Convergence in Regional Poverty Rates in Bangladesh

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Bangladesh has made remarkable progress in reduction of poverty headcounts, poverty gap, and squared poverty gap since 2000. While scores of studies rigorously looked into drivers of poverty reduction from the perspective of sources, both the cross country and single country literature on poverty convergence is scant. Even most of these convergence estimates are biased arising out of omitted variable due to ignorance of unobserved individual heterogeneity and endogeneity of at least a subset of regressors. This paper exploits a unique set of data to provide credible evidence of convergence in poverty across the districts of Bangladesh during 2000-2016 using the Arellano-Bond system dynamic panel estimator and panel generalized method of moments estimator. We find that poverty convergence is present during this period both through direct estimation and decomposition with relevant indirect estimates. Our results are robust to the alternative frequency of data (cross-section vis-à-vis panel) and the consequent estimation techniques, sources of data (direct estimates from the Household Income and Expenditure Surveys vis-à-vis small area estimates) and the alternative transformation of the dependent variables. Both growth-accounted poverty convergence effect and strong growth effect dominate the adverse effect of initial poverty on growth effectiveness to ensure strong overall poverty convergence found across the districts.

Keywords: Bangladesh, Poverty, Income, Convergence
JEL Classification: I32, O47, O53

I. INTRODUCTION

The convergence in per capita income following the neoclassical growth model (Solow 1956, Swan 1956), coupled with the fact that higher mean income is usually associated with lower incidence of poverty, implies convergence in poverty where initial rates hardly matter. However, using cross-country cross-

sectional data, Ravallion (2012) found that countries with higher initial poverty incidences did hardly experience faster reduction in poverty even though they did enjoy faster growth in per capita income and concludes that initial high poverty rates nullified the growth in per capita income.[1] However, cross-section analysis, with or without instrumental variables, suffers from omitted variable bias due to individual heterogeneity and endogeneity of at least a subset of regressors as Caselli, Esquivel and Lefort (1996) detailed in the context of convergence in per capita income. Insofar as the analytical form of poverty convergence is similar to that of per capita income, the above observations do apply equally. Be that as it may, Ravallion's (2012) cross-country may not satisfactorily address perhaps a more relevant issue: do countries enjoy faster subsequent poverty reduction within themselves as their initial poverty incidences decline over time? Even if it does, national average data may mask disparities in poverty rates across regions within a country and hence is of little help to the policymakers. That begs second relevant question: do regions within a country experience convergence even if one fails to see convergence across countries? These issues are vital to policymakers as sustained disparities across regions may not only wreak havoc on social cohesion but also are likely to adversely affect subsequent growth. Hence, these imperatives act as early warnings to policymakers for undertaking different initiatives to forestall such untoward outcomes. From a policy making perspective, there are several grounds for one to expect regional convergence within a country. *First*, a national government is more informed about the economic situation as well as proximate causes of poverty and backwardness of regions within the country due to informational advantage. *Second*, a national government can better coordinate activities of different line agencies and channel funds in a targeted manner for poverty reduction exploiting the advantage of synergy (Ferreira, Leite and Ravallion 2010). *Third*, regions within a country are usually more connected and hence, have free movement of labour and goods in comparison to connectivity between countries at the global level where factors of production, especially labour, is, by and large, immobile.

Combating regional poverty and disparities is a vital policy issue in Bangladesh. The successive plan documents demonstrate government's commitment to reducing regional poverty and disparities through promoting growth and development (GoB 2015). The strategy suggests a six-fold plan for the lagging regions: (i) creation of lagging region fund for priority investment in

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[1] Cuaresma, Klasen and Wacker (2017) argued that Ravallion's (2012) failure to detect convergence in headcount poverty rate was due to logarithmic transformation of data.

human and physical capital; (ii) prioritisation of public infrastructures for bridging gaps between more and less integrated regions; (iii) provision of special incentives for private investment in less integrated regions; (iv) provision of agricultural credit and construction of storage facilities to enhance agricultural growth and employment; (v) establishment of technical and vocational training institutions to impart skill and facilitate migration; and (vi) development of salinity tolerant seeds together with adoption of disaster mitigation strategies in the southwest region and development of drought tolerant seeds in the northwest region. Besides, several safety net programmes are put in place through poverty targeting (Yunus 2016) at the regional level.[2] Finally, special economic zones (SEZs) with attractive incentive packages are encouraged to create employment in the backward areas and regions (Yunus 2019).

Several studies focused on regional disparities in Bangladesh. These studies attributed differences in poverty and inequality to geographical indicators (Ravallion and Wodon 1999), human capital, and urban dynamism (Sen 2005), low incidence of critical infrastructural facilities (GoB 2008), natural border created by the rivers causing differences in returns between regions to persist and coined the term "east-west divide"[3] based on the district level poverty map (World Bank 2008). Another strand of literature looked into factors behind the recent decline or reversal of the east-west divide. While World Bank (2013) reported withering of the "divide" and attributed changes in both labour income and the adult population as the two most important contributors to poverty reduction, Sen, Ahmed, Yunus and Ali (2014) attributed it to growth spurt in agriculture, flourishing small and medium enterprises, growth of microfinance institutions, and better human capital in the west districts. The "divide" appeared to have re-emerged in the third quinquennium under consideration (World Bank 2019). While these studies enriched the debate on regional disparities with elegant analyses, none of them sheds light on whether poverty rates across district are converging or diverging. This issue warrants rigorous analysis to complement to findings of these studies so that informed policies can be planned and executed.

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[2]Poverty reduction in Bangladesh is mainly addressed through various *redistribution channels*. It is evident from the divisional poverty rates and the share of recipients of social safety net programmes: there are positive correlations between the upper and lower poverty lines vis-à-vis the share of recipients of social safety net assistance at 0.5 across administrative divisions (BBS 2019).

[3]However, such a delineation paints a distorted picture of regional poverty and hence growth. For a succinct analysis of the limitations of such delineation "east-west divide," see, for instance, Osmani, Ahmed, Latif and Sen (2015).

Literature on poverty convergence based on both cross country and single country data is sparse. Azevedo, Yang, Inan, Nguyen and Montes (2016) used NUTS 2 level[4] cross-section data in Turkey, and Ouyang, Shimeles and Thorbecke (2018) used district level panel data from Ethiopia and Rwanda and documented presence of convergence in poverty rates at the regional level. Further, Ouyang, Shimeles and Thorbecke (2019) found convergence in poverty rates in the Sub-Saharan African countries using the generalized method of moments (GMM) estimator. However, these findings do not explain the convergence or lack of it of the depth or the severity of poverty within or across countries. Besides, as these studies are based on cross-section data, the resulting estimates suffer from unobserved individual heterogeneity and omitted variable bias. As a preferred alternative, one needs panel data that offer flexibility in applying proper econometric techniques to produce estimates that are unbiased, efficient, and consistent.

The present paper implements a panel data approach to deal with some of these issues. It takes Ravallion (2012) as its starting point and examines how the results change when Arellano–Bover/Blundell–Bond system dynamic panel estimator (AB) and panel GMM estimator are applied on district level data of Bangladesh. To that end, it contributes to methodological improvement in estimating poverty convergence. As a result, our estimates, which account for unobserved individual heterogeneity and endogeneity that may be cropped in at least a subset of regressors (Caselli, Esquivel and Lefort 1996), yield results that are more credible to ones obtained from cross-section, fixed effects, and random effects estimates. We find that there are convergences in poverty rates across districts, which are driven by not only convergence in per capita income but also a parallel channel dubbed as "growth-accounted poverty convergence effect"—an effect that is over and above the effect through the convergence in mean income growth.

The rest of the paper is organised as follows. Section II elaborates the empirical framework and estimation techniques. Section III sheds lights on the sources of data and characterisation through descriptive statistics of the dependent variables as well as a set of variables purported to act as initial conditions. Section IV presents the empirical results based on both AB-dynamic panel estimator and GMM estimator with or without initial conditions together with the decomposition

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[4]NUTS (Nomenclature des unités territoriales statistiques in French or Nomenclature of Territorial Units for Statistics in English) is usually a 3-tier territorial concept used for referencing sub-divisions of countries for statistical purposes in the EU countries. This category refers to regions belonging to the middle tier in the hierarchy.

of overall poverty convergence into four constituting parts. Section V succinctly describes the robustness of the results, presented in the previous section, from the viewpoint of alternative sources of poverty data, transformation of key variables and estimation methods. Section VI concludes the paper.

II. EMPIRICAL FRAMEWORK AND METHODS

2.1 Empirical Framework

Ravallion's (2012) conceptual motivation borrowed from convergence in per capita income is appealing and has been applied in analyses of poverty convergence in different studies (Azevedo, *et al.* 2016, Cuaresma, Klasen and Wacker 2017, Ouyang, Shimeles and Thorbecke 2018, 2019). Underlying his conceptual framework are a set of equations standard within the neoclassical growth model augmented to allow the corresponding initial level to affect the growth rate. Accordingly, Eq. (1) is used for identification of convergence in per capita income.

$$\Delta ln y_{it} = \beta_0 + \beta_1 ln y_{it-r} + \gamma_i + \epsilon_{it} \tag{1}$$

where y_{it} and y_{it-r} are, respectively, level of district i's mean per capita income [5] at time t and $t-r$ and $\Delta ln y_{it} \equiv (ln y_{it} - ln y_{it-r})/r$ is the annualized growth between time t and $(t-r)$. Coefficient β_1 is the mean convergence rate, which implies that if $ln y_{it-r}$ is lower by one per cent, growth in mean per capita income would increase by β_1 percentage points. Further, γ_i is the district fixed effect. Next, assuming a log-linear relationship[6] between poverty and mean per capita income at any time, one obtains Eq. (2) that will be used to test for poverty convergence.

$$\Delta ln P_{it} = \theta_0 + \theta_1 ln P_{it-r} + \gamma_i + \varsigma_{it} \tag{2}$$

where P_{it} and P_{it-r} are, respectively, level of region i's poverty rate at time t and $t-r$ and $\Delta ln P_{it} \equiv (ln P_{it} - ln P_{it-r})/r$ is the annualized rate of poverty reduction between time t and $(t-r)$. Coefficient θ_1 is the poverty convergence rate, which implies that if $ln P_{it-r}$ is higher by one per cent, poverty reduction rate would increase by θ_1 percentage points. Ravallion (2012) augmented Eq. (1) with initial poverty rates and other proximate initial conditions to assess how these variables affect growth:

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[5] Even though income is used throughout the paper, the variables are actually per capita consumption estimates based on small area estimation.

[6] Assumption of log-linearity remains a standard in the literature. However, it is considered a very strong assumption by critics, as the transformation may result in lack of convergence. See, for instance, Cuaresma, Klasen and Wacker (2017) for detail.

$$\Delta lny_{it} = \alpha + \beta_2 lny_{it-r} + \theta_2 lnP_{it-r} + \gamma_i + \xi_{it} \tag{3}$$

Eq. (3) helps identify two contributing effects of poverty convergence: a negative estimate of β_2 would suggest a convergence effect of per capita income conditional upon the initial poverty level, whereas a negative estimate of θ_2 would suggest a direct but adverse poverty effect conditional upon the initial mean per capita income that retards growth of income.

To decide whether the standard elasticity obtained from regressing rate in poverty reduction on growth in mean income is η or $\delta_1 + \eta$, one needs to run twin hypothesis tests $H_0 : \delta_1 = 0$ and $H_0 : \eta_0 + \eta_1 = 0$ from the regression: $\Delta lnP_{it} = \delta_0 + \delta_1 lnP_{it-r} + \eta_0 \Delta lny_{it} + \eta_1(P_{it-r} \times \Delta lny_{it}) + \gamma_i + \varepsilon_{it}$. Across regressions of poverty headcount rate, poverty gap, and squared poverty gap, while $H_0 : \delta_1 = 0$ is resoundingly rejected, the homogeneity test $H_0 : \eta_0 + \eta_1 = 0$ could not be rejected at 1 per cent level. The above outcomes point to the fact that poverty convergence is not explained by growth in per capita income alone. Instead, there may be other factors that affect poverty, such as inequality (Bourguignon 2003), and redistribution in the form of social safety nets (Lopez-Calva, Ortiz-Juarez and Rodriguez-Castelan 2019), with little bearing on growth in per capita income. This channel is termed as "growth-accounted poverty convergence effect." The upshot of the above analysis is that factors beyond growth in per capita income also significantly affect convergence in poverty rates. Therefore, Eq. (4) is used for the identification of "growth-accounted poverty convergence effect" and growth effectiveness of poverty effect:

$$\Delta lnP_{it} = \delta_0 + \delta_1 lnP_{it-r} + \eta(1 - P_{it-r})\Delta lny_{it} + \gamma_i + \varepsilon_{it} \tag{4}$$

Parameters δ_1 and η in this specification measure "growth-accounted poverty convergence effect" and "growth effectiveness effect" in reducing poverty, where growth is adjusted by the initial non-poverty levels. The above model implies that the relevant growth rate is not fully "poverty-adjusted rate" as found in Ravallion (2012). Instead, it suggests an additional channel which may be termed as "growth-accounted poverty convergence effect." Coefficients from Eq. (3) and Eq. (4) would then help decompose the poverty convergence elasticity as:

$$\frac{\partial \Delta lnP_{it}}{\partial lnP_{it-r}} = \delta_1 + \eta\beta_2(1 - P_{it-r})\left(\frac{\partial lnP_{it-r}}{\partial lny_{it-r}}\right)^{-1} + \eta\theta_2(1 - P_{it-r}) - \eta\Delta lny_{it}P_{it-r} \tag{5}$$

The first term in Eq. (5) is the *growth-accounted poverty convergence effect,* as mentioned above. It reinforces the effect of the second term, the *convergence effect of income,* which is the interaction between the corresponding initial levels of non-poverty and elasticity of the initial poverty rate with respect to the initial per capita income. The third term is the *direct adverse effect of poverty* which takes into account the levels of the initial non-poverty. It reinforces the fourth term, the

poverty elasticity effect, which is the interaction between the growth of per capita income and the respective poverty rates in the initial period. As we report later in details, AB-dynamic panel and panel GMM regressions do identify both initial mean per capita income and growth-accounted poverty effects as significant factors in overall poverty convergence across districts.

It may be noted that Eq. (5) is an accounting identity whose key parameters come from Eq. (3) and Eq. (4) and is used to identify the relative magnitude of the four effects discussed above. It is expected that the sum of the four effects largely matches the empirical poverty convergence rate from Eq. (2) if the model includes all major factors contributing to poverty convergence. Further, the signs and sizes of the four terms in Eq. (5) are empirically determined and do not have to always fully account for the actual change in poverty when different data points and parameter estimates are examined (Ouyang, Shimeles and Thorbecke 2019). In contrast, if the computed and empirical rates are very different, it may suggest that poverty convergence or lack of it is driven by factors (such as policy orientations) not included in the model specifications or inappropriate estimation methods applied. However, testing of these hypotheses is beyond the scope of this paper.

2.2 Econometric Methods

The empirical literature on convergence in poverty is replete with cross-section analyses (Ravallion 2012, Cuaresma, Klasen and Wacker 2017, Ouyang, Shimeles and Thorbecke 2018, 2019, Lopez-Calva, Ortiz-Juarez and Rodriguez-Castelan 2019) often dictated by limited availability of data or discarding suitability of panel specification as "the changes over time in growth almost certainly have a low signal-to-noise ratio" (Ravallion 2012). Insofar as an inevitable feature of poverty convergence analysis is that the dependent variable is a type of "growth rate," these cross-section estimates are likely to be biased due to their ignorance of individual heterogeneity that gives rise to omitted variable bias, dynamic panel bias known as Nickell (1981) bias as well as endogeneity of at least a subset of regressors. Caselli, Esquivel and Lefort (1996) show that covariance between the lagged dependent variable and the unobserved individual heterogeneity is not likely to be zero as at least the variance of unobserved individual heterogeneity itself is not non-zero. In fact, the above expectation is likely to be positive, as the unobserved individual heterogeneity proxies for the level of poverty rates the district is converging to; its omission introduces an upward bias in θ_1 in Eq. (2), which, in turn, translates into a downward bias in the speed of convergence. Besides, the expectation between the lagged dependent variable is also non-zero as the lagged error term jointly influences the lagged dependent variable and the current error term. The other source of bias originates from the endogeneity of the regressors apart from the lagged dependent variable. In most specifications of these "growth

models," at least a subset of the variables is conceptually endogenous. For instance, it is reasonable to suppose that literacy rate, migration rate, electrification rate, etc. are simultaneously determined with poverty reduction rates. Caselli, Esquivel and Lefort (1996) proposed to use past values of regressors as instruments which aptly fit into the dynamic panel estimation techniques that address the unobserved heterogeneity, endogeneity, and dynamic panel bias. Therefore, a two-step system dynamic panel estimation technique (Blundell and Bond 1998) was used to address these issues.

Even though AB estimator produces results with robust standard errors, it is uncertain how it deals with unknown heteroscedasticity. To address this issue, panel GMM estimation technique (Hansen 1982) is used, which controls for endogeneity like a regular instrumental variable estimator but improves its efficiency in the presence of heteroskedasticity of unknown form (Baum, Schaffer and Stillman 2003) by using the orthogonality conditions. District dummies were used to mimic a fixed effect model. Besides, cluster robust weight matrix as $W=S^{-1}$, where S is the inverse of the covariance matrix of the moment conditions of the instruments, is used so that panel GMM computes a weight matrix that does not assume that the innovations are independent within clusters identified by the particulars of the district.

III. SOURCES AND DESCRIPTION OF DATA

In contrast to the literature on poverty convergence based on cross country data, the unit of observation in this exercise is a district in Bangladesh in order to explore the dynamics across regions within a country. Availability of consumption and related data was a serious constraint in the exercise, as the requisite data for only the 2016 round of the *Household Income and Expenditure Survey* (HIES), conducted by the Bangladesh Bureau of Statistics (BBS), are representative at the district level. In contrast, similar data for the three rounds of the HIES between 2000 and 2010 are representative only at the division level. Fortunately, small area estimation (SAE) was undertaken by the BBS for 2000, 2005 and 2010 to generate representative estimates of poverty rates and per capita expenditures at the district level and even lower level. In all cases, Elbers, Lanjouw and Lanjouw (2003) was followed based on comparable data from the *Population and Housing Census*, 2001 and 2011 along with the relevant HIES data. In each data point, the HIES survey is a random sample of the corresponding census' sample frame, thus allowing for strict comparability of the distributions of a given variable between both data sources. These SAE data were juxtaposed with the corresponding 2016 HIES data in this exercise. However, mixing of data from two sources raises a valid concern: are the district level SAE poverty measures representative of the

districts? Linear regressions separately for 2000, 2005 and 2010 show that SAE estimates closely track the HIES estimates, as the respective regression lines pass through the origin and the slope coefficients are not significantly different from unity except in a few cases/spells (Yunus 2020).[7]

A set of initial conditions was also used for the estimation of conditional convergence as suggested by the relevant literature. The set includes (i) literacy rates of 7 years and above, (ii) per cent of households with electricity connections, (iii) per cent of households with sanitary toilets, (iv) per cent of households with pucca dwelling houses, (v) refined economic activity rate, (vi) overseas migration rate, and (vii) within country migration rate. These data were extracted from the *Population and Housing Census*, 1991, 2001, and 2011 and *Report on Bangladesh Sample Vital Statistics* (various years).[8] Data on the initial conditions were matched as closely as possible to HIES rounds 2000, 2005, and 2010.

TABLE I

**DESCRIPTIVE STATISTICS ON POVERTY RATES
AND RELATED INITIAL CONDITIONS**

Year	2000	2005	2010	2016
HCR SAE (HIES) (%)	50.2 (48.9)	42.5 (40.0)	32.3 (31.5)	24.3
PG SAE (HIES) (%)	13.2 (12.8)	10.2 (9.0)	6.7 (6.5)	5.0
SPG SAE (HIES) (%)	4.8 (4.6)	3.4 (2.9)	2.0 (2.0)	1.5
Per Capita Consumption (Tk.)	799.63	1139.01	2262.29	3497.33
Initial Conditions for the				
Year Interval	2000-2005		2005-2010	2010-2016
7 Years and Above Literacy Rate (%)	30.87		44.48	50.17
Household Electrification Rate (%)	28.38		38.86	52.51
Sanitary Toilet Rate (%)	36.54		51.64	63.24
Pucca Building Rate (%)	5.93		7.03	9.05
Refined Economic Activity Rate (%)	42,86		38.87	43.47
Overseas Migration Rate (%)	0.17		0.41	0.39
Within Country Migration Rate (%)	6.83		7.12	6.76

Sources: (1) Small Area Estimates and HIES, 2000, 2005, 2010, and 2016 for the upper panel. (2*) Population and Housing Census*, 1991, 2001, and 2011, (3*) Report on Bangladesh Sample Vital Statistics*, various issues, and Hill and Endara (2019) for the lower panel.

Table I presents the data on poverty measures, monthly per capita consumption expenditures and initial conditions.[9] It may be noted that Bangladesh experienced

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[7]Even though estimates of poverty and income through the SAE are better alternatives when representative disaggregated data from the HIES are not available, it may be noted that the SAE estimates themselves are likely to be less reliable due to modelling errors.

[8]Along with other specific covariates, these initial conditions/covariates are generally used in analyses of determinants of or convergence in poverty. See, for instance, Datt and Ravallion (1998), Deshingkar (2006), Hoynes, Page and Stevens (2006), Stephen and van Steen (2011), and Hill and Endara (2019).

[9]The per capita income series is deflated with national CPI to make it constant at 2010 prices.

a steady rise in per capita consumption expenditure during this period.[10] This has led the national poverty headcount rate, poverty gap, and squared poverty gap to decline during the three quinquennia. The poverty headcount rates measured by the costs of basic needs (CBN) declined annually by 1.8 percentage points between 2000 and 2005, 1.7 percentage points between 2005 and 2010, and 1.2 percentage points between 2010 and 2016. It may be noted that the headcount rate of poverty gives only the percentage value of poverty incidence; it does not measure the distance of the poor households from the poverty line(s). For that purpose, the poverty gap estimates about the depth of poverty of the population are required to estimate the average distance of the poor households from the poverty line and the average of the variations dubbed as the squared poverty gap.

The estimates of the trends in poverty gaps and squared poverty gaps are also presented in Table I. While poverty gap declines initially by 0.86 percentage points annually, it tapers down to 0.25 percentage points in recent years. Similarly, the squared poverty gap—which measures the severity of poverty—declines by 0.34 percentage points initially to taper down to 0.08 percentage points in recent years. This indicates that the incidence, depth and severity of poverty have reduced during the period. In the regression analyses that follow, specific focus would be on spatial trends in annual per capita income growth and poverty measures in 64 districts of the country over 16 years, with or without initial conditions extracted from decennial *Population and Housing Census* in 1991, 2001 and 2011, *Report on Bangladesh Sample Vital Statistics* in different rounds, both conducted by the BBS, as well as overseas migration and within country migration rates used from Hill and Endara (2019).

IV. EMPIRICAL RESULTS

Have the districts in nearly past two decades experienced a faster subsequent reduction in poverty indicators as their initial poverty incidences, poverty gaps, and squared poverty gaps declined over time at the national level? Have these reductions led to convergence to wipe out the so-called "east-west divide" and similar disparities? Are these convergences unconditional or they depend on a set of initial conditions? What are these initial conditions that could explain the presence or absence of poverty convergence across the districts? This section

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[10]Consumption expenditure is viewed as a better welfare measure than income estimated from *Household Income and Expenditures Surveys*.

presents the empirical results revolving around these issues. As shown in Table II, the 64 districts considered a group did experience poverty convergence, as higher poverty reduction rates (larger negative values) are significantly associated with higher initial poverty incidence. Under AB-GMM estimation, the speed of convergence for poverty headcount rate was found at 3.1 per cent; it declines to 2.8 per cent and 2.6 per cent respectively for poverty gap and squared poverty gap. The same trends are observed under panel GMM although the magnitudes of the coefficients are somewhat lower. These findings are robust to the type of poverty measures used and the alternative estimation methods applied as the null of Sargan-Hansen overidentifying restrictions (Sargan 1958, Hansen 1982) could not be rejected.[11] For all three types of poverty measures, the speed of convergence intensifies once the initial conditions are controlled for.[12] While higher incidence of human capital (literacy rate) and within country migration appear to intensify convergence rates, the higher incidence of pucca building and refined economic activity rate dampen it. One plausible explanation of the positive coefficients (negative association) of the pucca building rate and refined economic activity rate with poverty reduction is that districts with higher incidence of pucca building and refined economic activity rates tend to have lower poverty rates and hence, further poverty reduction with initial lower poverty rate appears to be formidable to achieve. Another generally interesting feature of the results is that the factors that favourably or adversely affect poverty reduction becomes larger in numbers under panel GMM estimation technique compared to the AB-GMM estimation technique.

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[11] The Sargan-Hansen J test is based on the assumption that model parameters are identified via *a priori* restrictions on the coefficients, and tests the validity of over-identifying restrictions.

[12] See Table A1 in Appendix A for speeds of poverty convergence without initial conditions.

TABLE II

CONDITIONAL CONVERGENCE IN POVERTY RATES

Variables	Poverty Headcount	Poverty Gap	Squared Poverty Gap
AB-GMM			
Lagged Poverty Reduction Rate	0.2475	0.1068	0.0545
	(0.1789)	(0.1542)	(0.1449)
Ln (Initial Poverty Rate)	-0.0312***	-0.0279***	-0.0263***
	(0.0037)	(0.0033)	(0.0035)
Ln (Initial Literacy Rate)	-0.0684***	-0.0733***	-0.0731***
	(0.0171)	(0.0220)	(0.0268)
Ln (Initial Electricity Rate)	-0.0014	-0.0022	-0.0029
	(0.0036)	(0.0053)	(0.0064)
Ln (Initial Sanitary Toilet Rate)	0.0029	0.0013	0.0013
	(0.0040)	(0.0051)	(0.0062)
Ln (Initial Pucca Building Rate)	0.0048**	0.0057**	0.0062**
	(0.0020)	(0.0026)	(0.0031)
Ln (Initial Refined Economic Activity Rate)	0.0059***	0.0069***	0.0069***
	(0.0014)	(0.0021)	(0.0026)
Ln (Initial Overseas Migration Rate)	0.0021	0.0014	0.0007
	(0.0014)	(0.0025)	(0.0034)
Ln (Initial Within Country Migration Rate)	-0.0110***	-0.0128***	-0.0140***
	(0.0033)	(0.0042)	(0.0049)
Constant	0.3634***	0.3279***	0.2901***
	(0.0577)	(0.0707)	(0.0857)
Sargan Statistic [$\chi^2(1)$]	0.631	1.923	3.073
	[0.427]	[0.166]	[0.08]
Wald Statistic [$\chi^2(9)$]	290.41	344.02	307.98
	[0.00]	[0.00]	[0.00]
Number of Observations	128	128	128
Panel GMM			
Ln (Initial Poverty Rate)	-0.0266***	-0.0258***	-0.0254***
	(0.0012)	(0.0014)	(0.0012)
Ln (Initial Literacy Rate)	-0.0077***	-0.0086***	-0.0074***
	(0.0010)	(0.0022)	(0.0023)
Ln (Initial Electricity Rate)	-0.0041***	-0.0060***	-0.0070***
	(0.0003)	(0.0006)	(0.0009)
Ln (Initial Sanitary Toilet Rate)	0.0053***	0.0068***	0.0084***
	(0.0007)	(0.0010)	(0.0011)
Ln (Initial Pucca Building Rate)	0.0007**	0.0011**	0.0011**
	(0.0003)	(0.0004)	(0.0005)
Ln (Initial Refined Economic Activity Rate)	0.0018	0.0011	0.0028
	(0.0013)	(0.0034)	(0.0025)
Ln (Initial Overseas Migration Rate)	-0.0024***	-0.0029***	-0.0038***
	(0.0001)	(0.0003)	(0.0004)
Ln (Initial Within Country Migration Rate)	-0.0018***	-0.0023***	-0.0028***
	(0.0003)	(0.0004)	(0.0005)
Constant	0.0472***	0.0290	-0.0056
	(0.0086)	(0.0196)	(0.0168)
Hansen's J [$\chi^2(55)$]	53.9783	56.2116	58.8869
	[0.514]	[0.429]	[0. 0.335]
Number of Observations	192	192	192

Source: Author's estimates.

Notes: Robust standard errors are in parentheses and p-values in brackets. Figures with ***, ** and * respectively indicate significance at 1%, 5%, and 10% levels.

Although it is a formidable challenge, the poverty convergence can occur through redistribution mechanism. Even though tax collection effort is lax compared with the neighbouring countries, the successive governments in the country introduced and intensified a large number of social safety net programmes. At present, there are more than 140 social safety net programmes, some of which target particular groups while others target a particular region. About 13 per cent of the annual budget or more than 2 per cent of GDP is spent on these safety net programmes through various forms of targeting. Thus, poverty reduction can be achieved to some extent even when there is hardly any growth in per capita income. However, such poverty reduction cannot be sustained in the medium- to long-run.

TABLE III

CONDITIONAL CONVERGENCE IN PER CAPITA INCOME

Variables	AB-GMM	Panel GMM
Lagged Growth Rate of Per Capita Income	0.1069	-
	(0.0949)	-
Ln (Initial Per Capita income)	-0.0233***	-0.0188***
	(0.0023)	(0.0075)
Ln (Initial Literacy Rate)	0.0182***	0.0036***
	(0.0042)	(0.0004)
Ln (Initial Electricity Rate)	-0.0003	0.0008***
	(0.0011)	(0.0003)
Ln (Initial Sanitary Toilet Rate)	-0.0010	-0.0007***
	(0.0010)	(0.0002)
Ln (Initial Pucca Building Rate)	-0.0009*	-0.0002***
	(0.0005)	(0.0001)
Ln (Initial Refined Economic Activity Rate)	-0.0015***	-0.0009**
	(0.0004)	(0.0004)
Ln (Initial Overseas Migration Rate)	-0.0006*	0.0011***
	(0.0003)	(0.0001)
Ln (Initial Within Country Migration Rate)	0.0028***	0.0008***
	(0.0009)	(0.0001)
Constant	0.1026***	0.0861***
	(0.0138)	(0.0038)
Sargan Statistic [$\chi^2(1)$]/Hansen's J Statistic [$\chi^2(55)$]	1.280	60.2368
	[]0.258	[0.2920]
Wald Statistic [$\chi^2(9)$]	733.57	-
	[0.00]	-
Number of Observations	128	192

Source: Author's estimates.

Notes: Robust standard errors are in parentheses and p-values in brackets. Figures with ***, ** and * respectively indicate significance at 1%, 5%, and 10% levels.

If per capita income follows a lognormal distribution, then any change in the poverty headcount rate is determined by both changes in income and changes in the distribution of income. Therefore, Bourguignon (2003) shows that higher growth rate in per capita income leads to a higher poverty reduction. To verify that

convergence in poverty reduction observed above is an outcome of growth, we estimate Eq. (1), which explores the mean convergence in per capita income. The results presented in Table III vindicate that convergence in the poverty reduction observed above is at least partly explained by the growth in per capita income. The speeds of convergence in per capita income are 2.3 per cent and 1.9 per cent under AB-GMM and panel GMM estimation methods respectively. It appears that higher literacy rate, electricity rate, and higher migration rate favourably affect convergence in per capita income, while higher incidence of sanitary toilet, pucca building and refined economic activity rate dampen the speeds of convergence in per capita income. Besides, data also suggest that higher growth rates are associated with higher (proportionate) rates of poverty reduction for all three measures: The AB-GMM regression coefficients of growth of headcount, poverty gap, and squared poverty gap rates on that of per capita income are -1.381 (robust s. e.= 0.185), -1.896 (robust s. e. = 0.262) and -2.258 (robust s. e. = 0.300), respectively. The corresponding panel GMM estimates are -1.562 (robust s. e.= 0.055), -2.354 (robust s. e. = 0.045) and -2.713 (robust s. e. = 0.085), respectively.

To see what explains the strong poverty convergence found in the regions, Eq. (3), which is Eq. (1) augmented with initial poverty levels, was estimated to assess the interrelationship between the growth in mean and poverty reduction. Regression estimates in Table IV suggest two things. *First*, for a given initial poverty level, districts starting out with lower levels of initial mean income subsequently enjoyed a faster growth in mean income. *Second,* controlling for initial mean per capita income level, initial poverty does not retard subsequent growth in mean income, except for the poverty headcount rate under AB-GMM estimation method. These results are robust to the choice of poverty measures under both the AB-GMM and panel GMM estimation methods but are at odds with Ravallion (2012) that empirically found that higher initial (headcount) poverty rate does in fact retard subsequent growth across developing countries. However, the inclusion of respective poverty rate does not change the nature of influence of the initial conditions. It may be noted that higher literacy rate and higher within country migration rate actually accelerate growth in per capita income. One of the possible explanations could be that historically poor districts could have lower educational attainment. In contrast, there is a clear indication in the results that higher pucca building rate and higher economic activity rate have a negative impact on growth in per capita income and hence poverty reduction. One plausible explanation could be that perhaps districts with higher incidence of pucca building and higher economic activity rate had already had higher per capita income, thereby scope of further growth is limited.

TABLE IV

CONDITIONAL CONVERGENCE IN PER CAPITA
INCOME WITH INITIAL POVERTY RATES

Variables	Poverty Headcount	Poverty Gap	Squared Poverty Gap
	AB-GMM		
Lagged Growth Rate of Per Capita Income	0.0727	0.0844	0.0902
	(0.0922)	(0.0901)	(0.0897)
Ln (Initial Per Capita Income)	-0.0197***	-0.0206***	-0.0212***
	(0.0025)	(0.0028)	(0.0027)
Ln (Initial Poverty Rate)	0.0016**	0.0009	0.0006
	(0.0007)	(0.0006)	(0.0005)
Ln (Initial Literacy Rate)	0.0158***	0.0164***	0.0168***
	(0.0042)	(0.0043)	(0.0043)
Ln (Initial Electricity Rate)	-0.0007	-0.0005	-0.0003
	(0.0010)	(0.0011)	(0.0011)
Ln (Initial Sanitary Toilet Rate)	-0.0006	-0.0008	-0.0009
	(0.0011)	(0.0011)	(0.0011)
Ln (Initial Pucca Building Rate)	-0.0009**	-0.0010**	-0.0010**
	(0.0005)	(0.0005)	(0.0005)
Ln (Initial Refined Economic Activity Rate)	-0.0014***	-0.0015***	-0.0015***
	(0.0004)	(0.0004)	(0.0004)
Ln (Initial Overseas Migration Rate)	-0.0006*	-0.0006*	-0.0006*
	(0.0003)	(0.0003)	(0.0003)
Ln (Initial Within Country Migration Rate)	0.0028***	0.0027***	0.0027***
	(0.0009)	(0.0009)	(0.0009)
Constant	0.0803***	0.0886***	0.0931***
	(0.0139)	(0.0150)	(0.0140)
Sargan Statistic [$\chi^2(1)$]	1.070	1.016	1.039
	[0.301]	[0.313]	[0.308]
Wald Statistic [$\chi^2(10)$]	958.40	958.32	932.03
	[0.00]	[0.00]	[0.00]
Number of Observations	128	128	128
	Panel GMM		
Ln (Initial Per Capita Income)	-0.0185***	-0.0168***	-0.0180***
	(0.0017)	(0.0021)	(0.0015)
Ln (Initial Poverty Rate)	0.0003	0.0006	0.0003
	(0.0005)	(0.0004)	(0.0002)
Ln (Initial Literacy Rate)	0.0037***	0.0036***	0.0036***
	(0.0005)	(0.0005)	(0.0005)
Ln (Initial Electricity Rate)	0.0009***	0.0009***	0.0009***
	(0.0003)	(0.0003)	(0.0003)
Ln (Initial Sanitary Toilet Rate)	-0.0008***	-0.0009***	-0.0008***
	(0.0002)	(0.0003)	(0.0002)
Ln (Initial Pucca Building Rate)	-0.0002***	-0.0003**	-0.0003***
	(0.0001)	(0.0001)	(0.0001)
Ln (Initial Refined Economic Activity Rate)	-0.0010***	-0.0010**	-0.0010**
	(0.0003)	(0.0004)	(0.0004)
Ln (Initial Overseas Migration Rate)	0.0012***	0.0012***	0.0012***
	(0.0001)	(0.0001)	(0.0001)
Ln (Initial Within Country Migration Rate)	0.0008***	0.0008***	0.0008***
	(0.0001)	(0.0001)	(0.0001)
Constant	0.0843***	0.0771***	0.0828***
	(0.0091)	(0.0100)	(0.0070)
Hansen's J Statistic [$\chi^2(54)$]	61.1876	60.6277	60.8333
	[0.2337]	[0.2492]	[0.2435]
Number of Observations	192	192	192

Source: Author's estimates.

Notes: Robust standard errors are in parentheses and p-values in brackets. Figures with ***, ** and * respectively indicate significance at 1%, 5%, and 10% levels.

It is thus evident that there is convergence in per capita income and growth of per capita income tends to reduce poverty and districts with higher poverty rates do not tend to experience slower growth rates in per capita income. It is, therefore, important to assess how the growth elasticity of poverty reduction depends on initial distribution in order to isolate the effects of various confounding factors. Following Ravallion (2012), this can be thought of as the direct effect of the initial distribution on the pace of poverty reduction, as distinct from the indirect effect via the rate of growth in per capita income. The results in Table A2 in Appendix A indicate that the (absolute) growth elasticity of poverty reduction tends to be lower in districts with a higher initial poverty rate. It is also evident that there is sign of growth-accounted poverty convergence in addition to the income channel; as found earlier, the null that $\delta_1 = 0$ is strongly rejected. In contrast, the homogeneity test for the null: $\eta_0 + \eta = 0$ could not be rejected, which indicates that the district growth rates are not "poverty-adjusted rates" alone.

This is not surprising as the so-called encompassing argument holds only when one observes convergence in per capita income but not poverty convergence (see, for instance, Ravallion 2012, and Ouyang, Shimeles and Thorbecke 2019). In contrast, we observe convergence in both growth in per capita income and poverty reduction rates. Besides, speeds of poverty convergence (Table II) are higher than that in per capita income (Tables III and IV). In such a situation, fulfilment of the encompassing tests is a distant possibility. Instead, we found that similar results occur when poverty adjusted growth rates are replaced by inequality-corrected growth rate. This set of findings is consistent with Bourguignon (2003) that posits that redistribution effect through containment of inequality may also accelerate poverty reduction which poverty-adjusted growth cannot subsume alone. Besides, when the above specification is augmented with the per cent of social safety net beneficiaries, the respective coefficients show sign towards accentuating poverty convergence although the estimates suffer from low precision levels. Thus, given the presence of growth-accounted poverty convergence ($\delta_1 \neq 0$) due to backwardness and other factors and failure to reject the null: $\eta_0 + \eta = 0$, one should estimate a parsimonious model as specified in Eq. (4). Table V presents the results of the parsimonious model together with the initial conditions.

TABLE V

GROWTH-ACCOUNTED AND GROWTH-ADJUSTED POVERTY CONVERGENCE

Variables	Poverty Headcount	Poverty Gap	Squared Poverty Gap
AB-GMM			
Lagged Growth Rate of Per Capita Income	0.0293	0.0507	0.0091
	(0.1779)	(0.1310)	(0.1132)
Ln (Initial Poverty Rate)	-0.0152**	-0.0163***	-0.0165***
	(0.0066)	(0.0054)	(0.0047)
(1- Initial Poverty Rate) × Growth in Per Capita Income	-2.4757***	-2.1338***	-2.1211***
	(0.6110)	(0.4825)	(0.4517)
Ln (Initial Literacy Rate)	-0.0612***	-0.0676***	-0.0676***
	(0.0143)	(0.0183)	(0.0216)
Ln (Initial Electricity Rate)	-0.0065**	-0.0095**	-0.0108**
	(0.0032)	(0.0045)	(0.0052)
Ln (Initial Sanitary Toilet Rate)	0.0032	0.0003	-0.0002
	(0.0030)	(0.0037)	(0.0046)
Ln (Initial Pucca Building Rate)	0.0038**	0.0033*	0.0034
	(0.0015)	(0.0020)	(0.0024)
Ln (Initial Refined Economic Activity Rate)	0.0049***	0.0046**	0.0041*
	(0.0013)	(0.0019)	(0.0023)
Ln (Initial Overseas Migration Rate)	0.0023**	0.0019	0.0015
	(0.0010)	(0.0017)	(0.0023)
Ln (Initial Within Country Migration Rate)	-0.0065**	-0.0082*	-0.0097*
	(0.0031)	(0.0042)	(0.0051)
Constant	0.2986***	0.3266***	0.3148***
	(0.0552)	(0.0630)	(0.0723)
Sargan Statistic [$\chi^2(1)$]	0.1058	1.950	2.918
	[0.745]	[0.163]	[]0.088]
Wald Statistic [$\chi^2(10)$]	382.85	464.17	426.63
	[0.00]	[0.00]	[0.00]
Number of Observations	128	128	128
Panel GMM			
Ln (Initial Poverty Rate)	-0.0071***	-0.0077***	-0.0092***
	(0.0009)	(0.0011)	(0.0008)
(1- Initial Poverty Rate) × Growth in Per Capita Income	-2.8774***	-2.3328***	-2.6086***
	(0.1705)	(0.1769)	(0.1498)
Ln (Initial Literacy Rate)	-0.0003	-0.0018**	-0.0005
	(0.0010)	(0.0007)	(0.0017)
Ln (Initial Electricity Rate)	-0.0036***	-0.0038***	-0.0042***
	(0.0005)	(0.0007)	(0.0005)
Ln (Initial Sanitary Toilet Rate)	0.0005	0.0012*	0.0016**
	(0.0005)	(0.0007)	(0.0006)
Ln (Initial Pucca Building Rate)	0.0005**	0.0000	-0.0005***
	(0.0002)	(0.0002)	(0.0002)
Ln (Initial Refined Economic Activity Rate)	0.0002	-0.0019**	-0.0015
	(0.0012)	(0.0009)	(0.0026)
Ln (Initial Overseas Migration Rate)	0.0001	-0.0005***	-0.0011***
	(0.0002)	(0.0002)	(0.0002)
Ln (Initial Within Country Migration Rate)	-0.0000	-0.0003	-0.0006*
	(0.0003)	(0.0003)	(0.0003)
Constant	0.0273***	0.0298***	0.0160
	(0.0085)	(0.0057)	(0.0143)
Hansen's J Statistic [$\chi^2(54)$]	53.2677	55.2825	55.9696
	[0.5026]	[0.4260]	[0.4008]
Number of Observations	192	192	192

Source: Author's estimates.

Notes: District robust standard errors are in parentheses and p-values in brackets. Figures with ***, ** and * respectively indicate significance at 1%, 5%, and 10% levels.

With estimates from Table IV and Table V and Table A3 in the Appendix A together with the sample means of the relevant variables, one can calculate the magnitudes of the four contributing effects – growth-accounted poverty convergence effect, convergence effect of per capita income, direct poverty effect, and poverty elasticity effect – to gauge the direction and extent of poverty convergence as derived in Eq. (5).

TABLE VI

DECOMPOSITION OF REGIONAL POVERTY CONVERGENCE ELASTICITY

Components	Poverty Headcount	Poverty Gap	Squared Poverty Gap
AB-GMM			
1. Convergence Effect of Per Capita Income	-0.0196	-0.0171	-0.0156
2. Direct Poverty Effect	0.0000	0.0000	0.0000
3. Poverty Elasticity Effect	0.0021	0.0004	0.0001
4. Growth-accounted Poverty Convergence Effect	-0.0152	-0.0163	-0.0165
Convergence Elasticity Effect:(1)+(2)+(3)+(4)	-0.0327	-0.0330	-0.0320
Empirical Estimate (Table 2)	-0.0312	-0.0279	-0.0263
Panel GMM			
1. Convergence Effect of Per Capita Income	-0.0215	-0.0161	-0.0180
2. Direct Poverty Effect	0.0000	0.0000	0.0000
3. Poverty Elasticity Effect	0.0025	0.0005	0.0002
4. Growth-accounted Poverty Convergence Effect	-0.0071	-0.0077	-0.0092
Convergence Elasticity Effect: (1)+(2)+(3)+(4)	-0.0261	-0.0233	-0.0270
Empirical Estimate (Table 2)	-0.0266	-0.0258	-0.0254

Source: Author's calculations based on estimates in Table IV, Table V, and Table A3.

The decomposition results are presented in Table VI. It may be noted that the sum of the four effects matches the empirical poverty convergence rates reasonably well, suggesting that they are important contributing factors for poverty convergence found in districts during the period 2000-2016. As the corresponding coefficients of the direct poverty effect are imprecise, we set this comment with zero effect. Hence, the convergence elasticity effect is explained by a strong convergence effect of per capita income as well as growth-accounted poverty convergence effect. Hence, the sum of these two favourable effects is partly cancelled by less sizeable poverty elasticity effect, the overall convergence effect of poverty sustains thanks to growth-accounted poverty convergence effect. The growth-accounted poverty convergence effect is so strong that it accounts for about half of the convergence elasticity effect under AB-GMM and about one third under panel GMM estimates.

V. ROBUSTNESS OF THE RESULTS

It may be noted that our results are at odds with Ravallion (2012). The natural question that arises is: what are driving the contrasting outcomes vis-à-vis Ravallion? At the outset, it should be borne in mind that Ravallion's results are based on cross-country data and ours are on single country data. We applied AB-GMM and panel GMM vis-à-vis his cross-section analysis. Be that as it may, is it driven by the method/technique applied? In principle, the answer is maybe, as Caselli, Esquivel and Lefort (1996) show, cross-section, fixed effects and random effects estimates introduce downward bias in the convergence rates. To that end, we tried to mimic Ravallion by running cross-section regressions. Even though these estimates are biased for reasons discussed in the text, the ensuing qualitative conclusions still conform to the AB-GMM and panel GMM ones. Even though panel GMM takes care of endogeneity of regressors as the principle is to mimic population relationship based on sample analogy, the technique is silent about its treatment of unobserved individual heterogeneity. As an alternative, we ran panel fixed effect estimates. Again, the magnitude of the coefficients roughly corresponds to the panel GMM ones and hence the qualitative conclusions do not change.

Is it a transformation of key variables, especially the poverty reduction rates? Cuaresma, Klasen and Wacker (2017) observed that Ravallion (2012) failed to find poverty convergence because of logarithmic transformation of the poverty reduction rate that wipes much of variations in data. To that end, we redefined the poverty reduction variable as $\Delta P_{it} \equiv (P_{it} - P_{it-r})/r$ following Cuaresma, Klasen and Wacker (2017). Again, the qualitative conclusions do not change. Finally, is it the sources of data definition i.e., SAE estimates vis-à-vis direct HIES estimates of poverty measures that is driving the results? We applied the same estimation techniques on the data directly extracted from the HIES. Even though coefficients of a few key variables become imprecise with the HIES data, the overall conclusions do not change.

VI. CONCLUSIONS

The paper found four distinct channels – convergence effect of per capita income, growth-accounted poverty convergence effect, direct poverty effect, and poverty elasticity effect – that affect poverty district level reduction in Bangladesh. While the first two channels accentuate the rate of poverty reduction, poverty elasticity effect retards it and the direct poverty effect plays a neutral role due to imprecise estimates of key coefficients. Thus, the evidence of overall district level
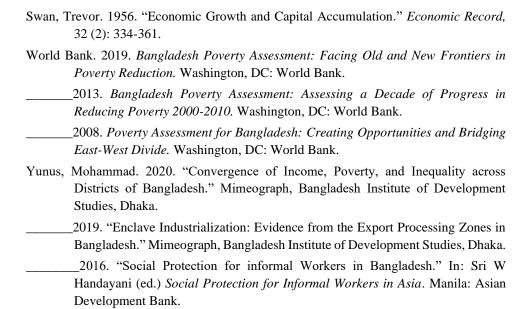
poverty convergence in Bangladesh suggests that the convergence in per capita income as well as growth-accounted poverty convergence effects more than offset the poverty elasticity effect. The dynamics of regional poverty convergence appears to exist with or without initial conditions that help or impede growth and poverty reduction. Despite niceties of the above decomposition, the analysis in this paper left out the possible impact of the inequality and redistribution. Data limitation constrains us to explore if and how speeds of poverty convergence hinge on these critical variables. Amidst these limitations, we tried to make a few points. *First*, building on the literature of growth convergence, we succinctly described that cross-section, fixed effects and random effects analyses of poverty convergence are fraught with biases and cautioned that these estimates should not be taken seriously. In contrast, one can take our estimates with confidence as these are unbiased due to application of appropriate estimation techniques, given the nature of econometric models specified. However, one need not expect similar results between ours and extant cross-country literature and draw a hasty conclusion as the underlying data and context are different. *Second*, the empirical literature on convergence in poverty itself is scant let alone focusing on a single country. With estimates from Bangladesh, these findings would, therefore, contribute to the empirical literature on single country poverty convergence. *Finally*, it is one of the few papers that looks into dynamics of poverty across districts of Bangladesh over time to help make informed policy to deal with the regional disparities in key development indicators such as various types of income poverty rates.

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Appendix A: Supplementary Results

Table A1: **Absolute Convergence in Poverty Rates**

Variables	Poverty Headcount	Poverty Gap	Squared Poverty Gap
AB-GMM			
Lagged Poverty Reduction Rate	-0.175	-0.217	-0.197
	(0.192)	(0.162)	(0.134)
Ln (Initial Poverty Rate)	-0.018***	-0.016***	-0.016***
	(0.004)	(0.004)	(0.003)
Constant	0.057***	0.024***	0.004
	(0.016)	(0.009)	(0.004)
Sargan Statistic [$\chi^2(1)$]	0.32	0.66	0.53
	[0.57]	[0.42]	[0.47]
Wald Statistic [$\chi^2(2)$]	106.00	113.56	118.36
	[0.00]	[0.00]	[0.00]
Number of Observations	128	128	128
Panel GMM			
Ln (Initial Poverty Rate)	-0.0142***	-0.0160***	-0.0164***
	(0.0002)	(0.0004)	(0.0002)
Constant	0.0219***	0.0116***	0.0014***
	(0.0004)	(0.0004)	(0.0001)
Hansen's J [$\chi^2(62)$]	61.852	62.263	63.817
	[0.4814]	[0.467]	[0.412]
Number of Observations	192	192	192

Source: Author's estimates.

Notes: Robust standard errors are in parentheses and p-values in brackets. Figures with ***, ** and * respectively indicate significance at 1%, 5%, and 10% levels.

Table A2: **Regression of Poverty Reduction Rate on Growth in Per Capita Income and Initial Poverty Rate**

Variables	Poverty Headcount	Poverty Gap	Squared Poverty Gap
AB-GMM			
Lagged Poverty Reduction Rate	-0.0444	-0.0658	-0.0862
	(0.1843)	(0.1286)	(0.1124)
Ln (Initial Poverty Rate)	-0.0139**	-0.0150***	-0.0159***
	(0.0061)	(0.0043)	(0.0038)
Growth in Per Capita Income	-2.9222***	-2.8307***	-2.6245***
	(0.8358)	(0.5807)	(0.4767)
Initial Poverty Rate × Growth in Per Capita Income	3.7302**	10.6112***	22.1890**
	(1.5872)	(4.1008)	(10.0201)
Ln (Initial Literacy Rate)	-0.0598***	-0.0689***	-0.0723***
	(0.0144)	(0.0174)	(0.0204)
Ln (Initial Electricity Rate)	-0.0052*	-0.0058	-0.0064
	(0.0029)	(0.0040)	(0.0048)
Ln (Initial Sanitary Toilet Rate)	0.0036	0.0005	-0.0005
	(0.0030)	(0.0035)	(0.0043)
Ln (Initial Pucca Building Rate)	0.0041***	0.0042**	0.0045**
	(0.0015)	(0.0019)	(0.0022)
Ln (Initial Refined Economic Activity Rate)	0.0052***	0.0052***	0.0047**
	(0.0013)	(0.0019)	(0.0023)
Ln (Initial Overseas Migration Rate)	0.0026**	0.0029*	0.0028
	(0.0011)	(0.0017)	(0.0022)
Ln (Initial Within Country Migration Rate)	-0.0062**	-0.0079*	-0.0094**
	(0.0031)	(0.0040)	(0.0048)
Constant	0.2815***	0.3150***	0.3192***
	(0.0565)	(0.0582)	(0.0661)
Homogeneity Test [$\chi^2(1)$]	0.82	4.39	4.00
	[0.367]	[0.036]	[0.045]
Sargan Statistic [$\chi^2(1)$]	0.221	0.895	1.513
	[0.882]	[0.344]	[0.219]
Wald Statistic [$\chi^2(11)$]	418.39	499.37	540.03
	[0.00]	[0.00]	[0.00]
Number of Observations	128	128	128
Panel GMM			
Ln (Initial Poverty Rate)	-0.0082***	-0.0082***	-0.0116***
	(0.0010)	(0.0016)	(0.0010)
Growth in Per Capita Income	-2.2924***	-2.1641***	-2.3614***
	(0.3115)	(0.2426)	(0.2811)
Initial Poverty Rate × Growth in Per Capita Income	1.4295***	-1.6721	-4.7323
	(0.5485)	(1.8180)	(5.2421)
Ln (Initial Literacy Rate)	-0.0011	-0.0006	-0.0000
	(0.0010)	(0.0014)	(0.0018)
Ln (Initial Electricity Rate)	-0.0035***	-0.0042***	-0.0048***
	(0.0005)	(0.0008)	(0.0008)

(Contd. Table A2)

Variables	Poverty Headcount	Poverty Gap	Squared Poverty Gap
Ln (Initial Sanitary Toilet Rate)	0.0010*	0.0020***	0.0021***
	(0.0005)	(0.0008)	(0.0007)
Ln (Initial Pucca Building Rate)	0.0003	-0.0004	-0.0006***
	(0.0002)	(0.0003)	(0.0002)
Ln (Initial Refined Economic Activity Rate)	-0.0001	0.0001	-0.0021
	(0.0013)	(0.0026)	(0.0025)
Ln (Initial Overseas Migration Rate)	-0.0001	-0.0006**	-0.0012***
	(0.0002)	(0.0003)	(0.0002)
Ln (Initial Within Country Migration Rate)	-0.0001	-0.0003	-0.0005*
	(0.0003)	(0.0005)	(0.0003)
Constant	0.0271***	0.0152	0.0164
	(0.0088)	(0.0115)	(0.0135)
Homogeneity Test [$\chi^2(1)$]	0.866	7.142	9.111
	[0.648]	[0.992]	[0.997]
Hansen's J Statistic [$\chi^2(53)$]	48.2488	50.0201	54.5199
	[0.6594]	[0.5909]	[0.4165]
Number of Observations	192	192	192

Source: Author's estimates.
Notes: Robust standard errors are in parentheses and p-values in brackets. Figures with ***, ** and * respectively indicate significance at 1%, 5%, and 10% levels.

Table A3: **Poverty Rate-Per Capita Income Relationship**

Variables	Poverty Headcount	Poverty Gap	Squared Poverty Gap
AB-GMM			
Lagged Ln (Poverty Rate)	-0.1707	-0.0736	-0.0075
	(0.1573)	(0.0985)	(0.0916)
Ln (Initial Per Capita Income)	-1.5388***	-2.3394***	-2.7899***
	(0.2469)	(0.2815)	(0.3486)
Ln (Initial Literacy Rate)	0.9007	1.2500*	1.4399*
	(0.6240)	(0.7069)	(0.8647)
Ln (Initial Electricity Rate)	0.0361	0.0679	0.0322
	(0.2049)	(0.2291)	(0.3035)
Ln (Initial Sanitary Toilet Rate)	-0.1462	-0.1598	-0.1201
	(0.1079)	(0.1433)	(0.1985)
Ln (Initial Pucca Building Rate)	0.0692	0.1392*	0.2040*
	(0.0511)	(0.0742)	(0.1063)
Ln (Initial Refined Economic Activity Rate)	-0.0001	0.0105	0.0417
	(0.0552)	(0.0629)	(0.0828)
Ln (Initial Overseas Migration Rate)	-0.1015	-0.0798	-0.0698
	(0.0985)	(0.0578)	(0.0610)
Ln (Within Country Migration Rate)	0.0657	0.0489	-0.0462
	(0.1870)	(0.2103)	(0.2846)
Constant	11.3524***	13.5949***	14.6525***
	(2.3696)	(2.4971)	(3.2298)

(Contd. Table A3)

Variables	Poverty Headcount	Poverty Gap	Squared Poverty Gap
Sargan Statistic [$\chi^2(1)$]	3.5387	0.1145	0.4335
	[0.0600]	[0.735]	[0.5103]
Wald Statistic [$\chi^2(9)$]	251.24	329.10	244.51
	[0.00]	[0.00]	[0.00]
Number of Observations	128	128	128
Panel GMM			
Ln (Initial Per Capita Income)	-1.5274***	-2.2166***	-2.5329***
	(0.0391)	(0.0546)	(0.0842)
Ln (Initial Literacy Rate)	0.0645**	0.1913***	0.0883
	(0.0293)	(0.0423)	(0.0763)
Ln (Initial Electricity Rate)	0.0196	-0.0327	-0.1074***
	(0.0165)	(0.0277)	(0.0173)
Ln (Initial Sanitary Toilet Rate)	0.1394***	0.2631***	0.3375***
	(0.0295)	(0.0316)	(0.0471)
Ln (Initial Pucca Building Rate)	-0.0143*	-0.0236**	-0.0125
	(0.0084)	(0.0118)	(0.0119)
Ln (Initial Refined Economic Activity Rate)	0.1569***	0.2718***	0.2483**
	(0.0282)	(0.0244)	(0.1019)
Ln (Initial Overseas Migration Rate)	-0.0249***	-0.0154	-0.0100
	(0.0054)	(0.0099)	(0.0129)
Ln (Initial Within Country Migration Rate)	-0.0435***	-0.0325***	-0.0119
	(0.0069)	(0.0111)	(0.0189)
Constant	12.9322***	15.1643***	16.6698***
	(0.2365)	(0.3874)	(0.9434)
Hansen's J Statistic [$\chi^2(55)$]	57.6109	59.1497	56.1227
	[0.3789]	[0.3266]	[0.4326]
Number of Observations	192	192	192

Source: Author's estimates.

Notes: Robust standard errors are in parentheses and p-values in brackets. Figures with ***, ** and * respectively indicate significance at 1%, 5%, and 10% levels.