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Regional Income Dynamics in Bangladesh: The Road to a Balanced Development is in the Middle*

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Abstract

Bangladesh's remarkable achievements in economic and social progress put itself in a position that would have been unthinkable until a few decades ago. But did the improvement in development outcomes accrue equally to all areas in the country? We tackle this question by analyzing district-level income per capita constructed from the 2000 and 2016 rounds of the Household Income and Expenditure Survey. Estimating models based on the standard neoclassical theory of economic convergence built to take into account the impact of natural disasters, we find essentially no evidence of convergence. This implies the persistence of income differentials among Bangladesh's 64 districts. To check for the possibility of multiple steady states, we estimated models with a three-club structure based on the year 2000 income percentiles. The results now support the hypothesis of convergence within the group of middle-income districts, with a speed of 1.6% per annum (half-life 43 years)—close to Barro's "2% iron law". A remarkable finding is the positive and significant effect of education on this club's steady state income level. Overall, these results are consistent with the notion of a rising middle class in Bangladesh in recent years. We also explore latent club structures using automatic algorithms, but we do not find any further evidence of convergence. The key policy implication of our study is that, to ensure a balanced regional

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development, it would be, at a minimum, necessary to enact policies extending the convergence process to the club of the poorer districts as well.

JEL codes: O47, R11.

Keywords: Bangladesh, Convergence, Regional income disparity, Middle class.

1 Introduction

Since its independence exactly fifty years ago in 1971, Bangladesh has done better than other developing countries in two unique ways. First, contrary to the theory of demographic transition, Bangladesh was able to reduce its fertility rate significantly before its income rose steadily[1]. By contrast, in English-speaking and northwest European countries, the reduction in population growth followed long after the continuous rise in income from 1850 onwards, corresponding to the onset of industrial revolution (Lucas, 2004). Second, despite its low per capita income, since 1980 Bangladesh has achieved a higher level of social development outcomes in education, health, demographic and gender equality, compared with countries at a similar level of economic development (see, for example, Mahmud 2008; Mahmud et al. 2013; Hossain 2017; and World Bank 2012). The surprising combination of higher social development and lower income level is now popularly dubbed the "Bangladesh conundrum" in the literature on economic development (Asadullah et al., 2014). An article in The Economist (2012) magazine that succinctly summarizes Bangladesh's success in comparison to India and Pakistan, helped to popularize Bangladesh's development surprise to a much larger audience of policymakers and the public.

In spite of the gains in its development, poverty in Bangladesh did not fall sharply until around 2000. In the 1980s and the 1990s, the poverty headcount ratio at \$1.90 a day (2011 PPP) averaged 38%, whereas over 2005–2016, the average came down under 20%. The fall in poverty since 2000 was associated with a comparably higher economic growth than earlier decades[2], but for its amount of growth poverty fell disproportionately

[1]More precisely, from 6.92 in 1972 to 3.07 in 2001. Over the same time span, GDP per capita grew from \$322 to \$541 (in 2010 prices). This large reduction in fertility is invariably associated with high rates of contraceptive use prior to the projected increase in income (Rashid et al., 2005)

[2]Real GDP growth averaged 4.35% during 1980-2000 and 6.23% after 2001.

more. This leads to an obvious question: Did the gain in development outcomes accrue equally to all areas in the country? Arthur Lewis (1976) once famously said that "... development must be inegalitarian because it does not start in every part of the economy at the same time." Has this been true for Bangladesh? As we shall see in more detail below in Section 3, there are several reasons why regional disparity might be present in Bangladesh. However, development is a multifaceted phenomenon, and we have seen above that, contrary to the general rule, looking at nationwide data, demographic and social developments in Bangladesh seem to have anticipated economic growth. Thus, the relationship between regional disparities and income growth might well be an exception as well.

Unfortunately, much of the existing literature on the issue considers only very broad partitions (eastern versus western, or at most a handful of regions), see, for instance, Sen et al. (2014). Hence, substantial heterogeneity at lower levels may go unnoticed. Thus, our aim is testing Lewis's intuition for Bangladesh, assessing whether in Bangladesh regional income disparity over the recent past (2000–2016) was persistent, or, at the opposite, shrinking. To this end, we will consider the, relatively high, disaggregation level of the 64 districts, never used before.[3] One difficulty of working at this area level is that the standard income measure, Gross Domestic Product (GDP) per capita, is unavailable. We overcome this problem by constructing district income data based on family-level data from the Household Income and Expenditure Survey (HIES). This is the second feature of our study which innovates on the literature.

The paper is organised as follows: in section 2 we review the relevant literature, then in section 3 we present the main facts of Bangladesh's recent economic development and some preliminary, descriptive data analysis. We move to model estimation in section 4, with basic conditional convergence regressions in section 4.1 and club modelling in sections 4.2–4.3. Some conclusions are finally drawn in section 5.

2 Literature review

Due to data limitations, several earlier studies of regional disparity in Bangladesh have primarily relied upon regional or divisional data, the lowest level of spatial disaggregation.

[3]District average population is about 2.5 million, 80% of the maximum value of level 2 areas of European Union's NUTS regional classification (3 million) and less than 40% of the average population of the U.S. states (about 6.5 million).

Wodon (1999) combined five cross-sectional surveys for fourteen geographical areas spanning the years 1983 to 1996 to analyze the impact of growth on poverty and inequality. Regional panel estimates indicate that growth reduces poverty in both rural and urban areas, although it is more associated with inequality in urban than in rural areas. Hossain (2000) is the first attempt to explore the convergence of per capita output levels across regions of Bangladesh over the period 1982–1997. He investigated beta, conditional beta, and sigma convergence and found strong convergence during 1982–1991 but no convergence for the later 1991–1997 period. He identified the diffusion of the high yield crop varieties, development of economic and social infrastructure, and labor mobility as factors behind the convergence of per capita output levels. On the opposite, the rapid opening up of the economy in the early 1990s favored a few regions (Dhaka and Chittagong) over the rest of the country and weakened the regional convergence process. Rahman and Hossain (2009) examine per capita income convergence across six divisions of Bangladesh over the period 1977–2000. Both OLS and time series tests (unit root and cointegration) point to the lack of empirical support for (absolute) convergence, suggesting that the lagging regions fail to catch up to the leaders. A point to emphasize here is that unit root and cointegration tests require large sample sizes, a condition hardly fulfilled by the 23 annual observations used by these authors.

Sen et al. (2014) investigate the persistence of regional welfare gaps—measured by real per capita consumption expenditure—in Bangladesh based on HIES data for the years 2000, 2005, and 2010. They divided the country into two regions (east versus west) based on geographic and economic considerations. The western region lags behind the eastern region with higher poverty rates, lower per capita consumption expenditure, adverse geography, and poor communication and infrastructure. Remarkably, however, the western region had higher initial human development than the eastern region, in part due to the active role and presence of Non-Government Organisations. Their empirical results reveal that, although the welfare gap between the two areas has narrowed over the period 2000–2010, the remaining gap is attributed mainly to higher factor returns from human capital and urbanization in the leading eastern region over the lagging western part. Moreover, the eastern region's unequal access to foreign remittance also played an important role in widening the welfare gap between the two areas. To state the results in another way, the western region of Bangladesh is not poor because of its lower endowments (i.e., human capital, land availability), instead the returns to these endowments were lower in comparison to the eastern region because of the high economic density of activity in the latter region. Further results suggest the presence of neighbourhood effect as a complementary force fostering spatial integration.

As clear from the above discussion, whether one uses consumption or income, the literature offers evidence of growing regional inequality in Bangladesh. Different measures of economic activity are also considered in a few papers investigating regional disparities. As public expenditure plays a prominent role in reducing poverty, CPD (2008) investigates whether economically better-off regions receive higher public expenditure allocations. After controlling for population density, political influence and other observed characteristics, CPD (2008) finds a systematic pattern of preferences of higher expenditure allocations towards more advanced regions. The inequality in public spending is also evident when considering disaggregated public expenditure items such as road, health, and education, but at moderate levels. A similar imbalance is also observed when looking at satellite data from nighttime lights that serve as a proxy for economic activity. Using nighttime lights data across 544 subdistricts over the period 1992–2013, Basher et al. (2021) find that lagging subdistricts of Bangladesh are catching up with the more advanced ones. However, a considerable number of subdistricts are also converging with their neighbours or peers (a phenomenon known as 'club convergence' in the literature on economic growth). The estimated unconditional and conditional convergence speeds are slow compared with similar estimates reported in the literature.

We now review selected studies from South Asia and Southeast Asia, which can be potentially helpful to understand the local economic conditions of Bangladesh. Aginta et al. (2021) investigate income disparity among Indonesia's 514 districts over the period 2000–2017, a time period that overlaps with our sample. They find the presence of five convergence clubs, indicating that the growth of income per capita converged to multiple steady states. Their results suggest spatial agglomeration of economic activity since districts of the same province are inclined towards the same club. For an exceptionally geographically dispersed country like Indonesia, this result is natural. Like Bangladesh, there is also an east-west divide in economic well-being; though for Indonesia, the eastern regions of the archipelago are lagging behind the western region.

Of the many studies on the unbalanced nature of growth in India, the most relevant to our analysis is Das et al. (2015), who investigated the pattern of growth among India's 575 districts for the years 2001 and 2008.[4] They find evidence of conditional convergence in income per capita with an annual convergence rate of 1–2%. But more importantly, districts that are near an urban agglomeration experienced transitional growth rates—a result that may have some relevance to Bangladesh. The factors that explain the divergence in growth rates across India's districts are urbanization rate, electricity connection, and state characteristics, implying that policies can play a significant role in reversing India's uneven growth.[5]

A concise summary of previous studies on regional income convergence in China is available in Tian et al. (2016). They show that Chinese provincial incomes are converging into two clubs, with seven eastern-coastal provinces and Inner Mongolia are converging into a high-income club, while the remaining 23 central and western provinces are converging into a low-income club. It is somewhat surprising that a similar eastern-western divide like the one in Bangladesh is causing regional income disparity in China.

Finally, to date, the most comprehensive statistical investigation of regional income disparity worldwide is by Gennaioli et al. (2014), who collect annual GDP data along with other covariates for 1,528 regions across 83 countries. Using 5-year average yearly growth rates of real per capita regional GDP as dependent variable, they find, among other results, that the estimated rate of the regional convergence rate is about 2% per year, similar to those found in cross-country studies. Moreover, the speed of regional convergence is faster in richer than poorer countries, as implied by the neoclassical growth model.

[4] Districts in India are functionally equivalent to counties in the United States. As a comparison, Indian districts are comparable to subdistricts (known as *upazilas*) in Bangladesh.

[5] However, using nighttime light data as a proxy for district-level income, Chanda and Kabiraj (2020) find evidence of absolute convergence across India's districts. Their results also show that rural areas including disadvantaged districts have grown faster over the 1996–2010 sample period. Physical geography has played quite a limited role in their convergence regressions. The reason for this contrasting result is difficult to speculate, but a study on regional convergence in China shows – rather unsurprisingly – that regions with high GDP growth tend to show low nighttime light growth and vice versa (Xiao et al. 2021). Further, factors that cause GDP growth and nighttime light growth are different. For example, industrial structure has a significant effect on economic growth in China's eastern regions. Whereas, population growth, foreign direct investment, and coal consumption play an essential role in nighttime light growth mainly in the central and western regions of China. The most likely upshot of these results is that nighttime light is not necessarily a good substitute for GDP, at least for China.

3 The social and economic development of Bangladesh from 2000 to 2016: some facts

Between 2000 and 2016, Bangladesh's GDP grew at an annual average rate of 5.87% (in real terms), while per capita real GDP grew at a yearly average of 4.43%. To put these figures in perspective, in 2000 nearly half of Bangladesh's population lived below the national poverty line; by 2016, this figure had fallen to 1 in 4.[6] Accordingly, the percentage of people living in extreme poverty had fallen from about 34% in 2000 to 13% in 2016 (Hill et al. 2019).

Remarkably, the rate of poverty reduction was much higher in rural than urban areas. Between 2000 and 2016, poverty headcount rates declined from 52.3% to 26.7% (a fall of –25.6%) in rural areas, while only from 35.1% to 19.3% (a much smaller fall of –15.8%) in urban ones. A recent study by Hill and Endara (2019a) identified comparably higher returns to education and lowering fertility rates among rural households[7], among other factors, as contributing factors behind the rapid decline in poverty in rural Bangladesh. However, the progress with the poverty reduction was uneven across regions. For example, poverty had fallen comparatively lower in the historically poorer northwest region as well as in the remaining western part of the country. Whereas, poverty declined rapidly in the eastern part of the country, including in the Barisal division which is located in the west.

As the western part is predominantly an agriculturally active area, the fact that since 2000 agriculture has become less poverty-reducing enabler partly explains why poverty had fallen comparatively less in the western relative to the eastern part of the country. For example, decomposition of sectoral economic growth by Hill and Endara (2019b) shows that the implied growth-poverty elasticity in the agricultural sector declined from –1.4 during 2000–05 to –0.8 over 2011–2016. This shift in agriculture's role in poverty reduction is consistent with the rapid employment growth in the rural industrial sector than the agriculture and service sectors.[8]

[6] More precisely, 48.9% and 24.5%, respectively. In Bangladesh, poverty is measured based on the so-called *Cost of Basic Needs* (CBN) principle. The national poverty line (also known as the upper poverty line) defines a person as poor if he cannot afford the cost of a consumption basket that includes basic food and non-food items. Whereas, extreme poverty (or the lower poverty line) is defined as the inability to consume basic food and a small share of non-food items. See Hill et al. (2019) for further details.

[7] The average household size declined from 5.18 in 2000 to 4.06 in 2016, a significant reduction.

[8] For example, between 2000 and 2016, agriculture share of the workforce had fallen from 64.8% in 2000 to 41.1% in 2016. At the same time, both industry and service sector share of workers grew from, respectively, 10.7% and 24.5% in 2000 to 20.8% and 38% in 2016 (Hill and Endara, 2019b). An interesting side-effect of this structural transformation is that the agriculture sector (crop- and non-crop) has become more feminized over the years, while the male employment in rural manufacturing and construction has more than doubled

In addition, a number of potential explanations of persistent disparities in regional income can be advanced. First, economic activity is concentrated around a small number of geographic locations. For example, Dhaka and Chittagong hold 12% of the population and 47% of the country's GDP (Hussain, 2013). Second, the severity and frequency of natural disasters in particular regions over others is a major detrimental factor to growth and poverty reduction. For example, the coastal region of Barisal is known for having a high cyclone risk, while the western region of Rajshahi and Rangpur have much higher exposure to ecological hazards like floods and draughts. Third, gaps in human capital accumulation and returns to schooling continue to play a disequalising role in regional disparity in Bangladesh and elsewhere in the world. Sen et al. (2014) documented that not only returns to human capital are higher in the eastern region of Bangladesh, but over the last two decades the gap increased compared to the western part of the country.

To address the regional disparity, the government of Bangladesh has implemented a range of public policy initiatives.[9] Nevertheless, recent research suggests that for poorer households in rural areas, the gain from living in the east has been persistently higher than those living in the west (Hill and Endara, 2019a). Although the urban centers in the western regions did comparably better, the rural west has fallen behind in educational attainment and larger family size which tend to be strongly correlated with consumption growth. This disparity is consistent with international evidence on regional inequality reported by Gennaioli et al. (2014), who show that income inequality tends to be higher among regions of poor than rich countries.[10]

3.1 The construction of district-level income

As anticipated above, we base our empirical analysis on income. We prefer income to consumption—often used as a measure of economic wellbeing—for several reasons. First, as pointed out in Li and Xu (2008), while consumption is the most direct *measurement* of a

(Sen et al., 2021).

[9] These include, among others, increasing public investment in physical infrastructure (e.g., the construction of the Jamuna bridge in 1998 which significantly improved the connectivity between the eastern and westerns sides of Bangladesh), the expansion of public schools in the lagging regions (which was a contributing factor to higher female education and contraceptive use), and broadening of social protection against flood and other ecological risks. See Sen et al. (2014) for a quantitative assessment of these factors in the context of leading and lagging regions of Bangladesh.

[10] In their data set comprising 1,528 regions in 83 countries, the income gap between the richest and poorest region in the average country is 4.7, approximately the difference between the U.S. and South Africa.

household's living standard, income is its main *determinant.* Further, consumption may be harder to measure accurately than income (Attanasio and Pistaferri, 2016). Finally, income inequality is more pervasive than consumption inequality in Bangladesh. For example, in 2016—the last year of our sample period—consumption inequality measured by the Gini coefficient was 0.32, against an income Gini coefficient of 0.48 (CPD 2020).

As anticipated above, we measure income at the district level by aggregating income at the household level for each district. More precisely, a district's income is given by the mean value of the weighted households' income. Overall, a total of 7,440 (5,040 rural and 2,400 urban) and 46,076 (32,096 rural and 13,980 urban) households were interviewed for the HIES 2000 and HIES 2016/17, respectively. Each household's income is comprised of the sum of wage income (farm and non-farm), income from self employment (farm and non-farm), rental income, domestic and foreign remittance receipts, private transfers, public transfer, and other income.[11] These disaggregated income sources can be found in Sections 6-8 of the HIES questionnaire. Monthly wage income of households working in the agricultural sector is estimated by multiplying the average daily income of the household's earner with number of days worked in a month. In addition, all in-kind benefits converted into cash are added to monthly income. Whereas, non-farm self employment income includes proceeds from selling of livestock, poultry, fish, forestry, and other agricultural assets. For both wage- and self-employment incomes, the reference period used is previous 12 months. In-kind private and public transfers include gifts, alms givings such as *zakat* and *fitrah*, social safety net payments, gratuity, separation payment, retirement benefit, social and insurance income, and interest received from financial institutions. Finally, we divide income by the household size to get per capita measure. Table A1 in the Appendix reports monthly income per capita by Bangladesh's districts.

3.2 Data description

We now look at some descriptive statistics of our income per capita (briefly p.c.) data for 64 districts in 2000 and 2016. Anticipating our findings, the evidence is mixed. As it can be appreciated from Fig. 1, growth between 2000 to 2016 has been quite variable across

[11] A detailed description of the official household income estimates can be found in Ahmed et al. (2019). As is typical of household data, missing labor income, zero income and negative net income have been removed from the data.

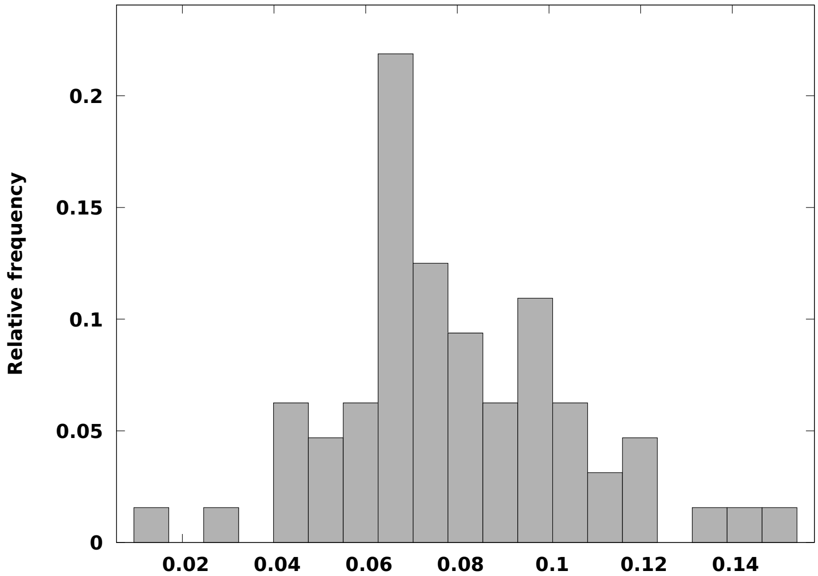

Figure 1: Distribution across Bangladesh districts of annual average growth 2000–2016 of nominal income per capita.

districts. Although in half of the districts annual average growth of nominal income p.c. has been concentrated between 6% and 10%, the tails of the distribution are somewhat spread out, with the minimum only marginally higher than 1% and the maximum around 15% (statistics in panel B of Table 1).

Moving to the income levels in 2000 and 2016, both the maps (Fig. 2) and the estimated densities[12] (Fig. 3) somehow convey an impression of divergence. The map for 2000 appears much more homogenous than that for 2016, when few districts with higher income (darker) stand out clearly against a rather light (lower income) general background, and the 2016 density (dotted line) is far more spread out than the 2000 density (solid line). However, summary statistics of income levels do not consistently support this conclusion. Between 2000 and 2016 the ratio between the highest and lowest values of income across districts dropped significantly (from 7.26 to 4.42), while the standard error of log income and the ratio of the 75% and 25% percentiles declined very marginally (respectively, to 0.29 from 0.31 and to 1.32 from 1.41; see panel A of Table 1 and the boxplots in Fig. 4). This, in contrast with the visual evidence, would suggest convergence. On the other hand, consistently with the visual analysis and much of the literature reviewed in Section 2, the coefficient of variation (standard deviation/mean) and the ratio of the 90 and 10 percentiles

[12]Note that to facilitate the comparison of the dispersion of the two distributions, incomes are centred on the respective means.

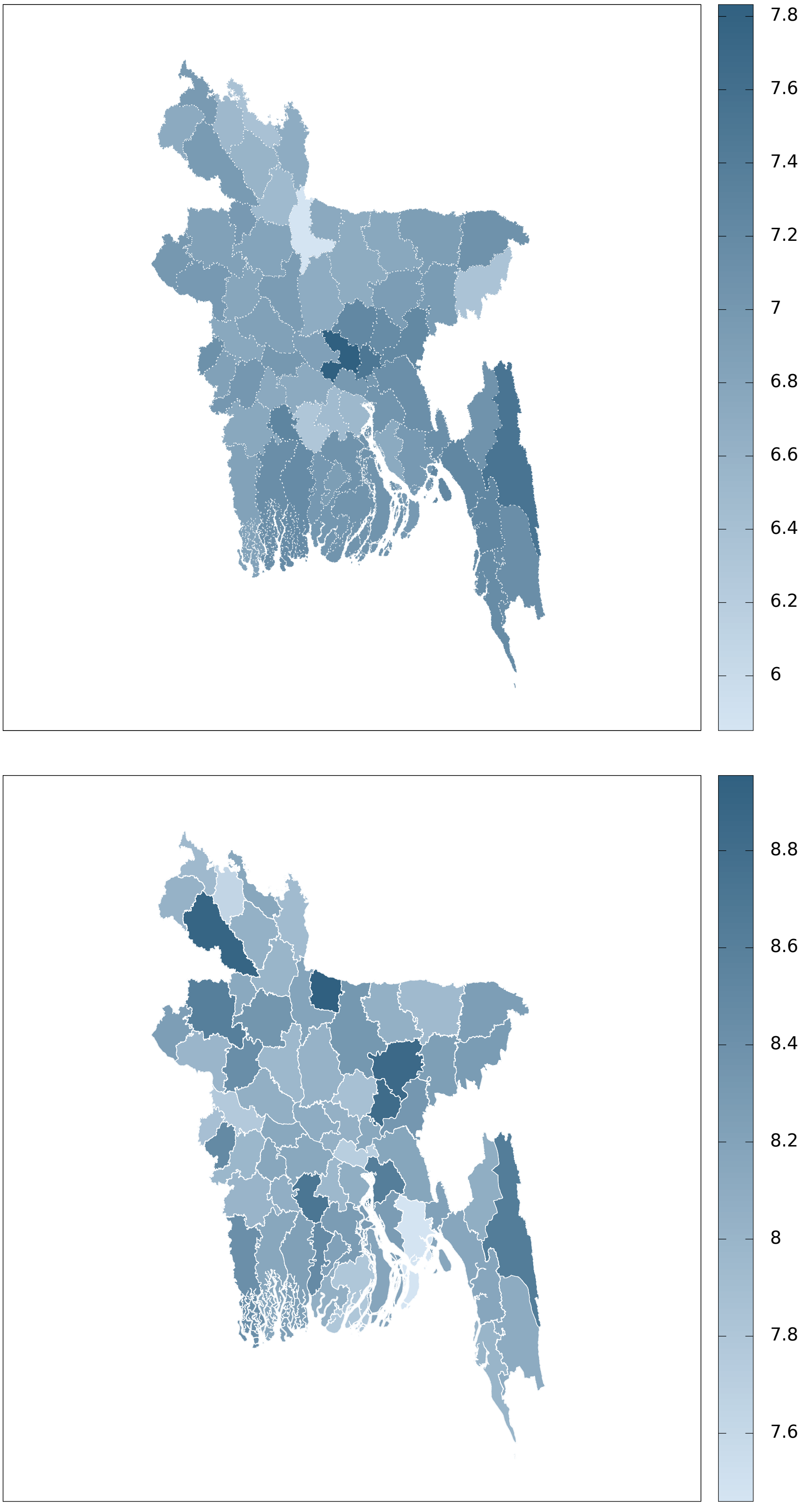

Figure 2: Log per capita income in Bangladesh's districts, 2000 (top) and 2016 (bottom).

are instead marginally higher in 2016 than in 2000 (respectively, 0.33 against 0.32 and 2.12 against 2.07). To summarise, it seems that we are in a borderline condition, which cannot be assessed on the basis of a simple descriptive analysis: we need to move to a model-based evaluation.

Table 1: Per capita income in Bangladesh's districts, 2000–2016

	A. Level				
	max/min	Q_{75}/Q_{25}	*c.v.*	σ_{log}	Q_{90}/Q_{10}
2000	7.26	1.41	0.32	0.31	2.07
2016	4.46	1.32	0.33	0.29	2.12
	B. Average annual growth $\times 100$				
	min	Q_{25}	*median*	Q_{75}	*max*
2000-2016	1.3	6.3	7.6	9.7	15.0

N=64; *c.v.*: standard deviation/mean;
Q_α : $\alpha-$percentile; σ_{log}: standard error of log income.

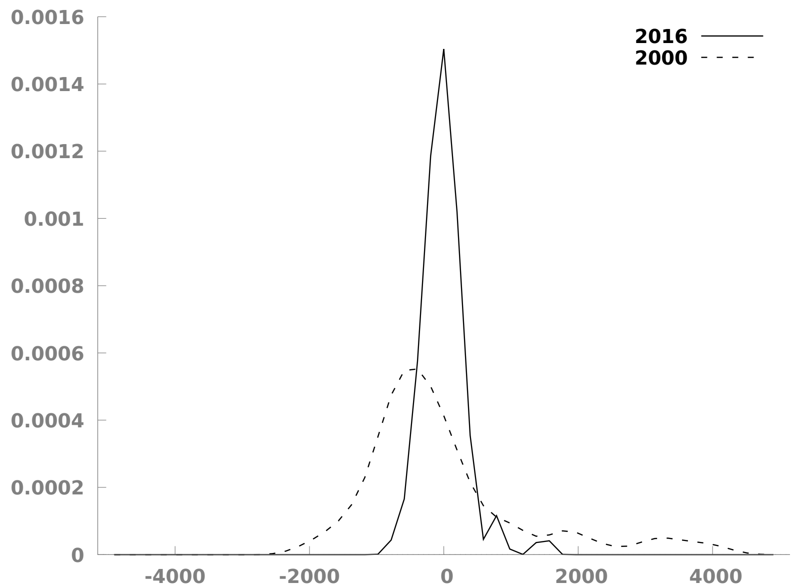

Figure 3: Per capita income (taka, centred on the mean income of each year) in Bangladesh districts, density functions 2000 and 2016.

4 Convergence regressions

4.1 Conditional $\beta-$convergence

The theoretical framework of convergence analysis is well established to say the least, but we sketch it here mainly in order to establish some notation. Define A as total factor pro-

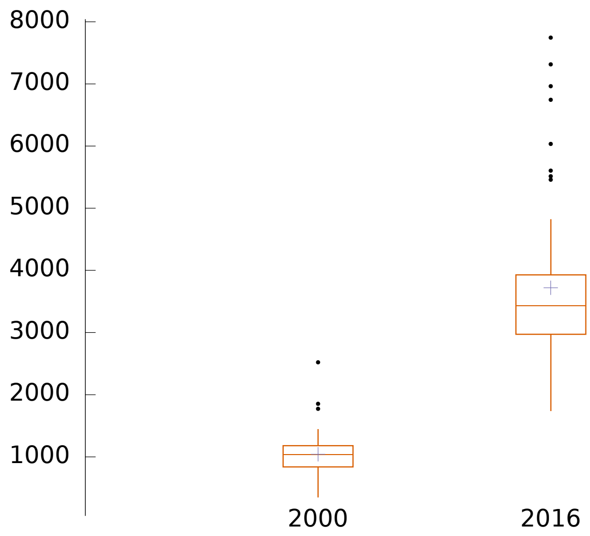

Figure 4: Per capita income at current prices (taka) in Bangladesh districts, 2000 and 2016. Box limits: Q_{25}, Q_{75}; "whiskers": $1.5\times(Q_{75} - Q_{25})$; horizontal line: median; "+": mean; dots: outliers.

ductivity and k as a broad aggregate (per capita) includes physical capital (infrastructures, plants and machinery, natural resources) as well as human capital. Then, ignoring spatial spillovers and following, *e.g.*, Gennaioli et al. (2014), we assume that income per capita y in district i is generated by a Cobb-Douglas production function

$$y_{it} = A_i k_{it}^{\alpha}. \tag{1}$$

Starting with Mankiw, Romer and Weil (1992), country-level studies derive from (1) conditional $\beta-$convergence empirical models for average annual income growth $\triangle y_i$ of the type

$$\triangle y_i = \theta + \beta y_{0i} + \boldsymbol{\gamma} \boldsymbol{Z}_{0i} + \varepsilon_i \tag{2}$$

where y_{0i} is the (log) level of initial (time 0) income and the set of variables $\boldsymbol{Z_{0i}}$ includes measures of the rates of accumulation of physical and human capital and the growth in labour supply. Since data on capital accumulation are typically not available at regional level, regional studies resort to various type of proxies aimed at capturing the initial endowment of broad capital. In our case, we managed to obtain some direct information on infrastructures, human and natural capital, but only a very indirect proxy for manufacturing capital, the share of manufacturing employment. Although obviously correlated with the average endowment of manufacturing capital, this proxy is clearly far from satisfactory. As we shall see, this limitation will require great care in the modelling process.

The full list of our conditioning variables $\boldsymbol{Z}$ is thus the following (more details in Table A2 and descriptive statistics in Table A4, both in the Appendix): human capital (Edu), employment rate ($Empl$), road length normalised by district's surface ($Roads$), cropped area per capita ($Crop$), share of farms operating in property land ($Prop_{land}$), share of manufacturing employment (Man_E), and population density ($Density$).

To this set of conditioning variables we added two shift dummies for the constant. The first, $d_{capital}$, captures the positive externalities of hosting the nation capital, located in the Dhaka district. The second, $d_{disaster}$, is an attempt to take into account the high vulnerability of Bangladesh to extreme weather and weather-related events such as floods, tornados, cyclones and landslides. Consulting a variety of sources we identified 27 districts which have been hit in a particularly severe way by extreme events over the 2000–2016 period (all details in Table A3 in the Appendix).

Estimation of model (2) yields the results reported in column (1) of Table 2, with diagnostics in the same column of Table 3. The model appears well specified, with no heteroskedasticity or spatial autocorrelation problems.[13] The latter finding is especially remarkable, and will be discussed in more depth below.

Overall, the estimates only partially confirm our theoretical framework. Of course, given the large use of proxies this is not really surprising. The (log) income in 2000 is strongly significant, with the usual negative coefficient, and Man_E, the share of manufacturing employment, is positive and significant. Of all the other variables, only $Crop$, the harvested area per capita, is significant, but with a spurious negative coefficient. Clearly, this is a consequence of the absence in the model of a satisfactory measure of manufacturing capital per capita, which can be expected to be higher in districts where agriculture is less important. This spurious effect is particularly likely in view of the strong asymmetry of the distribution of $Crop$, which takes very low values in a small number of districts.

[13] The spatial diagnostics reported have been computed with simple gravity spatial weights, but the use of quadratic gravity weights deliver similar results.

Table 2: Conditional $\beta-$convergence regressions, 2000–2016: estimates

	(1) Base model	(2) Split Crop	(3) Preferred model
constant	0.6394***	0.6545***	0.6156***
	(0.0786)	(0.0809)	(0.0602)
$d_{capital}$	−0.0181	−0.0392	0.0254
	(0.0217)	(0.0252)	(0.0166)
y_0	−0.0635***	−0.0658***	−0.0621***
	(0.0065)	(0.0066)	(0.0068)
Man_E	0.0077*	0.0085*	0.0112**
	(0.0049)	(0.0049)	(0.0048)
Roads	−0.0021	−0.0027	
	(0.0031)	(0.0031)	
Edu	0.0016	0.0015	0.0024**
	(0.0011)	(0.0011)	(0.0010)
Empl	0.0737**	0.0585	0.0427*
	(0.0268)	(0.0284)	(0.0254)
Density	−0.0010	−0.0021	
	(0.0031)	(0.0032)	
$Prop_{land}$	0.0242	0.0288	0.0480*
	(0.0259)	(0.0259)	(0.0253)
Crop	−0.0193***	−	
	(0.0064)	−	
$d_{disaster}$	−0.0066*	−0.0060	−0.0050
	(0.0040)	(0.0041)	(0.0041)
d_{low}	−	−0.0238	
	−	(0.0285)	
$Crop_{high}$	−	−0.0182	
	−	(0.0229)	
$Crop_{low}$	−	−0.0297***	
	−	(0.0090)	
speed of convergence	0.0041 (0.0004)	0.0043 (0.0004)	0.0040 (0.0005)
half-life^a *(s.e.)*	169 (30)	163 (24)	173 (30)
bootstrap c.i.^{b}	151, 191	144, 187	150, 204

Standard errors in parentheses; *,**,***: significant at 10%, 5%, 1%;
−: variable not included in initial specification;
(^{a}) years; (^{b}) confidence level 90%, details in the Appendix.

To assess if this is really the case, we estimated the regression reported in column (2), in which *Crop* is split in two variables, $Crop_{high}$ and $Crop_{low}$, defined as equal to *Crop* in districts where this variable is respectively above and below the median (hereafter respectively "high-rural" and "low-rural"), and zero otherwise. We also included a shift dummy d_{low} equal to 1 in "low-rural" districts. As expected, the coefficient of $Crop_{high}$ is essentially zero (p-value of the t-test approximately 50%), while that of $Crop_{low}$ is still negative and strongly significant. This confirms that this variable is not capturing the effects of the presence of natural capital (non-negative by definition), but proxying the absence of manufacturing capital, and should thus be excluded from the model even if significant.

Proceeding on this basis, sequential model selection leads to the favourite regression reported in column (3). Residuals appear again well-behaved, with no sign of heteroskedasticity nor spatial autocorrelation. Man_E (share of manufacturing employment) and $Prop_{land}$ (share of farms working in property land), expected to proxy physical production capital, have a significant positive effect on the steady state. Edu (the first principal component of education variables) also has a positive impact, while $Empl$, proxying the employment/population ratio, is close to be significant at 10%.

Table 3: Conditional $\beta-$convergence regressions, 2000–2016: Diagnostics

	(1) Base model	(2) Split Crop	(3) Preferred model
$\bar{R}^2$	0.68	0.68	0.64
$Log - Lik$	184.38	186.04	179.30
AIC	-346.76	-346.08	-342.59
BP [p-value]	9.87 [0.45]	11.82 [0.46]	2.86 [0.90]
$Moran$ [p-value]	-0.010 [0.30]	-0.010 [0.30]	-0.001 [0.19]
LM_{error} [p-value]	0.09 [0.77]	0.08 [0.77]	1.E-3 [0.97]
LM_{lag} [p-value]	0.01 [0.91]	0.01 [0.91]	0.01 [0.93]

BP: Breusch-Pagan LM test for heteroskedasticity;
LM_{error}: H_1 spatial error model; LM_{lag}: H_1 spatial lag model.

Initial income is strongly significant, so that the results are in principle compatible with $\beta-$convergence. However, the coefficient, essentially constant across specifications, is very small (about -0.06), and thus the rate of convergence[14] also very small: only 0.04%, one fifth of the " "iron-law" rate of 2% per year" (Barro, 2016, p. 3) reported in many convergence studies. Consequently, the estimates of the half-life to convergence (log(2)/speed of convergence) are all well over 160 years, in fact 173 years in the preferred model in column 3, with standard errors around 25–30 years.[15] We also computed 90% bootstrap confidence intervals, reported in the bottom row of Table 2 (details in the Appendix). These intervals,

[14]Since our dependent variable is the average annual rate of growth, this is equal to $\lambda = -log\left(\beta + 1\right)/T$, where β is the coefficient of initial income and $T = 16$.

[15]Estimates of standard errors computed by the delta method, as the half-life is a non-linear function of the speed of convergence.

all approximately about (150, 200) years, confirm that the half-life is so high that, in spite of the significance of lagged income in regressions based upon (2), in practice income differentials among districts should be considered as persistent. That said, before concluding along these lines there are some aspects that need to be investigated in further depth.

First of all, spatial spillovers. Although these are excluded in (2), the residuals of our regressions are always free from spatial autocorrelation. Thus, spatial variation in income growth is adequately explained by that in the right-hand side variables of the model, income level and the various conditioning variables collected in $\boldsymbol{Z_0}$. This conclusion was further confirmed by the estimation of models including spatial spillovers in income growth, income level and conditioning variables:[16] none of the spatial lags was found to be significant (results not reported here, available on request).

Second, even if geographical proximity by itself does not appear to matter, we need to examine carefully the possibility that other forms of proximity may be relevant, a condition known as club convergence (see Durlauf and Johnson, 1995, and the references therein). In the easiest case, proximity is assumed to be driven by some known common feature. This makes the club structure known *a priori*, and club-convergence versions of (2) trivial to specify and estimate. We will examine this case in section 4.2. The case of latent common features is more difficult to handle, as it requires allocating the districts to different clubs on the basis of some endogeneous algorithm, and will be tackled in section 4.3.

4.2 Exogenous club convergence

4.2.1 A tale of two clubs

As a first step we considered a simple 2-club structure, created on the basis of the values in the year 2000 of two control variables. The first is income; here the idea is that the convergence process may differ between "rich" and "poor" districts (income respectively above and below the median). The second control variable we considered is cropped area per capita.[17] In this case the idea is that the process may differ in districts with a stronger rural specialisation ("high-rural", cropped area p.c. above the median) and the others ("low-rural", cropped area p.c. below the median).

[16] This specification is known in spatial econometrics as "Spatial Durbin Model".

[17] Although rural areas are often characterised by lower income levels, in Bangladesh in 2000 these two variables were essentially uncorrelated ($r = -0.03$).

For a given control variable x =*Income, Cropped area p.c.,* the empirical model (2) is then be replaced by

$$\triangle y_i = \begin{cases} \theta_1 + \beta_1 y_{0i} + \boldsymbol{\gamma}_1 \boldsymbol{Z}_{0i} + \varepsilon_i & x_i < median(x) \\ \theta_2 + \beta_2 y_{0i} + \boldsymbol{\gamma}_2 \boldsymbol{Z}_{0i} + \varepsilon_i & x_i \geq median(x) \end{cases} \tag{3}$$

which allows income to follow different paths, and the steady state to depend upon different variables, in the two clubs.

As it can be appreciated from Table 4, allowing for a polarisation of this type among districts does not change the picture obtained so far. In either case, although highly significant, the coefficients of initial income are always so small that convergence is essentially absent. The estimates of the half-life are between 165 and 220 years, with the lower limit of the confidence intervals never below 123 years. Interestingly, the variable *Edu* is significant in rich and low-rural districts, but not in poor or high-rural ones: investments in education seem to bear fruits only in areas where development has already reached a relatively high level.

These findings raise an obvious question: perhaps a 2-club structure is too simple, and we need to allow for more clubs? Although increasing excessively the number of clubs is somehow against the very idea of income convergence, a 3-club structure may still make sense, and will be examined in the next section.

4.2.2 Is the middle class different?

Taking the case of income in 2000 as a control variable, moving from two to three clubs we essentially restrict the sizes of the "rich" and "poor" clubs from one half to one third of the total, making room for a "middle class" club hosting the districts located in the central 33% of the distribution. In this way we allow these "middle class" districts to behave differently from "poor" and "rich" ones, where now these labels are redefined to describe the districts located at the opposite tails of the distribution[18]. Analogously, when using cropped area per capita as a control variable we introduce a "mid-rural" club and redefine the labels "low-rural" and "high-rural", associating them to the clubs respectively

[18] The labels are thus arguably closer to their common meaning, except for the fact that the clubs are based on income and not wealth.

including the bottom and top 33% of the distribution of the districts.

Our middle class classification also reflect a growing public discourse on national media regarding the rise of the middle class group in Bangladesh. Interestingly, global consulting firms such as Goldman Sachs and Boston Consulting Group predicted this outcome several years ago and have earmarked Bangladesh's rapidly growing consumer and durable markets as one of the world's next important growth markets (Goldman Sachs (2007, ch. 13), Munir et al. 2015). Based on a person's daily income between \$2 and \$3 (using 2005 PPP), the share of middle class families in Bangladesh increased from 9% in 1992 to 20% in 2010 (Bayes, 2018). Although this figure is below South-Asian (17%) and Sub-Saharan (26%) averages, given that Bangladesh's GDP has tripled between 2010 and 2020, one can safely predict that the proportion of middle class families in today's PPP prices would be much higher.

Formally, denoting the $\alpha - th$ percentile of a control variable x by $Q_{x,\alpha}$, for a control variable x the empirical model becames

$$\triangle y_i = \begin{cases} \theta_1 + \beta_1 y_{0i} + \boldsymbol{\gamma}_1 \boldsymbol{Z}_{0i} + \varepsilon_i & x_i < Q_{x,33} \\ \theta_2 + \beta_2 y_{0i} + \boldsymbol{\gamma}_2 \boldsymbol{Z}_{0i} + \varepsilon_i & Q_{x,33} \leq x_i < Q_{x,66} \\ \theta_3 + \beta_3 y_{0i} + \boldsymbol{\gamma}_3 \boldsymbol{Z}_{0i} + \varepsilon_i & x_i \geq Q_{x,66} \end{cases} \tag{4}$$

The results, reported in Table 5, are actually quite surprising. Starting with income clubs, we find that things do not change much for districts at the opposite ends of the distribution, with half-lives around 150 years, thus essentially no convergence. The "middle class" club shows instead a very different profile: the coefficient of y_0 is about three times as large from those of the "rich" and "poor" clubs, and significantly different from them (test in Table 6). As a result, the speed of convergence is 1.6%, not distant from the "2% iron law", and a half-life of 43 years, a time span definitely compatible with the notion of convergence. Thus, while "poorer" and "richer" districts remained such, "Lower-middle class" districts appear to have been able to improve their condition, getting closer to "Upper-middle class" ones.[19]

[19]Whereas, no convergence in the poor club means that the poorest districts do not even get closer to the "least poor", let alone the rich ones.

Table 4: Conditional 2-club $\beta-$convergence regressions, 2000–2016

Control variable	Income per capita 2000		Cropped area per capita	
	poor[a]	rich[b]	Low-rural[a]	High-rural[b]
$constant$	0.7002***	0.4363***	0.6602***	0.4659***
	(0.137)	(0.0940)	(0.0736)	(0.0963)
y_0	−0.0650***	−0.0489***	−0.0630***	−0.0529***
	(0.0138)	(0.0126)	(0.0077)	(0.0132)
Man_E		0.0143		0.0139**
		(0.0089)		(0.0056)
Edu		0.0020*	0.0028*	
		(0.0010)	(0.0016)	
$Empl$	0.0760*		0.0716*	
	(0.0445)		(0.0388)	
$Prop_{land}$	0.1288***		0.0755**	
	(0.0336)		(0.0340)	
$d_{capital}$	0.0349***		0.0279***	
	(0.0076)		(0.0074)	
speed of convergence	0.0042 (0.0009)	0.0031 (0.0008)	0.0041 (0.0005)	0.0034 (0.0009)
half-life	165 (62)	221 (99)	170 (37)	204 (88)
bootstrap c.i.	123, 248	157, 374	142, 213	145, 332
N	32	32	32	32
$\bar{R}^2$	0.67		0.63	
$Log - Lik$	177.56		178.61	
AIC	-337.11		-339.23	
BP [p-value]	7.51 [0.48]		6.84 0.55]	
$Moran$	-0.003 [0.23]		-0.003 [0.22]	
LM_{error}	0.01 [0.92]		0.01 [0.94]	
LM_{lag}	0.50 [0.48]		0.30 [0.58]	

(^{a}) $x_i < Q_{x,50}$, (^{b}) $x_i \geq Q_{x,50}$, where x = control variable; (^{c}) see the Appendix.
NB. The dummy $d_{disaster}$ and variables *Roads* and *Density* have been included in the initial specifications, but they were never significant.

As far as we are aware, this finding is new for Bangladesh and complements the few anecdotal evidence[20] regarding the rise of the middle class families since 2000. This finding is also consistent with the now-famous elephant chart of Lakner and Milanovic (2016) which suggests the rise of middle classes in the developing world but a vanishing middle class in the West. The current conditions in Bangladesh, therefore, are not confined entirely to Arthur Lewis's model of a *dual economy*, rather a burgeoning middle class that place greater emphasis, among others, on human capital accumulation (recall that in the "middle class" districts *Edu* is significant). The role and importance of this middle class, convergent club of districts for Bangladesh's economy at large is clearly an important question, which we leave for future research.

Clustering districts on the basis of the stronger or weaker rural nature we obtain somehow qualitatively similar results,[21] but no sign of convergence. Although in "mid-rural" districts the y_0 coefficient is significantly larger than in the others (test in Table 6), even for that club the speed of convergence is low (0.0046) and a very high half-life (150 years, with a bootstrap confidence interval of 133–170 years).

To summarise, our empirical analysis has so far found at most partial evidence of income convergence across Bangladesh's districts, namely for those which can be described as "middle class" in terms of income per capita in 2000. We cannot however exclude income convergence within clubs of possibly different sizes formed according to some other, unknown criterion. To assess this possibility we need to take a final step, namely considering clubs formed endogenously maximising an objective function, rather than on the basis of a pre-determined control variable as above.

[20] These are reported in newspaper articles citing the findings of a research paper by Binayak Sen not available in the public domain.

[21] For instance, *Edu* is significant in low- and mid-rural districts.

Table 5: Conditional 3-club $\beta-$convergence regressions, 2000–2016

Control variable	Income 2000			Cropped area per capita		
	poor[a]	middle class[b]	rich[c]	low-rural[a]	mid-rural[b]	High-rural[c]
$constant$	0.6213***	1.644***	0.5509***	0.6782***	0.5913***	0.4265***
	(0.08236)	(0.4042)	(0.09194)	(0.08441)	(0.04035)	(0.1304)
y_0	−0.07414***	−0.2265***	−0.06422***	−0.04389***	−0.07145***	−0.05046***
	(0.01222)	(0.05859)	(0.01264)	(0.01025)	(0.005422)	(0.01841)
Man_E	0.02210***		0.01552*		0.01081*	
	(0.006051)		(0.008503)		(0.006380)	
Edu		0.004543**	0.001976*	0.005591***	0.002821**	
		(0.001708)	(0.001165)	(0.001745)	(0.001331)	
$Empl$				0.1506***		
				(0.04551)		
$Prop_{land}$				0.1227***		
				(0.03263)		
$d_{capital}$		0.03618***				
		(0.006816)				
$d_{disaster}$					−0.008145**	
					(0.004009)	
speed of convergence	0.0048 (0.0008)	0.0161 (0.0047)	0.0042 (0.0008)	0.0028 (0.0007)	0.0046 (0.0004)	0.0032 (0.0012)
Half-life	144 (42)	43 (22)	167 (58)	247 (100)	150 (20)	214 (136)
bootstrap c.i.	114, 191	29, 74	128, 239	181, 383	133, 170	135, 505
N	21	21	22	21	21	22
$\bar{R}^2$		0.7057			0.7257	
$Log-Lik$		181.6			183.8	
AIC		-341.13			-343.62	
BP [p-value]		5.22 [0.88]			9.36 [0.59]	
$Moran$		-0.018 [0.43]			-0.020 [0.55]	
LM_{error}		0.296 [0.59]			0.371 [0.54]	
LM_{lag}		0.204 [0.62]			0.370 [0.58]	

(^{a}) $x_i < Q_{x,33}$, (^{b}) $Q_{x,33} \leq x_i < Q_{x,66}$, (^{c}) $x_i \geq Q_{x,66}$, where x = control variable.
NB. Variables *Roads* and *Density* included in the initial specifications, but never significant.

Table 6: Test of the 3-clubs hypothesis

Restriction	Control variable: *Income*	Control variable: *Cropped area*
$\beta_1 = \beta_2, \beta_3 = \beta_2$	$F_{2,52} = 3.38$ [0.031]	$F_{2,52} = 3.20$ [0.049]

F-test, p-value in brackets.

4.3 Endogenous club convergence

Allocating units to different clubs on the basis of an endogenous rule is an extremely complex, high-dimensional spatial combinatorial problem. In our case, given a structure with three clubs of different, unconstrained sizes, the number of possible combinations of Bangladesh's 64 districts is of the order of billions. The simplest solution, adopted in the seminal paper by Durlauf and Johnson (1995), is the classical regression tree algorithm, which operates sequential optimal binary splits. Although efficient, this approach is clearly highly restrictive: only an extremely small subset of all possible partitions is examined. An entirely different way to tackle the problem, which can be described as machine learning,[22] is the following. First, choose the objective function to be maximised by the club structure. In practice, this will be given by some measure of goodness of fit, typically penalised so to favour clubs formed by contiguous units. To initialise the search, define a random allocation of the units to a predetermined number of clubs. Then, create a new allocation scheme moving the first unit to a different club at random. If this modification improves the objective function discard the old allocation and accept the new one. Continue, cycling over units, until an allocation scheme which is never discarded is found, which ends the search.[23]

Postiglione, Andreano and Benedetti (2013) adapted to the club convergence problem two algorithms of this type, Iterated Conditional Modes (Besag, 1986; briefly, ICM) and

[22] The origins are in the pattern recognition literature, where the task is separating the pixels of a digital image so to identify different objects appearing in it. Considering the various objects as "clubs of pixels" the analogy with our problem is obvious.

[23] For the given number of clubs (for instance, three). To extend the procedure to other structures, simply repeat for all desired numbers of clubs (for instance, three and four) and choose the allocation yielding the global maximum of the objective function

Simulated Annealing (*e.g.*, Goffe, Ferrier and Rogers, 1994; briefly SA). ICM is a deterministic implementation of the process outlined above, with a new allocation accepted if and only if the objective function improves. This approach grants speed, but the risk of choosing local maxima appear *a priori* not negligible. To avoid this problem, SA applies a stochastic acceptance rule. A new allocation is accepted with probability 1 if it improves the objective function, and with a probability falling rapidly with the difference between the old and new value when it worsens it.[24] Essentially, marginal reductions in the objective function considered are not significant, and the new (strictly speaking, inferior) allocation is sometimes accepted for the sake of keeping the algorithm moving on, in search of the global maximum, in flat regions. In principle both algorithms have been shown to converge to the optimal allocation of the units. However, some exploratory tests showed that with our data the estimated maximum is heavily dependent on the starting point, even for SA. To circumvent this problem we decided to run the two algorithms with different starting points an extremely large number of times (more precisely, 50,000 times for ICM and 5,000 for SA, which includes an internal stochastic search), and take the club structure yielding the best fit over all replications. Note that at this stage maximum fit is the only justification of the identified club structure. An economic, social or geographic rationale, provided it exists at all, would need to be found *ex post*.

In our case the two methods converge to almost exactly the same club structure, reported in detail in the Appendix. ICM allocates 20 districts to one club, henceforth "Club 1", 22 to a second club, "Club 2", and the remaining 22 to a "Club 3". SA replicates this partition, with the only difference of one district moved from Club 2 to Club 3. Quite remarkably, the districts are thus equally distributed across the three clubs, exactly as it happens when these are formed on the basis of the 33rd and 66th percentiles of a control variable. Using these club structures we obtained the results reported in Table 7.[25] As expected, the models with either ICM or SA club structure fit the data much better than the model using income-based clubs: the R^2 is about 0.97 as opposed to about 0.70, AIC about -480 as opposed to about -340. The key result is however, once again, no support

[24]To ensure convergence, the probability declines with the number of iterations, a feature termed "cooling". SA is also popular as an auxiliary tool for maximum likelihood estimation, see for instance Cottrell and Lucchetti (2021), p. 354-355.

[25]The details of the estimates of the coefficients of the conditioning variables—not reported in the table for brevity—are available on request.

for the convergence hypothesis. In Clubs 1 and 2 the half-life is always of the order of centuries, with a minimum of 95 years. For Club 3 results are slightly different if we consider club membership as identified by ICM and SA. In the former case the estimate of the coefficient on initial income is even positive and significant,[26] thus supporting *divergence*. Using SA clubs, the estimate is negative, but not significant and so small that the half-life is over 3,000 years. In view of these inconclusive results, these clubs have no special interest in convergence analysis, and thus we shall not investigate them in detail.

5 Conclusions

Our analysis of income convergence among 64 districts of Bangladesh over the period 2000–2016 suggests that regional income differential appears persistent at district level, except for those with income levels in 2000 between the 33% and the 66% percentiles. Income differentials within this group of "middle class" districts have been shrinking at an annual convergence rate of 1.6%, corresponding to a half-life of 43 years. We interpret this as evidence of rising middle class households in Bangladesh that has been documented in recent public narrative and discourse surrounding the country's emerging middle class and its implications for stability and socioeconomic progress in the years ahead. Clearly, for Bangladesh as a nation the challenge is to devise the policies necessary to extend this convergence process to the poorer districts as well.

Two caveats before we end the paper. First, our approach to regional income convergence was largely macroeconomic in nature (that is, we aggregated households' income at the district level, ignoring household and village heterogeneity that may have an important bearing on the context of income, poverty, and development). A worthwhile effort would be to examine whether districts with more middle class households are exhibiting income convergence or not. Second, as discussed in Hill and Endara (2019a), the quality of income data in HIES 2016/17 is different (less complete and noisier) than previous rounds of the survey. Besides, the sampling design for the HIES 2016/17 differs from earlier HIES in several important ways (Ahmed et al. 2017). We hope these issues are taken into account

[26] More precisely, it is equal to 0.0253, with standard error 0.0068.

Table 7: Conditional 3-club $\beta-$convergence regressions 2000–2016, ICM and SA estimates

	ICM$^{(a)}$		SA$^{(b)}$		
	club 1	*club 2*	*club 1*	*club 2*	*club 3*
y_0	-0.0589 (0.0018)	0.1099 (0.0025)	-0.0825 (0.0017)	-0.0682 (0.0020)	-0.0035 (0.0044)
speed of convergence	0.0038 (0.0001)	0.0073 (0.0002)	0.0054 (0.0001)	0.0044 (0.0001)	0.0002 (0.0003)
Half-life	183 (10)	95 (4)	129 (5)	157 (8)	3152 (6789)
bootstrap c.i.	173, 193	92, 99	124, 133	149, 165	-12703, 17634
N	20	22	20	21	23
$\bar{R}^2$	0.97		0.97		
$Log - Lik$	259.43		258.13		
AIC	-482.86		-480.27		
BP [p-value]	17.27 [0.44]		18.00 [0.33]		
$Moran$	-0.009 [0.44]		0.050 [0.09]		
LM_{error}	0.025 [0.88]		0.802 [0.37]		
LM_{lag}	0.286 [0.59]		0.005 [0.95]		

Model: $\triangle y_i = \sum_{j=1}^{3} \theta_j + \beta_j y_{0i} + \boldsymbol{\gamma}_j \boldsymbol{Z}_0 + \varepsilon_i$; $\boldsymbol{Z}_0$: $Man_E, Edu, Empl, Prop_{land}$. S.E.'s in brackets.

(^{a}) best of 50,000 runs; Club 3: the estimate of the coefficient of initial income is positive.

(^{b}) best of 5,000 runs; SA search parameters (see Postiglione et al., 2013): $\chi = 10 \times 10^{-3}; \theta = 0.9; T_0 = 0.005$.

in future research.

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Appendix

Table A1: Monthly income (taka) per capita in Bangladesh's districts

District	2000	2016	District	2000	2016
Bagerhat	1309.87	3747.94	Lalmonirhat	640.823	2871.36
Bandarban[a]	1252.61	3318.66	Madaripur	836.64	3472.70
Barguna	1101.62	3161.52	Magura	957.47	3279.72
Barisal	1167.01	3898.68	Manikganj	569.87	3929.22
Bhola	1154.91	3534.34	Maulvibazar	1211.06	2626.69
Bogra	908.45	4214.47	Meherpur	1074.41	2233.60
Brahmanbaria	1361.76	4142.77	Munshiganj	809.29	4119.76
Chandpur	1129.16	5513.93	Mymensingh	947.33	5457.67
Chapai Nababganj	1389.27	3495.43	Naogaon	1446.81	3191.11
Chittagong	943.96	4824.38	Narail	1773.18	3420.38
Chuadanga	1240.37	3520.34	Narayanganj	1299.31	6743.81
Comilla	1301.82	2970.91	Narsingdi	880.86	4606.98
Cox's bazar	2520.68	3114.96	Natore	1084.84	3835.13
Dhaka	1044.23	7313.16	Netrakona	858.25	3133.21
Dinajpur	823.99	3423.86	Nilphamari	668.93	2050.01
Faridpur	1237.77	3683.62	Noakhali	1065.04	1736.61
Feni	654.81	2959.69	Pabna	946.705	3172.86
Gaibandha	1380.26	2618.47	Panchagarh	1048.16	2817.02
Gazipur	544.78	6034.81	Patuakhali	1153.55	2421.28
Gopalganj	1027.21	3792.63	Pirojpur	1078.31	4786.32
Habiganj	347.37	3586.02	Rajbari	1087.67	3437.44
Jamalpur	855.45	2972.52	Rajshahi	1064.07	2942.89
Jessore	998.78	3684.27	Rangamati	1853.67	5604.31
Jhalokati	1100.91	2903.51	Rangpur	716.069	3104.56
Jhenaidah	1061.32	3394.75	Satkhira	935.966	4515.38
Joypurhat	1167.16	3211.41	Shariatpur	674.828	3215.43
Khagrachhari	1252.61	3469.28	Sherpur	840.13	7743.50
Khulna	1005.11	6962.51	Sirajganj	1020.49	2868.14
Kishoregonj	804.10	2759.34	Sunamganj	998.355	2799.11
Kurigram	852.93	2346.36	Sylhet	1184.43	3832.89
Kushtia	832.87	3923.06	Tangail	804.349	3048.17
Lakshmipur	583.52	3458.66	Thakurgaon	827.992	3064.87

Source: Authors' calculations using HIES 2010 and 2016/17. See the text for discussion on the construction of income data. The average household size in 2000 and 2016/17 was 5.17 and 4.03, respectively.

[a]: Estimated for the year 2000 by interpolation of the data of the two adjacent districts (Cox's Bazar and Rangamati).

Table A2: Description of the variables and data sources

Variable	Description
Income	Log of monthly income per capita. See Section 3.1 for a discussion on the construction of income. Source: authors' calculations using HIES 2010 and 2016/17.
Edu	Log of the first Principal Component of a set of variables capturing different dimensions of Education: education expenditure; share of population that can read; shares of population with: Grade 5 (Primary School); Grade 10, Grade 10 with degree after national exam, Grade 12 with degree after national exam (Secondary School); graduate education (16 years of education or more). All variables in logs, year 2000. Source: Bangladesh Population and Housing Census, 2001.
Empl	Inverse of average household size (year 2000). This is a proxy of the employment ratio, employment/population, to which it is exactly equal in a population with a single income earner per family. Source: Bangladesh Economic Census, 2001-03.
Roads	Kilometers of either *Non-rural roads* or *All roads* per square kilometer (year 2000). Source: Statistical Yearbook of Bangladesh, 2001.
Crop	Cropped surface per capita (year 2000). Source: Bangladesh Census of Agriculture, 1996.
$Prop_{land}$	Share of farms operating property land (year 2000). The intuition is that these farms are more likely to invest in equipment and land improvements projects. Source: Bangladesh Census of Agriculture, 1996.
Man_E	Share of manufacturing employment (year 2000). Source: Bangladesh Economic Census – 2001-03.
Density	Population density (year 2000). The intuition is that the most productive activities concentrate in districts including large cities. Source: Bangladesh Population and Housing Census, 2001.

Table A3: A compendium of natural disasters in Bangladesh during 2000–2016

Year	Disaster	Affected districts	Fatalities
2000	*Tornado*	Gazipur, Savar.	10
	Landslide	Chittagong.	13
	Flood	Bhola, Bogra, Chapai-Nawabganj, Chandpur, Faridpur, Gaibandha, Jamalpur, Kurigram, Kusthia, Lalmonirhat, Manikganj, Narayanganj, Narsingdi, Noakhali, Pabna, Rajshahi, Rajbari, Sirajganj, Shariatpur, Tangail.	36
2002	*Flood*	Most of the bordering districts in the north and northwest Bangladesh	51
2003	*Tornado*	Brahmanbaria.	20
	Flood	Bogra, Gaibandha, Jamalpur, Manikganj, Munshiganj, Madaripur, Pabna, Rajbari, Sirajganj, Tangail.	104
2004	*Flood*	Bogra, Bhola, Barisal, Faridpur, Gaibandha, Kurigram, Lalmonirhat, Moulvi Bazar, Nilphamari, Rangpur, Rajbari, Sirajganj, Sherpur, Sylhet, Sunamganj.	747
	Tornado	Mymensingh, Netrokona.	111
2005	*Tornado*	Gaibandha, Netrokona, Rangpur.	133
2006	*Tornado*	Bagerhat.	4
2007	*Landslide*	Chittagong.	135
	Flood	Gaibandha, Jamalpur, Kurigram, Sirajganj, Shariatpur.	800
	Cyclone (Sidr)	Barguna, Bagerhat, Patuakhali, Pirojpur.	3,406
2008	*Cyclone (Rashmi)*	Chittagong.	15
	Landslide	Chittagong, Cox's Bazar.	14
	Tornado	Barisal, Magura.	2
2009	*Landslide*	Bandarban.	10
	Cyclone (Bijli)	Bhola, Cox's Bazar, Chittagong, Noakhali, Rangpur, Thakurgaon.	7
	Cyclone (Aila)	Khulna, Satkhira.	190
2010	*Tornado*	Khulna.	1
	Landslide	Cox's Bazar.	96
2011	*Nor'westers and Torando*	Bogra, Gaibandha, Jamalpur, Joypurhat, Mymensingh, Sherpur, Thakurgaon.	12
2012	*Landslide*	Bandarban, Chittagong, Cox's Bazar.	122
2013	*Flood*	Wider part of north Bengal & part of central region along the Brahmaputra river.	9
	Torando	Brahmanbaria.	31
	Landslide	Chittagong.	2
	Cyclone (Mahasen)	Bhola, Barguna, Chittagong, Laxmipur, Noakhali, Pirojpur, Patuakhali, Satkhira.	17

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Year	Disaster	Affected districts	Fatalities
2014	*Tornado*	Northern Bangladesh.	20
	Flood	Gaibandha, Jamalpur, Kurigram, Lalmonirhat, Nilphamari, Rangpur, Sirajganj, Sunamgonj, Sylhet	17
2015	*Cyclone (Komen)*	Bandarban, Chittagong, Cox's Bazar, Teknaf.	45
	Flood	Bandarban, Bhola, Cox's Bazar, Chittagong, Feni, Noakhali.	19
2016	*Cyclone (Roanu)*	Feni, Hatia, Kutubdia, Sandwip, Sitakundu.	27
	Flood	Bogra, Faridpur, Gaibandha, Jamalpur, Kurigram, Kustia, Lalmonirhat, Madaripur, Manikganj, Nilphamari, Rajbari, Rangpur, Shariatpur, Sirajgonj, Sunamgonj, Tangail.	106

Source: Local newspapers, websites of national and international agencies. Itemized sources are available from authors on request. A disaster is considered as 'major' in terms of its geographic coverage as well as number of fatalities.

Table A4: Summary statistics of conditioning variables

	$Mean$	$Median$	Min	Max	cv	Q_5	Q_{95}
Man_E^a	0.21	0.19	0.07	0.58	0.48	0.10	0.43
$Non-Rural\ Roads^b$	0.04	0.03	0.003	0.14	0.70	0.006	0.10
$Total\ Roads^b$	0.16	0.14	0.04	0.45	0.51	0.07	0.36
Edu^c	0	0.18	-6.00	4.34	2.08^d	-4.05	2.94
$Empl^e$	0.21	0.21	0.17	0.25	0.08	0.18	0.24
$Density^f$	955	857	65	5859	0.79	242	1792
$Prop_{land}^g$	0.66	0.66	0.50	0.77	0.08	0.56	0.74
$Crop^h$	0.26	0.27	0.02	0.44	0.35	0.10	0.40

$^{(a)}$ share; $^{(b)}$ km's per square km; $^{(c)}$ log; $^{(d)}$ standard error (cv cannot be computed because the mean is zero); $^{(e)}$ (average household size)$^{-1}$;
$^{(f)}$ population per square km; $^{(g)}$ area in acres.

ICM and SA Clubs

Club 1: Bagerhat, Bandarban, Barisal, Brahmanbaria, Chapai, Nawabganj, Comilla, Cox's Bazar, Faridpur, Gopalganj, Habiganj, Lalmonirhat, Mymensingh, Narail, Narayangani, Patuakhali, Pirojpur, Rajshahi, Rangpur, Sherpur, Thakurgaon.

Club 2: Barguna, Bhola, Bogra, Chuadanga, Gaibandah, Gazipur, Jessore, Jhalokati, Jhenaidah, Joypurhat, [*ICM*: Khagrachhari], Lakshmipur, Manikganj, Moulvibazar, Naogaon, Netrokona, Noakhali, Pabna, Rajbari, Rangamati, Shariatpur, Sirajganj.

Club 3: Chandpur, Chittagong, Dhaka, Dinajpur, Feni, Jamalpur, [*SA*: Khagrachhari], Khulna, Kishoreganj, Kurigram, Kushtia, Madaripur, Magura, Meherpur, Munshiganj, Narsingdi, Natore, Nilphamari, Panchagarh, Satkhira, Sunamganj, Sylhet, Tangail.

Bootstrap confidence intervals for Half-life

Our empirical results consistently suggested the residuals of the estimated convergence regressions to be homoskedastic and not spatially autocorrelated. Thus, the application of the bootstrap is quite straigthforward: in principle even simple resampling of the residuals would be acceptable. However, the Wild bootstrap is an equally convenient and in our context a probably superior alternative (see for instance Klarl, 2014). The bootstrap confidence intervals for the Half-life implied by the coefficient estimates of a given model of interest, say $\triangle y_i = \widehat{\theta} + \widehat{\beta} y_{0i} + \widehat{\boldsymbol{\gamma}} \boldsymbol{Z}_{0i} + \widehat{\varepsilon}_i$, have thus been constructed by the percentile method applying the following algorithm.

1. Resample by the Wild Bootstrap the vector of residuals $\widehat{\boldsymbol{\varepsilon}}$ of the model of interest. We used a Rademacher density, defining for district i the boostrap pseudo-residual as $\varepsilon_i^* = \psi_i \widehat{\varepsilon}_i$, where
$$\psi_i = \begin{cases} 1 & with\, probability = 0.5 \\ -1 & with\, probability = 0.5 \end{cases}$$

2. construct the pseudodata $\triangle y_i^*$ using a fixed design: $\triangle y_i^* = \widehat{\theta} + \widehat{\beta} y_{0i} + \widehat{\boldsymbol{\gamma}} \boldsymbol{Z}_{0i} + \varepsilon_i^*$.

3. Estimate the model of interest for the set of data $(\triangle \boldsymbol{y}_i^*, \boldsymbol{y}_{0i}, \boldsymbol{Z}_{0i})$, obtain the estimate

β^* and implied Half-life HL^*.

4. Repeat steps 1-3 a large number of times, say B. We set B=5000.

5. Sort the B estimates of the Half-life in ascending order, say $HL_1^*, \ldots, HL_B^*$, and obtain the $(1-\alpha)-$level percentile interval as $\left[HL^*_{\lfloor \alpha B \rceil}, HL^*_{\lfloor (1-\alpha) B \rceil}\right]$, where $\lfloor \alpha B \rceil$, $\lfloor (1-\alpha)\, B \rceil$ denote the values αB, $(1-\alpha)\, B$ rounded to the nearest integer.