDP		Years of Schooling	
	Gennaioli et. al. (2012)	This Paper	Gennaioli et. al. (2012)	This Paper
Australia	1953, 1976, 1989â2010	2011-2017	1966, 2006	
Austria	1961â1992, 1995â2010	2011-2017	1964, 1971, 1981, 1991, 2001, 2009	2011
Belgium	1960â1968, 1995â2010	2011-2017	1961, 2001	
Bolivia	1980â1986, 1988â2010		1976, 1992, 2001	
Brazil	1950â1966, 1970, 1975, 1980, 1985â2010	2011-2015	1950, 1960, 1970, 1980, 1991, 2000, 2010	2010
Canada	1956, 1961â2010	2011-2017	1961, 1971, 1981, 1991, 2001, 2006	2010
Chile	1960â2010	2011-2017	1960, 1970, 1982, 1992, 2002	
China	1952â2010	2011-2017	1982, 1990, 2000, 2010	
Colombia	1950, 1960â2010	2011-2017	1964, 1973, 1985, 1993, 2005	
Denmark	1970â1991, 1993â2010	2011-2017	1970, 2006	2008-2019
France	1950, 1960, 1962â1969, 1977â2010	2015, 2016, 2017	1962, 1968, 1975, 1982, 1990, 1999, 2006	2011
Germany, West	1950, 1960, 1970â2010	2011-2017	1970, 1971, 1981, 1987, 2009	2011
Greece	1970, 1974, 1977â2010	2011-2017	1971, 1981, 1991, 2001	2011
Hungary	1975, 1994â2010	2011-2017	1970, 2005	2016
India	1980â1993, 1999â2010	2011-2017	1971, 2001	
Italy	1950, 1977â2009	2011-2017	1951, 1961, 1971, 1981, 1991, 2001	2011
Japan	1955â1965, 1975â2009	2010-2016	1960, 2000, 2010	
Kenya	1962, 2005	2013-2017	1962, 1989, 1999, 2009	
Korea, Rep.	1985â2010	2011-2017	1970, 1975, 1980, 1985, 1990, 1995, 2000, 2005, 2010	
Malaysia	1970, 1975, 1980, 1990, 1995, 2000, 2005â2010	2011-2015	1970, 1980, 1991, 2000	2010
Netherlands	1960, 1965, 1995â2010	2011-2017	2001	
Norway	1973, 1976, 1980, 1995, 1997â2010	2011-2017	1960, 2010	2019
Peru	1970â1995, 2001â2010	2011-2017	1961, 1993, 2007	
Portugal	1977â2010	2011-2017	1960, 1981, 1991, 2001, 2011	2011
South Africa	1970, 1975, 1980â1989, 1995â2010	2011-2016	1970, 1996, 2001, 2007	
Spain	1981â2008, 2010	2011-2017	1981, 1991, 2001	2011
Sweden	1985â2010	2011-2017	1985, 2010	
Switzerland	1965, 1970, 1975, 1978,1980â1995, 1998â2005, 2008â2010	2011-2017	1970, 1980, 1990, 2000, 2010	
Tanzania	1980, 1985, 1990, 1994, 2000â2010	2011-2016	1978, 1988, 2002	2012
United Kingdom	1950, 1960, 1970, 1995â2010	2011-2017	1951, 1991, 2001	
United States	1950â2010	2011-2017	1960, 1970, 1980, 1990, 2000, 2005	2010, 2015

B Representativeness

Table B.1: Overall

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	0.388	0.707	2.16%	1.79	31	43.52
1990-2000	0.380	0.659	2.93%	1.60	31	62.84
2000-2010	0.380	0.628	3.44%	0.95	31	92.11
2010-2020	0.377	0.549	1.74%	1.01	31	80.72
All Years	0.382	0.640	2.78%	1.12	31	331.48

Table B.2: Continents

Period	Share of Continent Population	Share of Continent GDP	Avg Growth GDP p.c.	Growth relative to Continent Avg	# Countries	Avg years of education
Africa	0.126	0.213	1.31%	0.87	3	145.05
Asia	0.348	0.409	4.06%	1.03	5	225.89
Europe	0.550	0.741	2.49%	1.21	15	302.69
North America	0.660	0.881	1.88%	1.18	2	206.58
South America	0.732	0.713	2.93%	0.98	5	199.06
Ocenia	0.785	0.849	2.11%	0.94	1	215.35
World	0.382	0.640	2.78%	1.12	31	331.48

Table B.3: Income Distribution

Income-class	Share of Income-class Population	Share of Income-class GDP	Avg Growth GDP p.c.	Growth relative to Class Avg	# Countries	Avg years of education
High Income	0.908	0.915	2.29%	1.05	16	317.38
Middle Income	0.524	0.580	3.70%	1.07	5	257.57
Low Income	0.291	0.239	3.38%	0.88	10	191.16

Notes: Countries grouped according to the United Nation's definition of low, middle, and high income in 1987.

C Heterogeneity in Estimates

Table C.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.

D Robustness

In this section, we use nightlights data to compliment 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 data span from 1993 to 2018 but we stop it in 2014 when the satellite changed and might affect the estimates. Figure ?? 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 ?? reports the change in β

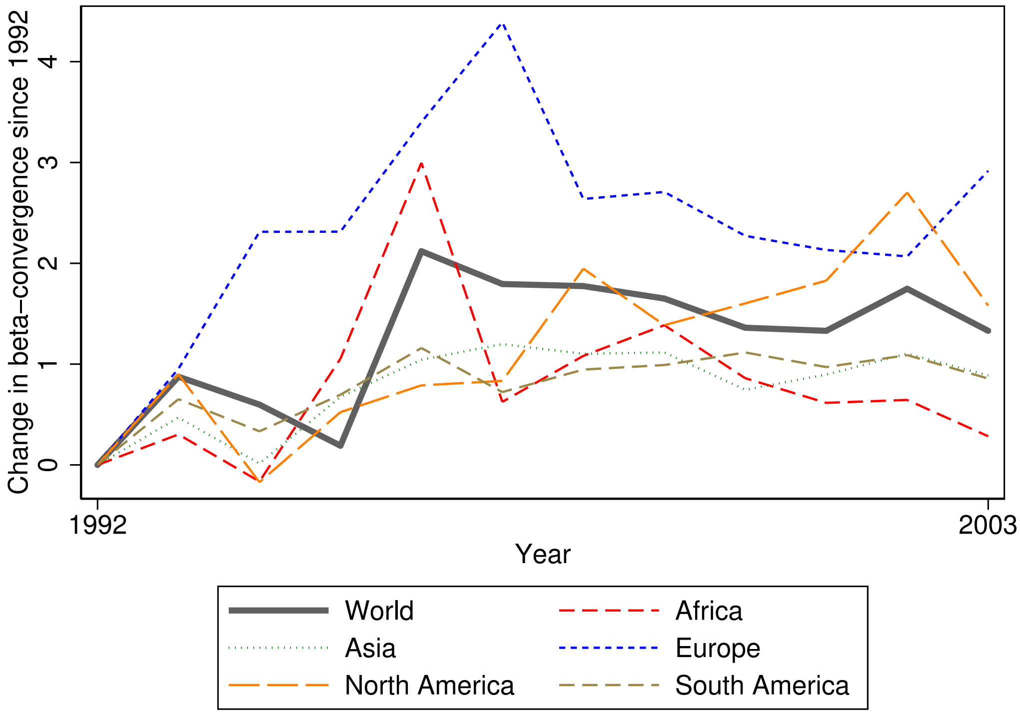

Figure D.1: β-Convergence within Country with Nightlights Data

within countries estimates for 10-year rolling windows using as baseline 1993-2003. Overall we find that β within-country 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.