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Is the Past Still Holding Us Back? A Study on Intergenerational Education Mobility in India

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Abstract

This paper explores various aspects of, and factors affecting intergenerational education mobility in India. We employ IHDS-II (2011-12) and prepare a representative dataset that goes beyond 'co-resident only' son-father pairs by utilizing the retrospective information conveying the educational attainment of the father of the male household head. From the resulting sample of 44,532 son-father pairs and appropriate cohort analysis, we find that there is still a high degree of intergenerational persistence in education, although the same is decreasing steadily over time. Through quantile regressions, we detect a non-linearity in the relationship between fathers' and sons' schooling outcomes along the education distribution. Moreover, the mobility gap between the historically advantaged subgroups (urban population, upper castes, Hindus, etc.) and the others (rural population, lower castes, Muslim, etc.) increasingly widens along the middle and upper quantiles of the distribution. Finally, "Higher Inequality (during fathers' generation) → Lesser Mobility" nexus in education plays out for the Indian scenario and thus corroborates the 'Great Gatsby Curve'. Other macro variables, economic growth and public expenditure in education, bear a positive association with education mobility.

***JEL Classification*:** I24, I28, J62, O15

***Keywords*:** Intergenerational mobility, education, quantile regression, co-residence, Great Gatsby Curve

1. Introduction

Inequality in a society can be roughly ascribed two reasons – one, a disparity in efforts of individuals or category of individuals, and two, differences in predetermined circumstances outside the locus of control of individuals. While the former is essential in a society to promote merit and provide incentives for individuals to work hard; the latter is unfair as it manifests into inequality of opportunity where the life chances of an individual are determined by the relative socio-economic status of his/her parents or ancestors. Collectively, in a society, such transmission of relative advantage (or disadvantage) from one generation to its next is an indicator of the intergenerational persistence prevalent in the society. Conversely, intergenerational mobility is a marker of the opportunity for a generation to move beyond its social origins (Fox, Torche & Waldfogel, 2016).

Mobility is an essential marker for the growth and development of a society. A child whose life chances are determined by the social or economic strata he/she belongs to and not by his/her industry in a rigid society is bound to have no inducement to try and wiggle out of the low-level equilibrium and contribute to nation's progress. This has been articulated to a similar effect by Bourguignon et al. (2007) who suggested that in a society where the poor and the rich (and their respective children) are equally likely to succeed, people have a higher incentive to work hard.

In this paper, we explore various aspects and channels of intergenerational mobility in India by essentially measuring the association between parents' and adult children's education as it has been reasoned, in several quarters, that education is one of the major channels of transmission of opportunity from parents to children. The direct and indirect mechanisms include – parents' schooling impacting children's schooling as the educated parents value their children's education more (cultural dependency), educated parents supporting their children in their studies (teaching practices), the relation between "parental economic ability" (owing to their educational attainment) and their children's education (funding), educated parents more likely to be residing in educated neighbourhoods (peer effects and externalities) (Becker & Tomes, 1979; Benabou, 1996; Hertz et al., 2007; Bussolo, Checchi & Peragine, 2017).

There are other cogent reasons behind our choice of education as a lens to study intergenerational mobility. Education is less prone to errors than income in terms of measurement, and in case of developing countries data on educational outcomes/attainment is mostly available unlike data on earnings, which is not reported in a typical household survey (Azam & Bhatt, 2015). Also, once an individual reaches mid-twenties, formal education gets fixed. This precludes life cycle biases which occur in the case of income measurement as they are volatile and age-dependent (Haider & Solon, 2006; Black & Devereux, 2011). It is cited in Hertz et al. (2007) that even though the "*main role of education is to promote social mobility*", however, at the same time "education is also *the main vehicle of social reproduction*" (Ganzeboom, Treiman, & Ultee, p. 284). Thus, the examination of equality or inequality of opportunity through the lens of education makes for an interesting and relevant study.

In this paper, we employ the latest round (2011-12) of Indian Human Development Survey (IHDS-II) data and utilize the retrospective information provided for the educational attainment of the father/husband of the male/female head of the household to prepare a representative dataset consisting of 44,532 adult males (age group 25-64) with paired educational details of their respective fathers. The retrospective information helps to preclude the 'co-resident only' sample restriction. Subsequently, apart from checking as well as updating the numbers (for the trends in intergenerational education mobility), we make two main contributions to the literature on intergenerational mobility in India. One, we explore the non-linearities in the intergenerational education relationship by employing quantile regressions. Two, we check if the 'Great Gatsby Curve' phenomenon, i.e. a negative relationship between income inequality and intergenerational mobility, works out in the case of 'education inequality – intergenerational education mobility' in India. Additionally, we estimate the effect of economic growth and public investment in education on intergenerational transmission of educational advantage or disadvantage.

The following are the main findings of the study – The intergenerational persistence in education remains high, i.e. a son's educational achievements are closely tied to his father's status, although the degree of such dependence has reduced since independence. The intergenerational mobility is higher among Brahmins and upper castes as compared to other backward castes, scheduled castes and scheduled tribes. Similarly, Hindus are held back by their circumstances to a much lower extent compared to the Muslims. Next, the quantile regression findings point to a non-linearity in the relationship between fathers' and sons' schooling outcomes along the education distribution. Moreover, the mobility gap between an urban citizen and a rural resident, a person belonging to the youngest age cohort vs one belonging to the oldest cohort, an upper caste Indian vs an OBC/SC/ST, a Hindu vs a Muslim, increasingly widens along the middle and upper quantiles of the educational distribution. Finally, we obtain a negative relationship between education inequality in the fathers' generation and the intergenerational mobility in education, thus confirming the 'Great Gatsby Curve' phenomenon. Also, both economic growth and public spending in education bear a positive relationship with education mobility, lending credence to their respective roles in levelling the playing field.

2. Review of Literature

Most of the literature on intergenerational mobility is rooted in Becker and Tomes' (1979) theory that incorporates the human capital approach to inequality. The authors establish determinants of intergenerational mobility through their models. A child's future outcomes are dependent on the degree of inheritability of endowments (of multiple traits including IQ, ability, and reputation), parents' propensity to invest in her human capital, and a random 'luck' component. According to Becker and Tomes (1979), other factors such as rate of economic growth, tax-subsidy and public expenditure systems, and discrimination against minorities, sometimes, have surprising implications on intergenerational transmission of advantage. Based on Becker and Tomes (1979), Solon (1999) presents an interpretation of the intergenerational income correlation via a theoretical model and extends the model in Solon (2004) to account for public investment in children's human capital which in turn may be progressive apropos of parental income. Consonant with expectation, the model has intergenerational income mobility increasing in the progressivity of public investments in human capital.

The model in Solon (2004) also depicts the theoretical framework intrinsic to the standard empirical procedure of estimating intergenerational persistence wherein the correlation/elasticity between the socioeconomic status of parents and their adult children is computed. The sign and magnitude of these correlations can help evaluate a society's success or failure in providing equality of opportunity to children from various family backgrounds based on the rate of transmission of inter-personal equality (Hertz et al., 2007). Most of the earlier studies dealt with computation of precise estimates of such correlations and elasticities for either a cross-section of countries (Corak, 2006; Jäntti et al., 2006; Hertz at al., 2007; Blanden, 2009) or individual countries – Sweden and US (Björklund & Jäntti, 1997), Germany (Couch & Dunn, 1997), United Kingdom (Dearden, Machin & Reed, 1997), Canada (Corak & Heisz, 1999).

Hertz et al. (2007) estimate 50-year trends in intergeneration education persistence for 42 countries (a mix of developed and developing countries) using comparable data and variable definitions. The regression coefficient demonstrates that the impact of parents' fortune on children's outcomes has decreased over time. On the other hand, for the countries in the sample, the intergenerational correlation coefficient has held steady, on an average, for a century. While the Latin American countries display the highest persistence, the Nordic countries stand out for their relatively higher measure of mobility.

Since Solon (1999), there has been a shift in favour of investigating the causal mechanisms that are fundamental to the association between a child's life chances and her parents' socioeconomic status (Black & Devereux, 2011). The channels have ranged from the predetermined genetic component to the part explained by an individual's childhood environment.

Using sibling correlation as a measure of intergenerational mobility, Björklund, Eriksson and Jäntti (2010) delineate the effect[1] of shared parental and neighbourhood factors on an individual's IQ, and hence her abilities. Bowles and Gintis (2002) decompose the intergenerational status (income or earnings) correlation into direct and indirect (child's IQ, schooling, etc.) components and note that IQ, race, and schooling can explain up to seven-tenths of the intergenerational transmission of the status. In view of the 'nature vs nurture' debate, by estimating the standard intergenerational regression models separately for Korean-American adopted children and their non-adopted American siblings, Sacerdote (2007) finds evidence[2] supporting the thesis that genetics and infant endowments matter more than nurture in influencing education outcomes of individuals. Adopting the IV approach, Oreopoulos, Page and Stevens (2008) use father's displacement from work as a source of variation in his income, unrelated to any other of his characteristics, to find the effect on children's outcomes. Employing

[1] Using IQ data from Swedish Military Enlistments tests, Björklund, Eriksson and Jäntti (2010) obtain a correlation of 0.347 between fathers IQ and sons IQ. The corresponding correlation between brothers IQ is 0.473 underlining the importance of family background (to the extent of almost 50%) on the IQ of individuals.

[2] Sacerdote (2007) regressed the child's years of schooling on mother's years of schooling and obtained a coefficient of 0.09 for the adoptees and 0.32 for the non-adoptees.

Canadian Administrative panel, they detect a nine per cent difference in annual earnings in favour of sons whose respective fathers didn't get displaced as compared to similar sons whose respective fathers experienced employment shock.

The causal estimates obtained by different identification strategies (identical twins, adoptees, IV estimation) and across different countries differ on account of systematic differences in identification strategies, and the violation of their internal or external validity assumptions. Different strategies tend to focus on different parts of socioeconomic status distribution; while twins are spread evenly across the status distribution, adopted children generally belong to the higher end of the distribution, and employment shocks, on an average, affect those belonging to the lower end of the distribution (Holmlund, Lindahl & Plug, 2011). Thus, as a part of this paper, we shall explore the extent of such non-linearities in the intergenerational education relationship.

2.1. The Indian Setting

India's economic growth since the 1980s has been concurrent with increasing inequalities in outcomes and consequently raises a concern of whether it reflects inequalities in opportunities in the society. As it is, the Indian society is deeply stratified by caste and beset by poor outcomes and low mobility (Gupta, 2004). And, this lack of mobility, as Maitra and Sharma (2009) contend, excludes many parts of our society from reaping rewards of the prolific levels growth the country has experienced during the last two decades.

The empirical literature on intergenerational mobility in India is scarce (Maitra & Sharma, 2009; Hnatkovska, Lahiri & Paul, 2013; Emran and Shilpi, 2015). The earliest paper in this regard is by Jalan and Murgai (2008) who use two rounds of National Family Health Survey (NFHS) in 1992-93 and 1998-99 to study inequalities in educational attainments and its persistence across generations for different groups of population in India. The results reflect significant and consistent improvements in education mobility and decreasing education gaps between various caste groups once other characteristics are controlled for.

Maitra and Sharma (2009) examine the intergenerational transmission of human capital by analyzing the role of two aspects of parents' education on child's educational attainment – the number of years of schooling and progression across different levels of schooling. Using data from the first round of the Indian Human Development Survey (IHDS) in 2004-05, the authors employ IV strategy. The findings affirm the results obtained by Jalan and Murgai (2008). One, there has been a significant increase in educational attainment over the last few decades and that the influence of parents' education on the education of their children is little, stressing upon the fact that public investments in education matter much more over private investments. Two, the sequential probit analysis of the school progression shows that while mother's education is an important determinant at the start of children's schooling and the middle school, father's education becomes crucial in the decision for the child to continue beyond post-secondary levels.

Employing successive thick rounds of National Sample Survey (NSS) Employment-Unemployment surveys during the period 1983 - 2005, Hnatkovska, Lahiri and Paul (2013) compare the intergenerational mobility rates of scheduled castes (SC) and scheduled tribes (ST) against the non-SC/ST households in terms of educational outcomes, occupation choices and wages. The results indicate that convergence has taken place in the intergenerational mobility rates, more so in case of educational attainment and wages, between the SC/STs and the others; although the non-SC/STs are still more likely to work in a different profession than their parents as compared to their SC/ST counterparts and their parents. Another key finding here is that the mobility improvement in education and income has occurred for both low and highly educated/ high-income households among SC/STs. The authors attribute these improvements in mobility rates to the structural changes in India during the period of research.

Azam and Bhatt (2015) make use of retrospective information, provided in IHDS-I, on father's/husband's educational attainment of the head of the household to create son-father matched pairs[3] representative of the adult male population of India. Through cohort analysis, they examine the trends in intergenerational education mobility. Contrary to the results obtained in Jalan and Murgai (2007) and Maitra and Sharma (2009), Azam and Bhatt observe a high degree of intergenerational stickiness in educational attainment. While intergenerational regression coefficient (elasticity) displays a falling trend, the intergenerational correlation coefficient shows no such decline over time. To tell apart the incompatibility in results, Azam and Bhatt (2015) decompose the intergenerational correlation and find that whilst mobility has improved at the lower end of the fathers' educational distribution, it has declined at the top end of

[3] In this pairing, all sons aged 20 – 65 (born between 1940 and 1985) were considered. The sons were subsequently resolved into nine birth cohorts of five-year intervals (1940-45, 1946-50, . . . 1981-85).

the distribution, thus giving rise to a neutral trend in the overall correlation between fathers and sons education. Owing to the comparability of IHDS data to the data set used by Hertz et al. (2007), the authors rank the average intergenerational correlation coefficient obtained for India against 42 nations following Hertz et al. (2007). While India fares better than Latin American countries in terms of educational mobility, its intergenerational educational persistence is higher than the World average and expectedly does worse than Western and Eastern Europe. An earlier study by Motiram and Singh (2012) complements these results with its take on intergenerational occupational mobility in India where the authors detect considerable occupational persistence, although with differences across occupational categories. Persistence in low-skilled/low-paying occupations for SC/STs is higher as compared to the same for non-SC/STs.

Emran and Shilpi (2015) draw on 1992-93 and 2006 rounds of NFHS and report Sibling Correlation (SC) and Intergenerational Correlation (IGC) for similar age cohorts as other studies. They detect strong intergenerational persistence in education (greater than in Latin America), largely unchanged over time of the study. The only improvements were those observed in the case of urban women, especially the low caste ones. Even after 15 years of liberalization, the sibling and intergenerational coefficients have declined only marginally and indicate more adverse equality of opportunity as compared to Latin American countries and other Asian countries. When accounted for neighbourhood fixed effects, geographic location emerged as an important factor in the measurement of sibling correlation and intergenerational correlation. For example, the SC is higher for urban men as compared to rural men, indicating a higher inequality of opportunities for the urban men.

In a later study, Emran, Greene and Shilpi (2017) illustrate the merit behind the preference of IGC over Intergenerational Regression Coefficient (IGRC), especially in the context of developing countries where data limitations restrict the study of the phenomenon to co-resident samples only. Using a simple model of truncation[4] followed up by an empirical exercise on household surveys of India and Bangladesh, the authors find a significant downward bias in IGRC as compared to IGC when the sample consideration is reduced to co-resident cases. Moreover, the downward truncation bias in IGRC (when compared to the bias in IGC) is inversely proportional to the extent of co-residency rates observed in the data. From this, it can

[4] Truncation in the data is due to children leaving their parental household.

be inferred that IGRC remains a sizably robust measure of interpreting intergenerational mobility in either of the two situations. One, the co-residency rates are high in the population. Two, parent-child pairs bearing the requisite information (on education, income, or occupation) can be created irrespective of whether they are co-resident in a household.

From the literature discussed so far, it is clear that the studies on intergenerational educational mobility in India have differed over the choice of measures and selection of data sources. Although a consensus doesn't emerge, some studies agree upon there being improvements in education mobility in India and attribute various reasons to the process ranging from structural changes following liberalization to the success of positive discrimination policies. However, to our knowledge, there is a paucity of literature in the Indian context to have dealt with ascertaining the channels underlying the transmission of advantage from one generation to its next. We investigate the effect of a few macro-level factors on intergenerational education mobility as a part of this study.

3. Variables and Data

Most evaluations on intergenerational mobility are carried out by either assessing variables across a repeated cross-section of the population or by measuring the variables across age-cohorts (Bussolo, Checchi & Peragine, 2017). In this study, we initially conduct a baseline analysis of the trends in intergenerational education mobility by dividing the sample of individuals into five and ten-year birth cohorts and estimating the following model -

$$S_i = \beta_0 + \beta_1 F_i + (\text{Controls}) + \epsilon_i$$

where, S_i denotes the number of years of schooling of the i^{th} son, F_i (the circumstance variable) is i^{th} father's educational attainment in terms of his completed years of schooling, and ϵ_i encapsulates the unobserved elements such as ability or/and effort of the individual. β_1 is the main variable of interest and is termed Intergenerational Regression Coefficient (IGRC). β_1 essentially captures the sensitivity of the expected educational outcome of the sons to unit changes in the educational attainment of the fathers. It conveys how strongly past circumstances affect the educational attainment of the son and in turn, his life chances. A value of zero denotes perfect mobility, and a value of one means perfect rigidity.

Each of the earlier mentioned strategies is further divided in their adoption of either co-resident household approach or two-sample instrumental variables approach (Mohammed, 2016). The three major sample surveys in India – NSSO, NFHS, and IHDS – amply facilitate co-resident household approach. However, consideration of only co-resident son-father pairs might generate attenuation bias as cohabitation might be systematically linked to decisions regarding human capital investments in a household. Moreover, as averred by Motiram and Singh (2012), we would be missing out on single-member households, two-member households consisting of husband and wife, and nuclear families (husband, wife, and children), which would by itself lead to a substantial loss in observations. Further, the nuclear family structure, which characterizes a significant proportion of the urban-middle-class households in the contemporary age and time, would be grossly underrepresented in a 'co-resident only' sample.

In part one of this study (Baseline Analysis and Trends), we resort to comparing β_1 across age-cohorts for – (i) Overall sample, (ii) Social classes, and (iii) Religions. We employ the data from the second round of the Indian Human Development Survey (IHDS-II) conducted in 2011-12. IHDS is a collaborative project between National Council of Applied Economic Research (NCAER) and the University of Maryland. IHDS-II is nationally representative and covers 42,152 households in 1420 villages and 1042 urban neighbourhoods across India. The survey includes household information on education, health, employment, economic status, social capital, fertility, etc.

With regards to the data requirements for this study, IHDS offers distinct advantages over NSSO and NFHS. One, both NSSO and NFHS report information on levels of schooling completed and thus entails imputation of the number of years of schooling resulting in discontinuities. IHDS, on the contrary, reports data on the actual number of completed years of schooling. Two, more importantly, IHDS contains retrospective questions[5] which expand the scope of the sample to those beyond co-resident pairs of father-son and hence precludes biases due to consideration of co-resident pairs alone.

We start by preparing a dataset in alignment with the one by Azam and Bhatt (2015) which they created for IHDS-I. The dataset is unique in the sense that in addition to matching father-son data

[5] Question 1.18c on page 3 of the Income and Social Capital Questionnaire. It enquires the educational attainment (in years of schooling completed) of the father/husband of the head of the household.

based on "Relationship to head of household" field in the household questionnaire which only ends up linking the co-resident pairs, we also use the retrospective question pertaining to the educational attainment of the head of the household[6]. The final sample consists of 44,532 observations with matched information on their respective father's educational attainment. We exclude females in this analysis due to following reasons – One, households with women as head are very few (2.95% of all cases). Even for such households, education data is provided for their husbands. Hence, the unique feature (refer to footnote 5) of the IHDS data cannot be utilized for daughter-father, daughter-mother, or son-mother pairing to create a representative sample of such pairings. Two, given the ubiquitous family structure in India, adult females reside in either nuclear households or joint families along with their respective husbands and kin belonging to the husband's side. Hence, the requisite pairing information is not available for a purported representative sample even if we just wish to consider just the co-residency condition. The downward bias due to such truncation is explained well through a simple model in Emran, Greene, and Shilpi (2017).

Next, using a simple OLS framework, we estimate several variants of the following base model –

$$S_i^c = \beta_0^c + \beta_1^c F_i^c + \gamma^c(\text{Social Class}) + \delta^c(\text{Religion}) + \sigma^c(\text{State}) + \epsilon_i^c$$

where, S_i^c and F_i^c have been defined earlier but appear with a superscript 'c' here that denotes the age cohort. We divide the sample into eight five-year age cohorts – 25-29, 30-34, 35-39, . . ., 60-64, and two ten-year age cohorts – 25-34 and 55-64. The ages of the respective individuals are as of the year 2011. Dummies for social classes are assigned in accordance with caste divisions as per IHDS – Brahmin, Forward/General (excluding Brahmin), OBC, SC, ST, and Others. Similarly, religion dummies are assigned to Hindus, Muslims, Christians, Sikhs, and Others (Buddhists, Jains, etc.). In all the specifications, IGRC[7] is preferred over IGC as we are more interested in understanding the trends and evolution of intergenerational education mobility, albeit unconditional on the dispersion of educational outcomes for each generation across various

[6] Co-resident pairs make up for only 34.58% of the adult male respondents (aged 20–65). In our final dataset, however, we capture 96.73% of the males in the said age group. At the last count, we drop those in the age group 20-24 as 27.01% of them are still enrolled in schools and run with adult male respondents in the age group 25-64.

[7] As clarified by Lefranc (2011), we take IGRC (i.e. β_1^c) to be a 'catch-all' measure of intergenerational education persistence that encompasses all possible channels of transmission.

cohorts and groupings. Moreover, since we have precluded the attenuation bias arising from the consideration of co-resident pairings alone, our approach can be considered robust.

4. Summary Statistics

Data summary for the sample is presented in tables 1 and 2. The overall sample contains information concerning the individual's and his father's respective educational attainments amongst other variables for 44,532 males in the age group 25-64. The rationale behind age bounds is borrowed from Behrman et al. (2001). The age floor ensures the inclusion of individuals who have completed their schooling; the age ceiling helps in preventing selection bias due to different survival rates of individuals hailing from different family backgrounds.

Table 1

Summary Statistics for the overall sample and other groupings

Variable	Observations	Mean	Std. Dev.	Min	Max
		Overall			
yrssch	44,532	7.331	4.942	0	16
fatheryrssch	44,532	3.422	4.362	0	16
		Rural India			
yrssch	28,138	6.306	4.791	0	16
fatheryrssch	28,138	2.487	3.723	0	16
		Urban India			
yrssch	16,394	9.092	4.695	0	16
fatheryrssch	16,394	5.027	4.880	0	16
		Brahmins and Other Upper Castes			
yrssch	13,124	9.117	4.755	0	16
fatheryrssch	13,124	5.071	4.891	0	16
		Other Backward Castes (OBCs)			
yrssch	17,981	7.084	4.743	0	16
fatheryrssch	17,981	3.150	4.081	0	16
		SCs and STs			
yrssch	12,702	5.835	4.842	0	16
fatheryrssch	12,702	2.094	3.551	0	16
		Hindu			
yrssch	36,369	7.474	4.930	0	16
fatheryrssch	36,369	3.464	4.383	0	16
		Muslim			

yrssch	5,264	5.910	4.900	0	16
fatheryrssch	5,264	2.787	4.023	0	16
		Others (Christians, Sikhs, Jains, etc.)			
yrssch	2,899	8.124	4.709	0	16
fatheryrssch	2,899	4.046	4.553	0	16

Notes: yrssch – Years of schooling of the individuals; fatheryrssch – Years of schooling of an individual's father; Rural/Urban classification is as per 2011 census.

In the overall sample and all other groupings, sons unequivocally have a higher mean educational attainment than fathers. We observe that the level of educational attainment is higher in urban India as compared to rural India for both fathers and sons. As for caste groups, Brahmins and other upper castes are significantly more educated than the lower castes. And, as far as religious groups are concerned, while Muslims are the least educated, the average educational outcomes for the rest of the population that includes Christians, Sikhs and Jains, are better than those of Hindus.

Table 2

Summary Statistics by age cohorts

Son's Age Cohort	Sample Size	Percent	Average Years of Schooling	
			Son	Father
25-29	7,827	17.58	8.842	4.658
30-34	6,702	15.05	8.213	4.214
35-39	6,524	14.65	7.865	3.627
40-44	5,943	13.35	7.151	3.175
45-49	5,738	12.89	6.499	2.734
50-54	4,660	10.46	6.332	2.776
55-59	3,882	8.72	5.989	2.493
60-64	3,256	7.31	5.645	2.109
Total	44,532	100		

Notes: The ages are as of the year 2011. Thus, the age cohorts could also be understood as the following respective birth cohorts – 1982-1986, 1977-1981, 1972-1976, 1967-1971, 1962-1966, 1957-1961, 1952-1956, and 1947-1951.

In table 2, we report the sample means of education attainment by age/birth cohorts. All cohorts are well represented in terms of their respective sample sizes. This data showcases that there has been a clear and steady growth in educational attainment over the years and across generations.

Sons have consistently exceeded their fathers w.r.t. the time they have spent in school since India's independence in 1947.

5. Baseline Analysis and Trends

In table 3, we lay out the OLS estimation results for the overall sample. For the base specification, the estimated intergenerational education coefficient is 0.588. The statistical and economic significance of the estimate underscores a high degree of dependency of an individual's life chances on his father's status. Next, we apply controls to account for factors that could have a bearing on schooling achievements of individuals. There is evidence available in literature regarding how caste plays a role in school participation of individuals (E.g. in Hickey & Stratton, 2007), how there exists a link between religion and education (E.g. in Booroah & Iyer, 2005), and how educational opportunity differs across states in India (Asadullah & Yalonetzky, 2012). Hence, we control for the three factors by employing respective dummy variables. From the last row, it is evident that the fit of the model improves with the addition of each control. Once the controls are accounted for, the degree of persistence decreases, in turn underlining the importance of caste, state, and religion in inequality of opportunity debate. The statistical significance of the results remains robust to the addition of controls. We also employed the Wald test to check for the equality of the coefficients on fathers' educational attainment across all specifications. Apart from the IGRCs obtained for specifications (1) and (4)[8], we fail to reject the null hypothesis of the equality between any two IGRCs in table 3 at 10% significance level[9].

Table 3[10]

Intergenerational Regression Coefficients (All India)

[8] Test – H_0: IGRC in (1) = IGRC in (4); F(1, 44526) = 1.88; Prob > F = 0.1703. We fail to reject the null hypothesis.

[9] Test – H_0: IGRC in (5) = IGRC in (7); F(1, 44368) = 2.93; Prob > F = 0.0863. We fail to accept the null hypothesis at the level of significance of 10%.

[10] We also estimate IGRCs for – one, the co-resident son-father pairs which captures only 26.63% of sons in the age group 25-64. We compute the truncation bias that creeps in due to the neglect of non-co-resident pairs. Two, by including mothers and daughters in the sample; we consider all sons and daughters in the age group 11-64 who are no longer enrolled in school and are co-resident with their respective fathers and mothers. Both sets of results can be found in the Appendix A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	yrssch	yrssch	yrssch	yrssch	yrssch	yrssch	yrssch
fatheryrssch	0.588***	0.544***	0.534***	0.582***	0.529***	0.570***	0.522***
	(0.00405)	(0.00426)	(0.00430)	(0.00406)	(0.00428)	(0.00413)	(0.00433)
cons	5.318***	7.131***	7.325***	5.456***	7.233***	6.684***	8.140***
	(0.0271)	(0.0827)	(0.162)	(0.0290)	(0.0824)	(0.145)	(0.165)
Caste Controls	No	Yes	Yes	No	Yes	No	Yes
State Controls	No	No	Yes	No	No	Yes	Yes
Religion Controls	No	No	No	Yes	Yes	Yes	Yes
N	44532	44411	44411	44532	44411	44532	44411
adj. R-sq.	0.270	0.287	0.306	0.276	0.299	0.296	0.316

Notes: Standard errors clustered at household level in parentheses; * p<0.05, ** p<0.01, *** p<0.001

Overall, the above results agree with the mobility estimates obtained in Azam and Bhatt[11] (2015) and Emran and Shilpi[12] (2015) but are a departure from the estimates in Jalan and Murgai[13] (2007) and Maitra and Sharma[14] (2009).

5.1. Intergenerational Education Mobility Across Cohorts

Here, we look at how educational mobility has evolved since independence. For this purpose, we perform a cohort trend analysis by estimating IGRCs in respective OLS regression models for each of the five-year age/birth cohorts. Table 4 presents the estimation results.

Table 4

Age cohort trend in Intergenerational Regression Coefficients (All India) (in presence of controls)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-64
fatheryrssch	0.430***	0.449***	0.444***	0.503***	0.498***	0.565***	0.609***	0.637***

[11] Azam and Bhatt (2015) obtained an IGRC of 0.634 from a similar exercise performed on IHDS-I data.
[12] Emran and Shilpi (2015) estimated sibling correlation (SC) ranging from 0.614 to 0.624 for brothers over two rounds of NFHS data (1993 and 2006). They also calculate IGCs for the males which come out to be 0.541 and 0.523 respectively for the two rounds.
[13] Jalan and Murgai (2007) worked with the 1998-99 round of NFHS and obtained IGRC estimates ranging from 0.236 for the 1969-1973 birth cohort of males to 0.153 for the males in the 1979-1983 birth cohort.
[14] The IGRC estimates for urban males and rural males in Maitra and Sharma (2009) stand at 0.3332 and 0.3831 respectively. Their study is based on IHDS-I data.

	(0.0098)	(0.0103)	(0.0109)	(0.0128)	(0.0140)	(0.0158)	(0.0169)	(0.0209)
cons	9.528***	9.357***	8.456***	7.210***	8.575***	7.333***	7.216***	7.315***
	(0.361)	(0.447)	(0.451)	(0.501)	(0.516)	(0.475)	(0.469)	(0.650)
Caste Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Religion Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7799	6681	6505	5933	5726	4651	3872	3244
adj. R-sq.	0.300	0.316	0.285	0.304	0.302	0.356	0.356	0.330

Notes: Standard errors clustered at household level in parentheses; * p<0.05, ** p<0.01, *** p<0.001

Progressing along the cohorts (from older to younger), there is a reduction in intergenerational persistence in educational attainments, although the decrease in non-monotonic (For example, in table 4, IGRC at age cohort of 40-44 is marginally higher than IGRC at 45-49, although the difference is not statistically significant). Father's education has a consistently positive and statistically significant effect (at a significance level of one per cent) on the son's education across all cohorts and even after accounting for caste, state, and religion differences. A decrease in IGRC from 0.637 (highly persistent relationship) for the oldest birth cohort (1947-1951) to 0.430 (moderately persistent) for the youngest birth cohorts (1982-1986) augurs well in the society’s path towards greater mobility, and in turn towards facilitating an economic environment of a greater equality of opportunity.

Considering the role caste and religion play in determining socio-economic outcomes and status in India, we determine the IGRC estimates for Brahmins and other Upper Castes, Other Backward Castes (OBCs), Scheduled Castes and Scheduled Tribes (SCs and STs), Hindus, and Muslims by age cohorts (the youngest 10-year age cohort – 25 to 34, and the oldest 10-year age cohort – 55 to 64) to understand its evolution in the subsamples and differences between them. These estimates are displayed in tables 5 and 6.

Table 5

Cohort trends in Intergenerational Regression Coefficient by Caste

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	Brahmins and Other UCs		OBCs		SCs and STs	
	25-34	55-64	25-34	55-64	25-34	55-64
fatheryrssch	0.422***	0.596***	0.449***	0.601***	0.447***	0.670***

	(0.0126)	(0.0188)	(0.0119)	(0.0221)	(0.0149)	(0.0376)
cons	9.190***	6.870***	8.511***	4.372***	7.549***	5.134***
	(0.357)	(0.450)	(0.612)	(0.691)	(0.431)	(1.146)
State Controls	Yes	Yes	Yes	Yes	Yes	Yes
Religion Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	4042	2217	5919	2931	4313	1882
adj. R-sq.	0.337	0.359	0.271	0.233	0.228	0.237

Notes: Standard errors clustered at household level in parentheses; * p<0.05, ** p<0.01, *** p<0.001

Table 6

Cohort trends in Intergenerational Regression Coefficient by Religion

	(7)	**(8)**	**(9)**	**(10)**
	Hindu		Muslim	
	25-34	55-64	25-34	55-64
fatheryrssch	0.426***	0.599***	0.533***	0.650***
	(0.00813)	(0.0146)	(0.0237)	(0.0452)
cons	8.595***	7.592***	7.159***	3.338***
	(0.326)	(0.492)	(0.404)	(0.498)
Caste Controls	Yes	Yes	Yes	Yes
State Controls	Yes	Yes	Yes	Yes
N	11700	5858	1899	771
adj. R-sq.	0.292	0.351	0.335	0.277

Notes: Standard errors clustered at household level in parentheses; * p<0.05, ** p<0.01, *** p<0.001

Within all categorizations in tables 5 and 6, there is a conspicuous improvement in education mobility across back-to-back generations since independence. The pace of this progress is different for different groups, though. Thanks to affirmative action policies (in education, public sector jobs, and state legislatures) by the government, especially in favour of SCs and STs, the improvement in their education mobility has happened at a faster rate as compared to the upper castes and the OBCs. IGRC for SCs and STs has fallen by 33.28% over 30 years as compared to 25.29% for OBCs and 29.19 per cent for the upper castes. Our arguments are in consonance with the general narrative (Jalan & Murgai, 2007; Hnatkovska, Lahiri & Paul, 2013). In fact, in addition to the reason mentioned earlier, Hnatkovska, Lahiri and Paul (2013) attribute breaking down of the caste-based shackles towards mobility on structural changes in the Indian economy in the last two decades, as well.

Apropos grouping by religion, Hindus have held precedence over Muslims in case of educational mobility. Moreover, the percentage decrease in intergenerational persistence across cohorts separated by 30 years for Hindus (at 28.88%) is more than 1.5 times than for Muslims (18%). The IGRC for Muslims in the age cohort of 25-34 is also much higher than the IGRC for the overall sample in that age cohort. The status of Muslims continues to be majorly hindered by their previous generations.

6. Nonlinearities

The standard intergenerational education persistence model assumes a linear relationship between son's and father's educational attainments. However, several studies have shown, theoretically and empirically, that the relationship could be non-linear across the educational distribution in view of credit market imperfections, differences in intra-family altruism, indivisibility of investment in human capital, neighbourhood effects etc. (Becker & Tomes, 1979, 1986; Galor & Zeira, 1993; Grawe, 2004; Jantti et al., 2006; Bratsberg et al., 2007). Chusseau, Hellier and Ben-Halima (2013) reason that intergenerational persistence is high at the lower end of the educational distribution due to under-education and poverty traps. As for high intergenerational persistence at the other end of the spectrum, they argue that highly placed families pass on the advantage to its next generation.

Building on the work of Becker and Tomes (1986), Bratsberg et al. (2007) stress on appropriately understanding the functional form of intergenerational earnings relationships across countries before making cross-country comparisons. Since education acts as the transmission mechanism in this relationship (Solon, 2004), it is essential to account for the functional form of intergenerational educational relationship as well. In figure 1, we fit a Lowess curve to represent the functional form between sons' and fathers' educational attainments.

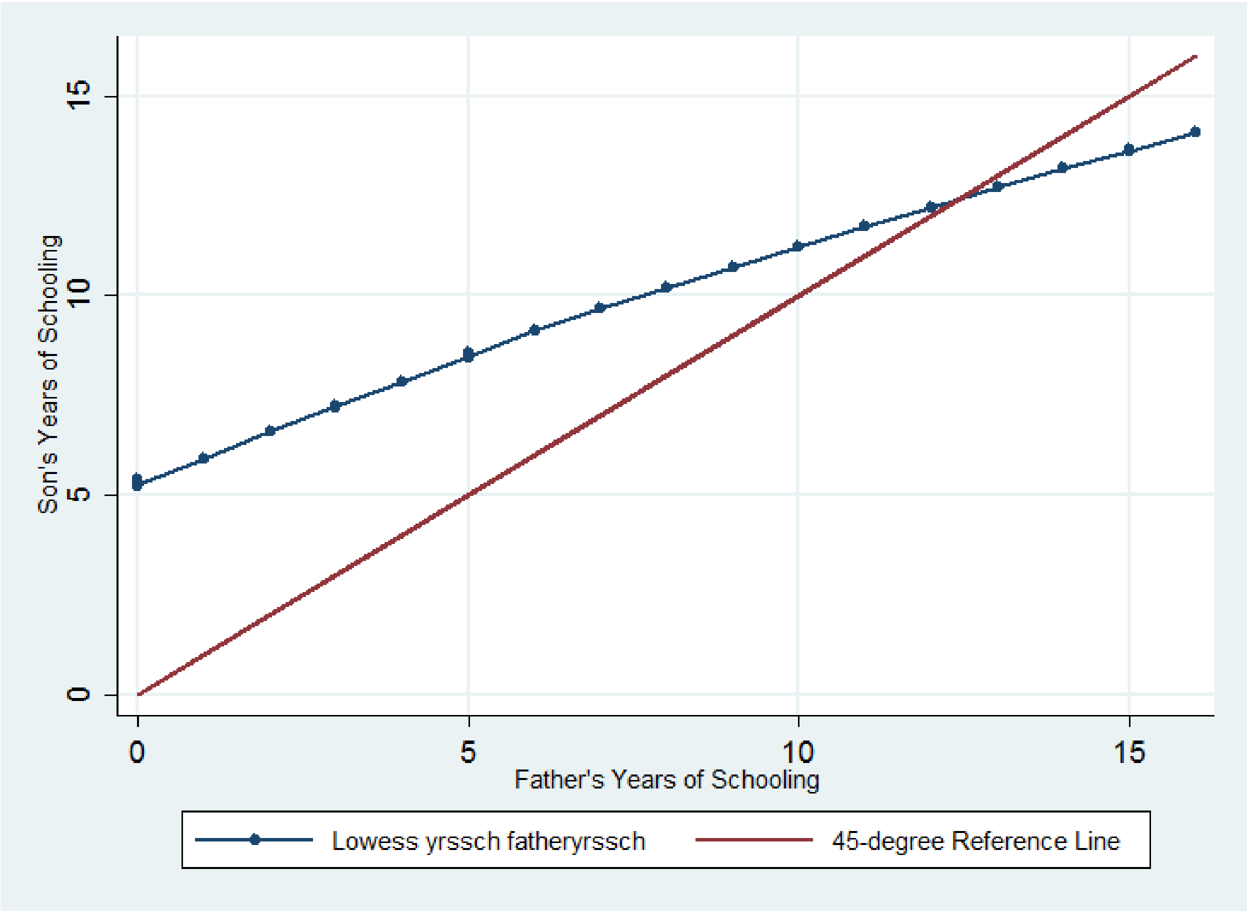

Figure 1. *Lowess plot of sons' and fathers' educational attainments in India*

The Lowess plot clearly indicates a non-linear relationship between sons' and fathers' educational outcomes. The sons' education profile appears flat at the top and steeper at the bottom of fathers' educational distribution. Hence, the high value of IGRC (from the previous section) overstates the educational persistence at the upper parts of the educational distribution. The concave shape of the curve corroborates with Becker and Tomes' (1986) conjecture of concavity in the face of imperfect capital markets. Thence, we infer that, in India, the credit constraints impact the poorest fathers and render them incapable of borrowing against their sons' future income/human capital potential. In absence of redistributive education policies that ensure basic education irrespective of socioeconomic status, a disadvantaged Indian son experiences strong intergenerational continuance.

To empirically assess the differences in effects of father's education on son's education along the distribution of the sons' educational attainments, we employ quantile regression. The following specification is estimated for the overall sample and subsamples –

$$Q_{\theta}(S_i/F_i) = \beta_0 + \beta_{\theta} F_i + \epsilon_i$$

where, $Q_{\theta}(S_i/F_i)$ represents θth centile of the distribution of the son's educational attainment conditional on father's years of schooling. The estimates are presented in table 7.

Table 7

Intergenerational Regression Coefficients along the distribution of sons' years of schooling (Dependent Variable – 'yrssch')

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Quantile (.10)	Quantile (.20)	Quantile (Median)	Quantile (.60)	Quantile (.75)	Quantile (.90)	Quantile (.95)
			All India				
fatheryrssch	0.667***	0.900***	0.667***	0.500***	0.438***	0.333***	0.200***
	(0.017)	(0.018)	(0.006)	(0.007)	(0.010)	(0.008)	(0.023)
cons	0	0	5***	7***	9***	12***	14***
	(0.100)	(0.110)	(0.030)	(0.040)	(0.060)	(0.080)	(0.130)
N	44532	44532	44532	44532	44532	44532	44532
			Rural Sample				
fatheryrssch	0.600***	0.833***	0.583***	0.500***	0.455***	0.500***	0.400***
	(0.059)	(0.038)	(0.007)	(0.008)	(0.005)	(0.010)	(0.013)
cons	0	0	5***	6.500***	8.182***	10***	12***
	(0.337)	(0.217)	(0.054)	(0.061)	(0.062)	(0.088)	(0.074)
N	28138	28138	28138	28138	28138	28138	28138
			Urban Sample				
fatheryrssch	0.750***	0.857***	0.500***	0.467***	0.400***	0.250***	0.0909***
	(0.032)	(0.019)	(0.007)	(0.006)	(0.004)	(0.034)	(0.006)
cons	0	0.714***	7***	8***	10***	13***	15***
	(0.217)	(0.182)	(0.052)	(0.049)	(0.027)	(0.274)	(0.043)
N	16394	16394	16394	16394	16394	16394	16394
			Age Cohort: 25-34				
fatheryrssch	0.714***	0.800***	0.455***	0.438***	0.467***	0.333***	0.111***
	(0.029)	(0.021)	(0.011)	(0.006)	(0.010)	(0.014)	(0.007)
cons	0	1***	7***	8***	9***	12***	14.78***
	(0.187)	(0.183)	(0.072)	(0.024)	(0.084)	(0.094)	(0.086)
N	14529	14529	14529	14529	14529	14529	14529

			Age Cohort: 55-64				
fatheryrs sch	0.667***	0.938***	0.733***	0.700***	0.533***	0.600***	0.500***
	(0.105)	(0.073)	(0.023)	(0.018)	(0.024)	(0.014)	(0.024)
cons	0	0	4***	5***	8***	10***	12***
	(0.597)	(0.413)	(0.148)	(0.080)	(0.088)	(0.025)	(0.135)
N	7138	7138	7138	7138	7138	7138	7138

Notes: Standard errors clustered at household level in parentheses; * p<0.05, ** p<0.01, *** p<0.001

It is clear from table 7 that the effect of fathers' education on sons' schooling is not linear[15] along the sons' schooling attainment distribution as IGRCs estimated at different centiles of the distribution are not equal. Apropos of regressions for each subsample, we observe a vaguely similar general trend. If we exclude sons with zero or very low educational attainments and thus restrict the sample to between 20th and 95th centile of son's educational distribution, intergenerational mobility in education (1 – IGRC) displays an increasing trend; although in some cases, the increase in non-monotonic. For the overall sample, the mobility stands at a value of 0.1 at the 20th percentile, and then maintains an upward trend along the rest of the distribution to reach an (almost) peak value of 0.8 at the 95th percentile. This means that the individuals at the highest point of educational attainment are the ones who are least bounded by their circumstances. Even for the rest of the subsamples (rural, urban, youngest 10-year age cohort, oldest 10-year age cohort), this holds true, albeit to different extents.

Rural inhabitants are often impeded by the lack of economic and educational opportunities as compared to their urban counterparts. As evident in the second and third panel of table 7, urban areas promote greater education mobility compared to rural regions. From the bottom two panels of table 7, we can safely contend that there has been a marked improvement in educational mobility over time at almost all points of the distribution. Next, we graphically present quantile regression IGRC plots through figures B.1 to B.10 in Appendix B. In addition to the overall sample and sub-groups in table 7, we include plots for caste groups (Hindus and other upper castes, OBCs, SCs and STs) and religion subsamples (Hindus and Muslims). The quantiles of

[15] We check if the use of quantile regression is justified by employing Breusch-Pagan / Cook-Weisberg test for heteroscedasticity. H_0: Variance of the error terms is constant. For the Overall Sample, chi2(1) = 2394.11; Rural Sample, chi2(1) = 529.25; Urban Sample, chi2(1) = 915.14; Age Cohort: 25-34, chi2(1) = 563.28; Age Cohort: 55-64, chi2(1) = 76.29. In all cases, Prob > chi2 = 0.0000. Hence, we reject the Null. Use of Quantile Regression is justified.

sons' years of schooling are on the x-axis and the coefficients are on the y-axis. The narrative of a son being less likely to be impeded by his father's status at higher educational levels is similar across all subsamples. However, the mobility gap between an urban citizen and a rural resident, a person belonging to the youngest age cohort vs one belonging to the oldest cohort, an upper caste Indian vs an OBC/SC/ST, a Hindu vs a Muslim, increasingly widens along the middle and upper quantiles of the educational distribution. Attributing specific causes behind the source of such differences in mobility rates across various subsamples of the population is beyond of the scope of this paper. Nonetheless, we shall attempt to shed some light on certain factors that are possibly intrinsic to the intergenerational educational relationship in the next section.

Next, we complement our results with an examination of the education transition matrix. As a summary measure, an education transition matrix maps education attainment levels of sons with the educational attainment levels of fathers. We construct the education transition matrix to gauge the intergenerational persistence along fathers' educational distribution; hence, the interpretation of each cell of the matrix is this - Given father's education level of F_L in the L^{th} row out of n rows representing n education levels, each cell in that row represents the probability of his son reaching one of the n education levels marked in n columns. So, a cell with an address (L, L) marks the probability $P(S_L|F_L)$ of a son attaining L^{th} level of education given his father's education attainment of L. Hence, the elements in a row add up to 100. In this exercise, we have resolved the number of years of schooling into seven education levels – level 0 (illiterates with zero years of schooling), level 1 (literate but below primary – one to three years of schooling), level 2 (primary – four to six years of schooling), level 3 (middle – seven or eight years of schooling), level 4 (secondary – nine and ten years of schooling), level 5 (higher secondary/diploma/certificate course – 11 to 14 years of schooling), and level 6 (15 or 16 years of schooling). The transition matrix is shown in table 8.

Table 8

Education Transition Matrix for the Overall Sample[16]

Levels	**Son's Education**						
	0	**1**	**2**	**3**	**4**	**5**	**6**

[16] We also prepare abridged education transition matrices for other sub-samples. The matrices are listed in Appendix C.

Father's Education	**0**	33.65	6.35	17.11	14.5	17.52	6.86	3.99
	1	10.3	10.18	18.66	15.85	26.72	10.57	7.73
	2	7.49	3.41	19.71	17.14	28.39	13.48	10.38
	3	3.62	1.84	8.19	18.94	30.45	19.18	17.79
	4	2.35	0.8	4.18	8.12	34.5	23.07	26.99
	5	1.2	0.53	2.59	4.99	20.74	30.12	39.83
	6	0.62	0.21	0.96	2.94	11.83	17.72	65.73

In table 8, the diagonal elements indicate intergenerational persistence. The upper-triangle non-diagonal elements reflect upward mobility and the lower-triangle non-diagonal cells reflect downward mobility. At the outset, we can attest to higher upward mobility than downward mobility in education for the overall sample. The left-most (33.65) and the right-most (65.73) diagonal elements suggest a large degree of intergenerational persistence at the lowest and the highest points of fathers' educational distribution. Although the quantile regression results agree with the findings for the bottom tail of fathers' educational distribution, there is a departure in the mobility rates for the respective upper tails of sons' educational distribution (table 7) and fathers' educational distribution (table 8). While the results for the respective bottom tails are consonant with Bratsberg et al. (2007), Torche (2015), Tassinari (2017), and Gaentzsch and Roman (2017)[17] in the respective contexts of the Nordic nations, Mexico, Italy and the Latin American Countries (Chile and Peru), we infer the departure (in the quantile regression results) with the help of the following discussion. In India, apropos of fathers' education distribution, a well-educated father, in most cases, hands down the advantage to his son and ensures intergenerational stickiness. However, at the top end of the sons' educational distribution, an individual has managed to break away from his circumstances, i.e. the educational attainment of the son is (almost) independent of his father's schooling outcomes. In comparison, in the lower and middle parts of the distribution, a son is still relatively encumbered by his background. To summarize, in India, the outcomes of the brightest sons are less dependent on their fathers' status than the outcomes of the sons who are at or below the average educational attainment levels

[17] Gaentzsch and Roman (2017) find evidence of high persistence at both upper and lower ends of the parents' education distribution and attributes the same to the ceiling and floor effects. Tassinari (2017) attributes stickiness at the top to the parental tendency of rich parents to pass on their respective advantages and social network effects.

(conditional on their fathers' outcomes). Nonetheless, a highly educated father hands over the advantage and thus fosters an educated son.

7. The Great Gatsby Curve and Other Channels

The Great Gatsby Curve (GGC) displays a positive relationship between economic inequality in one generation and intergenerational income immobility in the next for countries across the world (Krueger, 2012; Corak, 2013). The curve implies that the persistence in the circumstances handed over by parents to their children greatly depends on the economic inequality prevalent in the said region during parents' time. The ramification of the curve was deftly put by Noah (2012) – "it's harder to climb a ladder when the rungs are farther apart". We attempt to see if that indeed is true in the case of education in India. As education is one of the main channels of transmission of income advantage (or disadvantage) from parents to children, we estimate the relationship between education inequality experienced by a son while growing up (i.e. education inequality in the father's generation) and intergenerational education mobility as an adult. Subsequently, we examine the effect of public expenditure on education and economic growth during a son's childhood on the persistence in educational outcomes that got carried through. We shall account for cross-state heterogeneities and consider state-level variables.

In most cases, education materializes early on in one's life. The internal circumstances and the external environment experienced by the individual while growing up shapes his outcomes and life chances. If inequality in human capital levels among families is high for a given generation, the subsequent inequality of investment in children's education, directly and indirectly[18], conserves the status quo and impedes mobility. However, the countervailing forces of education spending by the government (Mayer and Lopoo, 2008; Aizer, 2014) and economic growth (Maoz & Moav, 1999; Hassler & Mora, 2000) work towards neutralizing the advantage due to a better family background and further intergenerational mobility.

[18] Direct effect is due to inequality in the parents' ability to invest in the human capital of their wards (the extent to which the parents are budget constrained) and the indirect effects are due to differences across households in terms of cultural dependency, teaching practices, neighbourhood effects and externalities, etc.

Going further, in this section, we consider children in the age group 6-18 as it has been pointed out in Chetty et al. (2014) that differences in mobility rates between two populations are induced by factors that affect individuals in their formative years. Given the IHDS-II data, we examine adult sons (aged 25 and above as on 2011) and hence operate with the cohort born during 1974 - 86. Consequently, we account for state-level variables of 'per capita expenditure on education as proportion of Gross State Domestic Product (GSDP) per capita' and 'year on year per capita GSDP growth' for the year 1992-93[19]. Information on the education expenditure variable is extracted from *CMIE States of India* Statistical Compendium. For GSDP growth rates, we referred *EPWRF India Time Series* economic indicators. Finally, Gini of educational attainment of fathers of individuals in the birth cohort 1974 - 1986 is computed to denote education inequality in fathers' generation.

We first plot the relationship between education inequality in fathers' generation and IGRC for the birth cohort 1974 - 1986 for the Indian states. The Gini coefficients and IGRCs for respective states are presented in table 9, and the resulting plot is shown in figure 2.

Table 9

State-wise Gini Coefficients of Education and IGRCs

State	Education Gini	IGRC
Daman & Diu	0.334	0.49
Meghalaya	0.316	0.586
Orissa	0.315	0.538
Arunachal Pradesh	0.304	0.335
Gujarat	0.299	0.528
Dadra & Nagar Haveli	0.298	0.627
Madhya Pradesh, Chhattisgarh	0.297	0.495
Karnataka	0.295	0.469
Maharashtra	0.286	0.379
West Bengal	0.284	0.668
Rajasthan	0.270	0.537
Tripura	0.267	0.343
Kerala	0.264	0.352

[19] To allow for transitory shocks and measurement errors, we average the two variables over five years (1990-91 to 1994-95) in place of a single value for the benchmark year 1992-93.

Andhra Pradesh	0.259	0.55
Tamil Nadu	0.258	0.452
Uttar Pradesh, Uttarakhand	0.249	0.551
Bihar, Jharkhand	0.249	0.598
Sikkim	0.248	0.221
Himachal Pradesh	0.247	0.273
Assam	0.244	0.48
Pondicherry	0.228	0.718
Mizoram	0.223	0.454
Delhi	0.215	0.436
Nagaland	0.214	0.223
Haryana	0.213	0.38
Punjab	0.209	0.459
Goa	0.209	0.18
Chandigarh	0.195	0.423
Jammu & Kashmir	0.191	0.404
Manipur	0.158	0.441

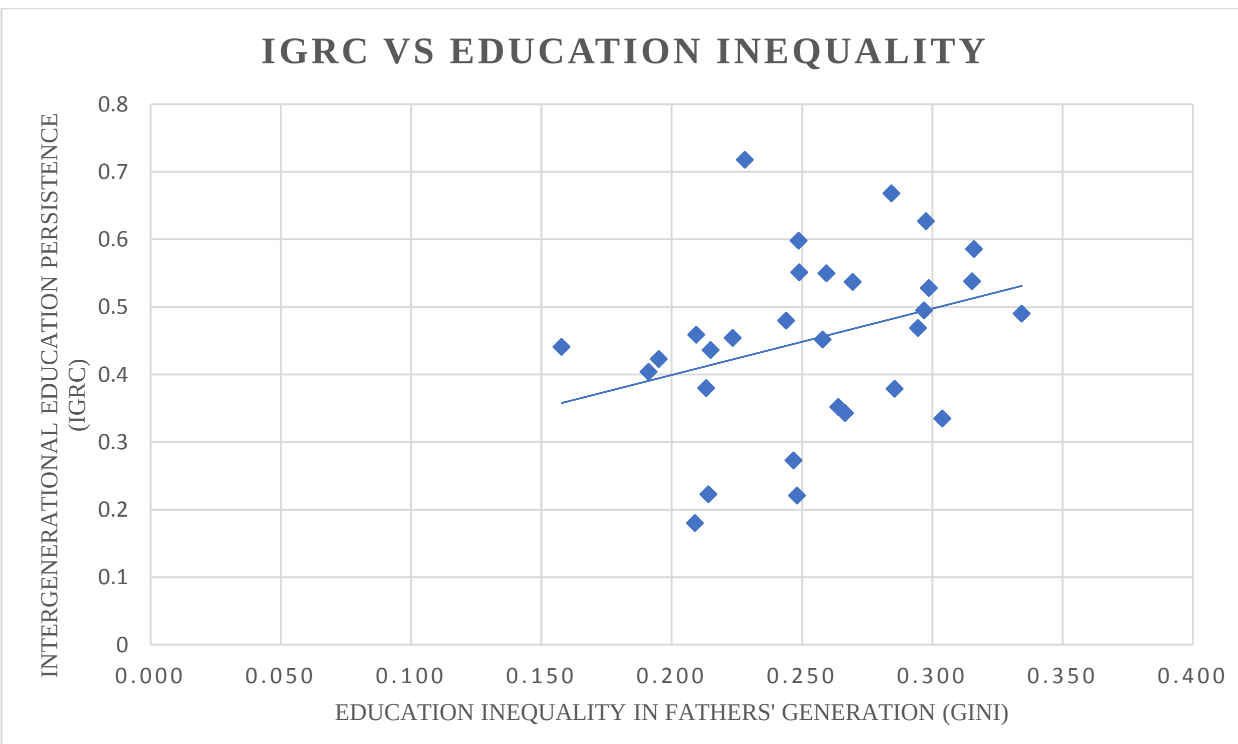

Figure 2. *Intergenerational Regression Coefficient vs Education Gini*

The cross-state relationship between the variables of interest in figure 2 corroborates the presence of The Great Gatsby Curve connection for education in India. In a state where education inequality is high during father's time, a son's educational attainment and in turn his life chances are dictated by his father's educational status. Hence, in such a state, on an average, a son of a father who is sparsely educated will find it difficult to climb the ladder of progress.

Next, to empirically test the hypothesis of a positive relationship between inequality and intergenerational immobility, and assess the effect of public expenditure in education and economic growth while a child is growing up on his opportunity to move beyond his fathers' status, we estimate various specifications of the following equation based on Neidhöfer (2016).

$$S_{is} = \beta_0 + \beta_1 F_{is} + \gamma_1 * F_{is} * G_s + \delta_1 G_s + \gamma_2 * F_{is} * E_s + \delta_2 E_s + \gamma_3 * F_{is} * R_s + \delta_3 R_s + \theta_s + \epsilon_{is}$$

where, the subscript s denotes individual i's state of residence, G_s represents the education Gini in fathers' generation, E_s indicates the state government's expenditure on human capital, R_s signifies economic growth, and θ_s encapsulates the state fixed effects. The positive/negative/negative sign on $\gamma_1/\gamma_2/\gamma_3$ signals an exacerbating/ameliorative/ameliorative effect of education inequality/public expenditure in education/economic growth on intergenerational education mobility. Table 10 displays the results. We report only the pertinent coefficients.

Table 10

The Great Gatsby Curve and other channels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	yrssch	yrssch	yrssch	yrssch	yrssch	yrssch	yrssch	yrssch
fatheryrssch	0.498***	0.487***	0.322***	0.282***	0.269***	0.269***	1.385***	2.206***
	(0.00581)	(0.00588)	(0.0453)	(0.0477)	(0.0526)	(0.0537)	(0.150)	(0.213)
GGC_int			0.658***	0.777***	1.004***	1.037***	0.289	0.196
			(0.171)	(0.179)	(0.206)	(0.214)	(0.201)	(0.203)
channel1a_int					-0.0144***	-0.015***		
					(0.0032)	(0.0036)		
channel1b_int							-0.12***	-0.21***
							(0.0161)	(0.0222)
channel2_int						-0.0027		-0.04***
						(0.0068)		(0.0082)
State FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes
N	18934	18934	18934	18934	18323	18286	18323	18286
adj. R-sq	0.251	0.278	0.253	0.278	0.280	0.279	0.281	0.281

Notes: * p<0.05, ** p<0.01, *** p<0.001;

1. The coefficient on 'fatheryrssch' is the IGRC. We control for age of the sons in all regressions;

2. 'GGC_int' is the slope coefficient of the interaction between Gini of Educational attainment in fathers' generation and IGRC;
3. 'channel1a_int' and 'channel1b_int' are the slope coefficients of the interaction between economic growth and IGRC. In 'channel1a_int', the definition of economic growth is - year on year per capita GSDP growth (Average from 1990-91 to 1994-95) (in %). In 'channel1b_int', the definition is – natural log of GSDP per Capita at Constant Prices (1980-81 Series) (Average from 1990-91 to 1994-95);
4. 'channel2_int' is the slope coefficient between Government expenditure on education and IGRC. The definition of Government expenditure on education is - Per Capita Expenditure on Education, sports, art & culture as proportion of GSDP per Capita (Average from 1990-91 to 1994-95) (in %);

In table 10, the IGRCs are reported in the top row and the coefficients of the interaction between fathers' education outcome and the channels under consideration are shown in the rows two to five. There are four main findings. First, the conditional relationship between sons' and fathers' educational attainment differ with respect to different macro-level variables. Once education inequality is controlled for, the IGRC drops significantly. Secondly, we obtain a confirmation of a positive relationship between education inequality and intergenerational education persistence. Evidently, in India's case, inequality subjects the life chances of an individual to majorly depend on his parents' background and lessens the role of his own hard work. Inequality in education ensures that a son of an educationally advantaged father has access to better schools, opportunity to study further, more educated connections (eliciting positive externalities) compared to his counterpart with a less educated father. Unless the less educated father can access credit against his son's potential and invest in the son's human capital, the circumstantial disadvantage continues onto the next generation, thereby stifling the equality of opportunity. As per Corak (2013), The Great Gatsby Curve phenomenon is also fueled by an increase in returns to education for the highly educated. The positive association between inequality and education immobility hints at the existence of an imperfect capital market situation and a strong heterogeneity in returns to higher education in India and thus calls upon a redistributive education policy (Bratsberg et al., 2007), rational wage settings institutions, a more functional welfare system, and better capital markets.

Thirdly, the negative and statistically significant interaction effect of economic growth with fathers' education on son's education establishes a positive relationship between economic growth and intergenerational mobility. This result agrees with the economic models proposed in

Maoz and Moav (1999) and Hassler and Mora (2000) where growth and mobility reinforce each other. Hassler and Mora (2000) examine the role of incentives to acquire education in phases of economic growth to demonstrate the effect of growth on intergenerational mobility and suggest redistributive taxation as a policy mechanism to stimulate growth in developing economies such as India. Finally, upholding the empirical findings in Mayer and Lopoo (2008), Blanden (2009), and Aizer (2014), we find a positive effect of public investment in education in reducing the association between a son's educational achievement and his father's status, although the effect is not always statistically significant. Nevertheless, a higher government spending in education doesn't always translate into a better equality of opportunity. In this regard, Corak (2013) emphasizes the importance of a progressive public spending regime which is directed towards making quality primary and secondary education more accessible than supplementing resources in higher levels of education accessible to only a few.

8. Summary and Conclusion

In this paper, we investigate the role of circumstances in shaping an individual's life chances in India. While an individual's circumstances are proxied by his father's education, his life chances are assumed to depend on his own educational outcomes. We have sought to prise out this information by conducting various exercises for categories and subcategories of individuals. In doing so, we have managed to check and update the numbers on intergenerational education mobility with the aid of the latest data (IHDS-II). More importantly, we have explored the non-linearity in the relationship between educational outcomes of successive generations for various cohorts and regions by employing quantile regressions. Lastly, we analyse the role of certain channels – education inequality in fathers' generation, economic growth, and government expenditure in education – fundamental to the transmission of advantage or disadvantage from a generation to its next.

Even after about 65 years of independence, a son's life chances are closely tied to his father's relative status in the society. This is reflected in the high values of intergenerational regression coefficients (IGRCs) that are obtained through various empirical exercises in this paper. Across age cohorts, the IGRC displays a decreasing trend. In the evolution of education persistence by groups, owing to affirmative action policies by the government since independence, the SCs and

STs are closing the gaps on the other castes and now stand less affected by their circumstances as compared to the OBCs, albeit marginally. Muslims, however, continue to languish as their rate of improvement in education mobility is much lesser than other sub-groups.

An important finding of this study is that education mobility is not linear along the distribution of educational attainment of individuals. For the overall sample as well as the sub-groups, sons are most likely to move beyond their circumstances and not be dictated by their fathers' educational status at the top tail of the sons' education distribution. Moreover, there has been an improvement in education mobility at almost all points of distribution for the youngest 10-year age cohort as compared to the oldest. Finally, the "Higher Inequality → Lesser Mobility" nexus in education plays out for the Indian scenario and thus corroborates the 'Great Gatsby Curve'. Also, economic growth and public investment in education are seen to have an ameliorative effect on intergenerational education mobility.

For equality of opportunity to improve in a society, public institutions need to play a major role and devise policies in a way to offset the disadvantage faced by the lowly endowed section of the population. Given the evidence our paper generates, in addition to the past literature, the government must look in the following directions – one, designing redistributive education policies that ensure basic and secondary education irrespective of socioeconomic status. This is in view of the high degree of education persistence at the primary and middle school levels across all sub-groups. Two, considering the spatial differences in mobility between urban and rural regions across the entire education distribution, it is essential to improve the accessibility as well as the quality of education in rural regions of the country. Three, it is crucial, in the face of inequality, to improve the access to credit and augment the welfare system to remove the element of the inability of a less educated father to invest in his son's human capital. Four, enhancing the access to, and upgrading the quality of higher educational institutions would go a long way in containing the wage premium and reducing the heterogeneity in returns to higher education in India, in turn suppressing the transmission of inequality and its effects.

Our paper is only the first step towards suggesting a comprehensive framework for policy. Going further, data constraints must be worked around and sufficient variables must be identified to facilitate research on discerning the effect of more factors and understanding the causal paths.

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Appendix A

Intergenerational Education Mobility in Co-resident Households

Co-resident household father-son pairs make up for only 26.63% of the potential pairings which could have been possible if information on father's education was expressly available for each male individual in the age-group of 25 – 64 from the survey. On the other hand, by making use of the unique feature of IHDS-II (question 1.18c on page 3 of the Income and Social Capital Questionnaire), we account for 96.73% of the potential pairings. Here, by estimating IGRCs for the co-resident father-son pairs, we highlight the truncation bias that creeps in due to the neglect of non-co-resident pairs. Table A.1 lists the results.

Table A.1

Intergenerational Regression Coefficients (All India) for co-resident pairs

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
	yrssch	yrssch	yrssch	yrssch	yrssch	yrssch	yrssch
fatheryrssch	0.487***	0.464***	0.456***	0.482***	0.453***	0.472***	0.446***
	(0.0069)	(0.0072)	(0.0072)	(0.0069)	(0.0072)	(0.0070)	(0.0073)
cons	6.711***	7.728***	8.237***	6.849***	7.822***	8.113***	9.005***
	(0.06)	(0.15)	(0.26)	(0.06)	(0.15)	(0.24)	(0.27)
Truncation Bias[20]	20.75%	17.24%	17.11%	20.75%	16.78%	20.76%	17.04%
Caste Controls	No	Yes	Yes	No	Yes	No	Yes
State Controls	No	No	Yes	No	No	Yes	Yes
Religion Controls	No	No	No	Yes	Yes	Yes	Yes
N	12227	12173	12173	12227	12173	12227	12173
adj. R-sq.	0.271	0.28	0.299	0.276	0.286	0.297	0.306

Notes: Standard errors clustered at household level in parentheses; * p<0.05, ** p<0.01, *** p<0.001

In Table A.1, the number of observations goes down massively and there is a downward truncation bias ranging from about 13% to 21% in the coefficients estimated from the co-resident pairs. The figures are in line with the estimates obtained from a similar comparative analysis in Azam and Bhatt (2015). This underscores the point made earlier about there being a severe issue with sample selection if 'co-resident only' father-son pairs are chosen.

[20] $Truncation\ Bias = \left(\frac{IGRC_{Table\ 3} - IGRC_{Table\ A.1}}{IGRC_{Table\ A.1}}\right) * 100$

Intergenerational Education Mobility – Bringing Mothers and Daughters into Conversation

In the overall sample spanning all age groups, fathers are co-resident with their respective sons or daughters in 44.08% of all cases and mothers are co-resident with their respective offspring in 51.17% of the cases. Here, we consider all sons and daughters in the age group 11 - 64 (both ages included) who are no longer enrolled in school and have their respective mothers and fathers residing in the same household. As measures of parental education, we use the number of years of schooling of both the mother and the father of each son/daughter conforming with Jalan and Murgai (2007). Various specifications of the following model are then estimated using an OLS framework.

$$C_i = \beta_0 + \beta_1 F_i + \beta_2 M_i + (\text{Controls}) + \epsilon_i$$

where, C_i is the number of years of schooling of the child (son/daughter), and F_i and M_i are the numbers of years of schooling of father and mother respectively. The coefficients, β_1 and β_2, are the measures of intergenerational educational persistence emerging from father and mother respectively. Table A.2 contains the regression results.

Table A.2

Intergenerational Regression Coefficients (All India) for co-resident children and their parents

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
	yrssch	yrssch	yrssch	yrssch	yrssch	yrssch	yrssch
fatheryrssch	0.367***	0.355***	0.362***	0.356***	0.338***	0.363***	0.347***
	(0.00631)	(0.00639)	(0.00637)	(0.00631)	(0.00639)	(0.00632)	(0.00637)
motheryrssch	0.275***	0.265***	0.223***	0.273***	0.253***	0.236***	0.216***
	(0.00720)	(0.00729)	(0.00758)	(0.00722)	(0.00733)	(0.00746)	(0.00754)
cons	5.908***	6.893***	7.450***	6.208***	7.100***	7.479***	8.328***
	(0.0376)	(0.120)	(0.206)	(0.0406)	(0.120)	(0.182)	(0.211)
Caste Controls	**No**	**Yes**	**Yes**	**No**	**Yes**	**No**	**Yes**
State Controls	No	No	Yes	No	No	Yes	Yes
Religion Controls	No	No	No	Yes	Yes	Yes	Yes
N	24148	24090	24090	24148	24090	24148	24090
adj. R-sq	0.291	0.295	0.330	0.304	0.312	0.336	0.343

Notes: Standard errors clustered at household level in parentheses; * p<0.05, ** p<0.01, *** p<0.001

In Table A.2, the β_1s indicate a much greater degree of intergenerational educational mobility when compared to the IGRCs obtained in the main text of the paper. This sample cannot be considered representative of the population due to the limitation imposed by the co-residency condition. Moreover, the co-resident combinations cannot be argued to be randomly spread in the population. Hence, the coefficients reflect downward truncation bias. The magnitude of truncation bias cannot be calculated as mother's educational attainment cannot be ascertained for the sample, barring the co-resident combinations.

Appendix B

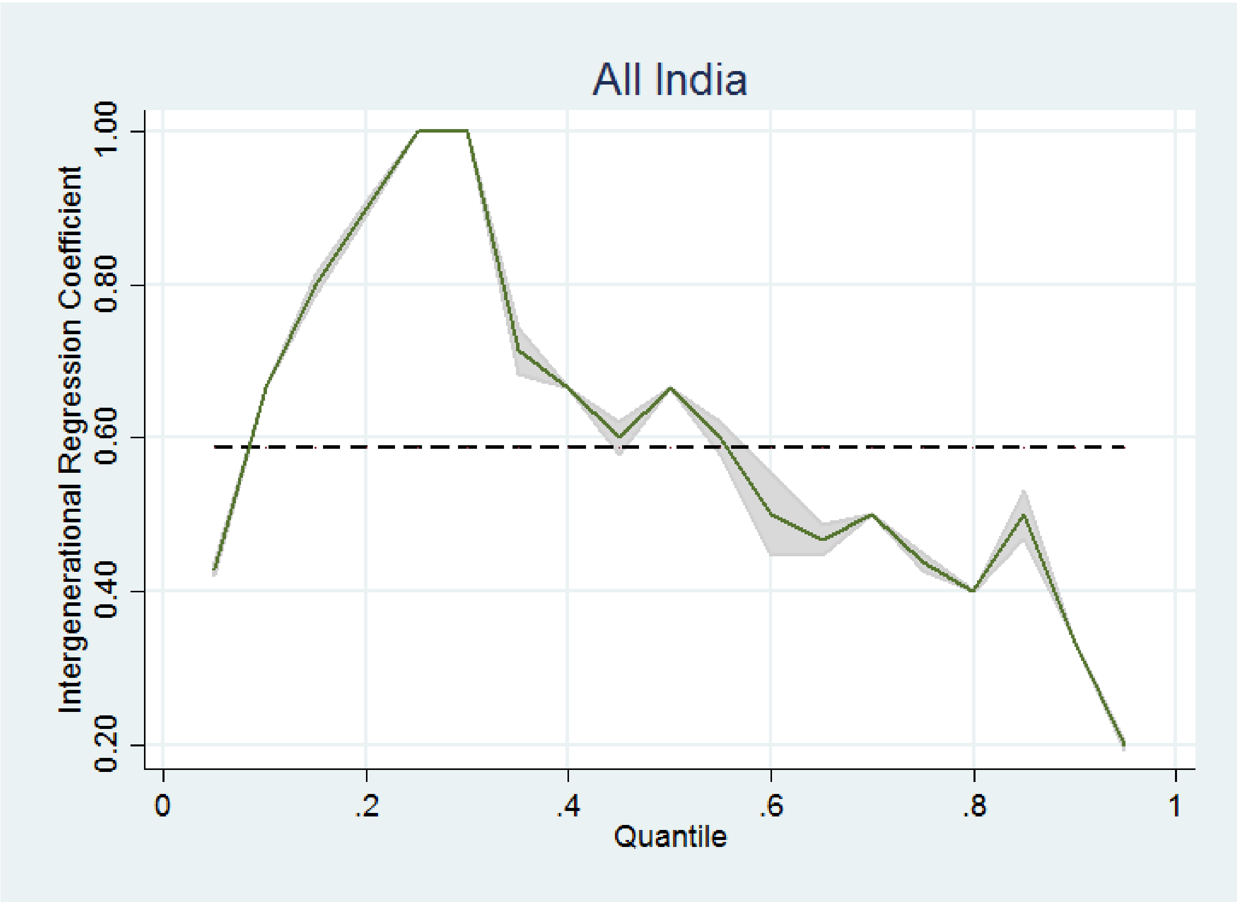

Figure B.1. *Quantile Regression IGRCs (Overall Sample)*

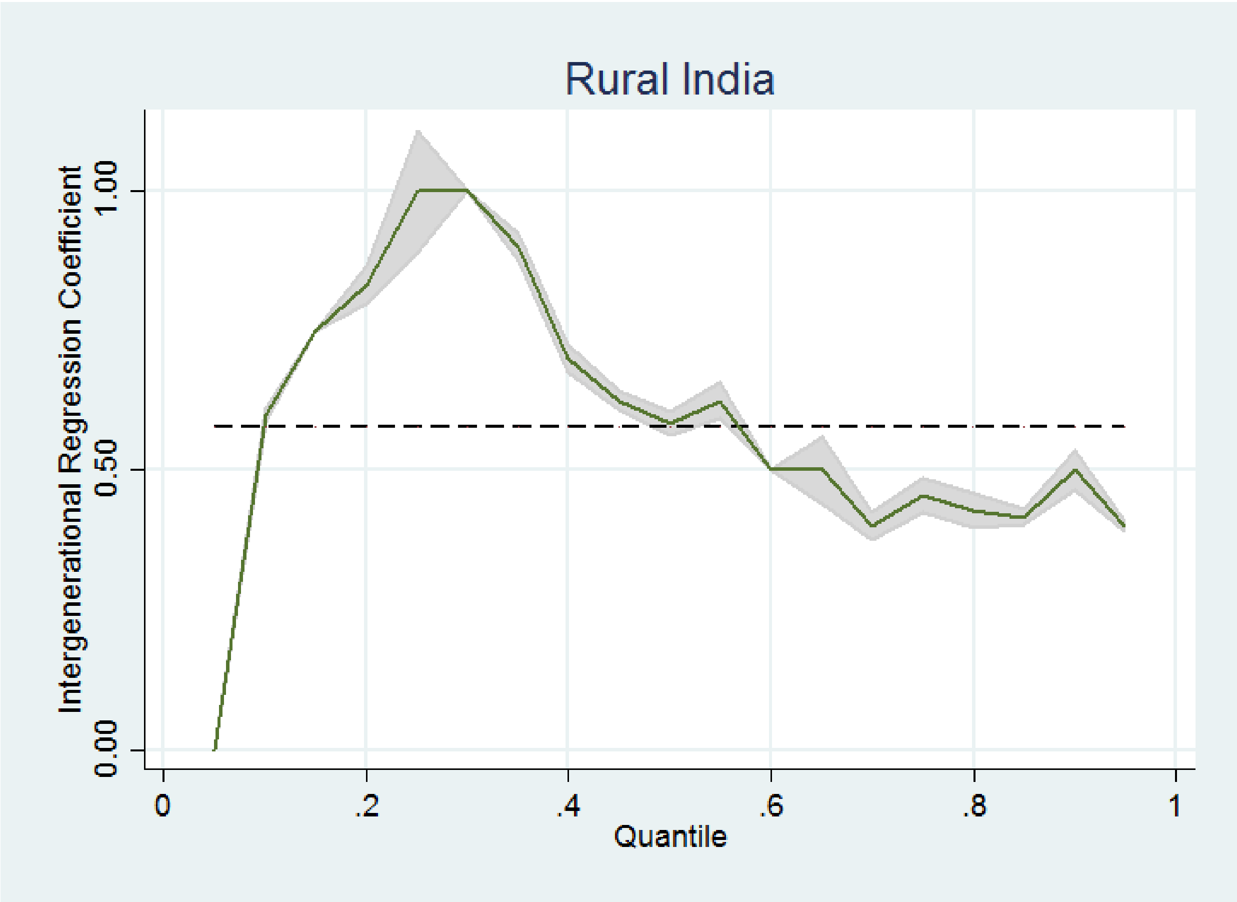

Figure B.2. *Quantile Regression IGRCs (Rural Sample)*

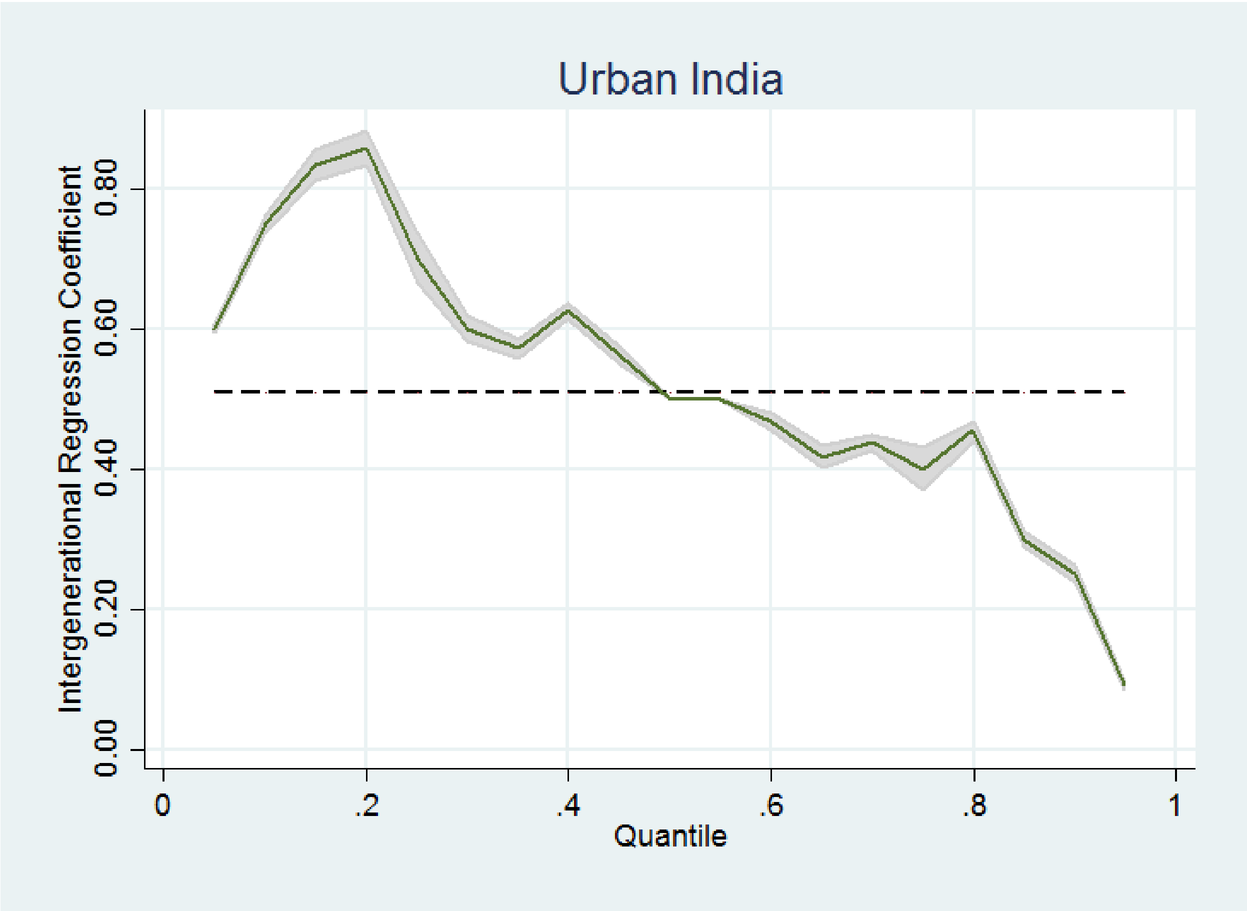

Figure B.3. *Quantile Regression IGRCs (Urban Sample)*

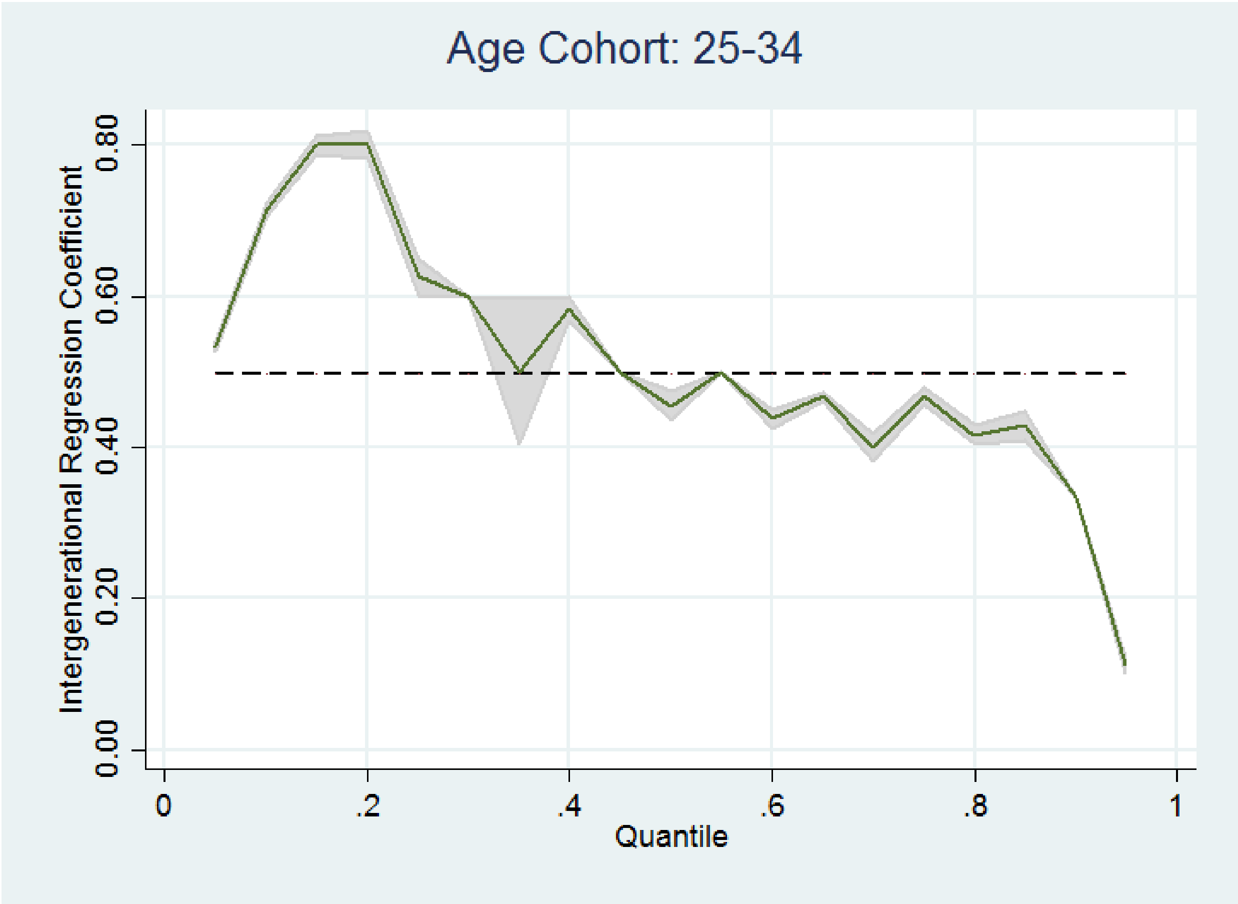

Figure B.4. *Quantile Regression IGRCs (Age Cohort: 25-34)*

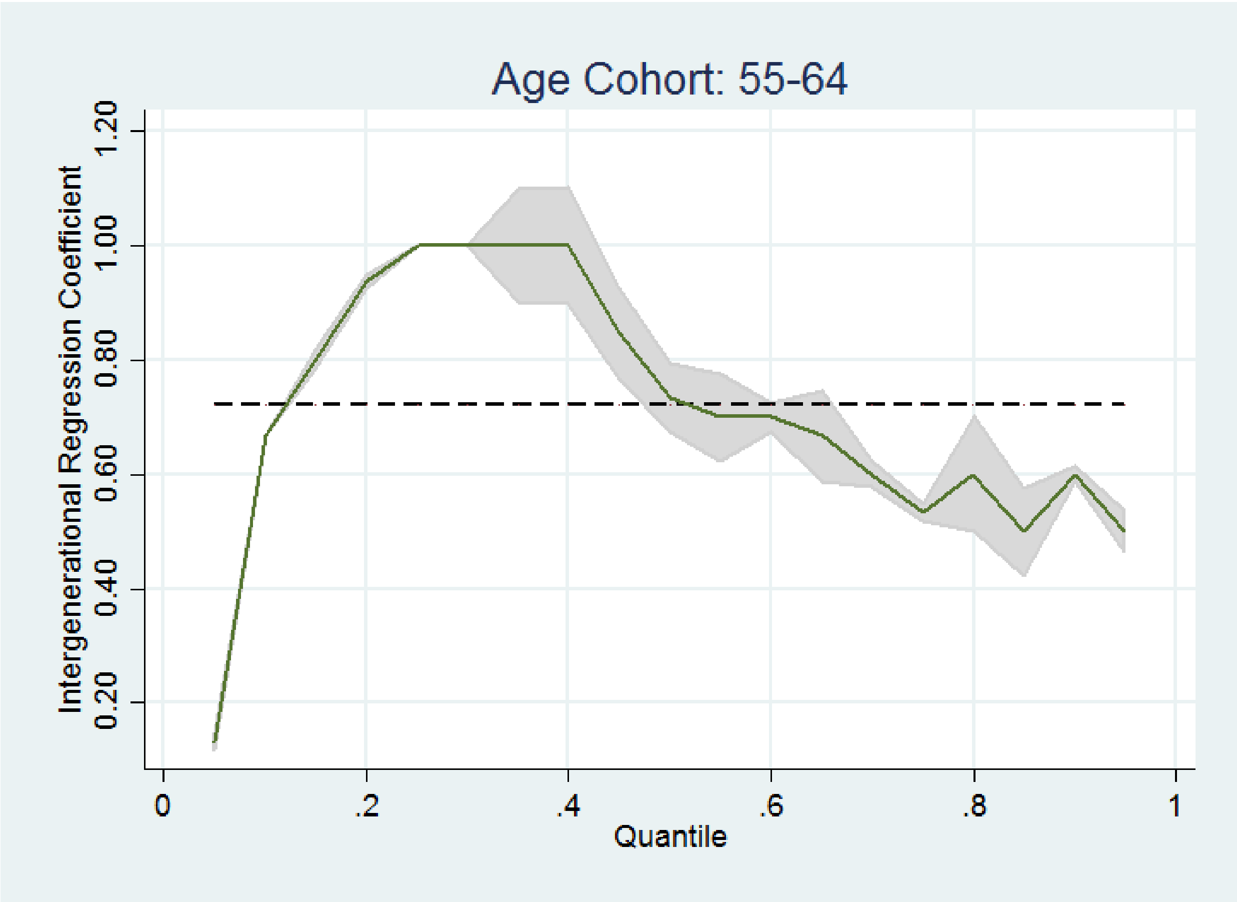

Figure B. 5. *Quantile Regression IGRCs (Age Cohort: 55-64)*

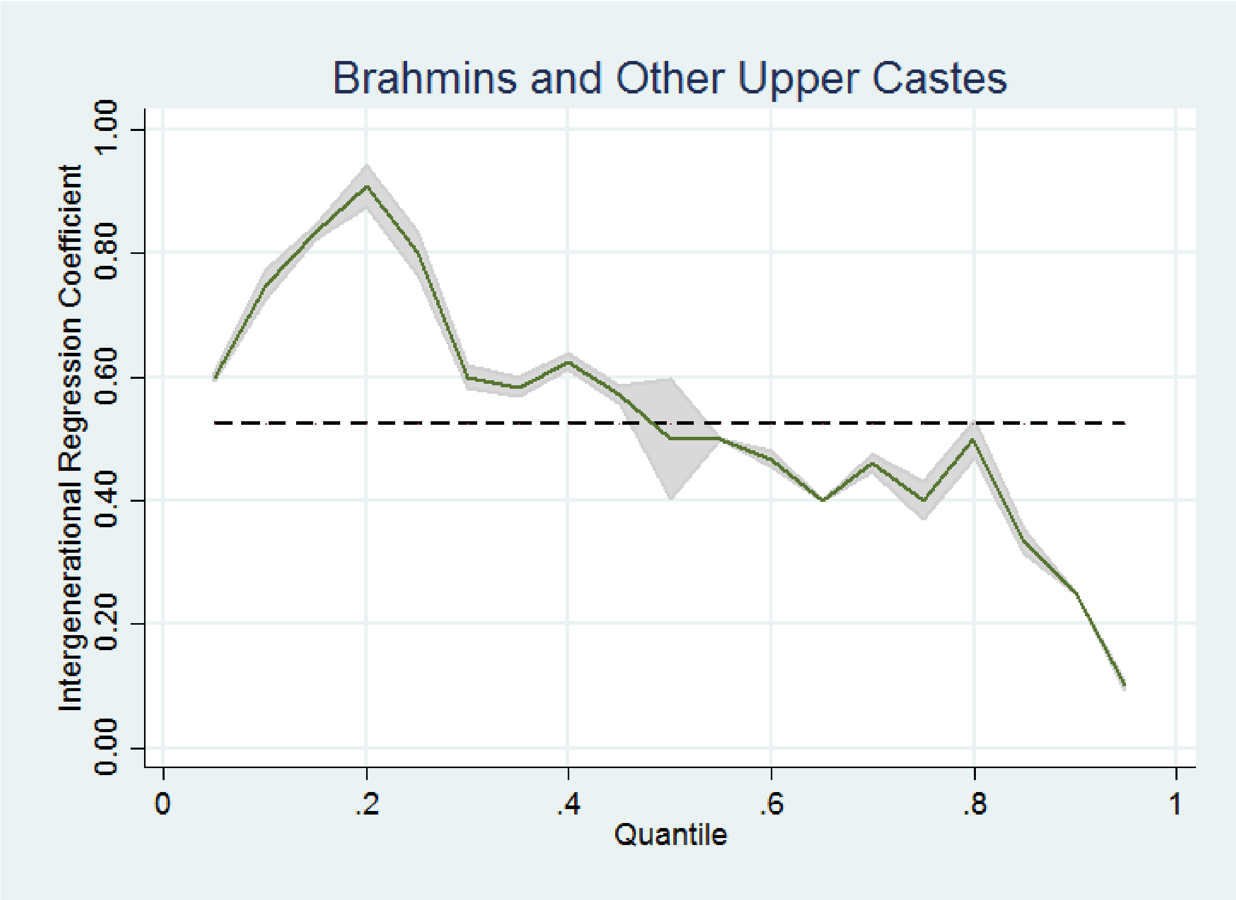

Figure B.6. *Quantile Regression IGRCs (Brahmins and Other Upper Castes)*

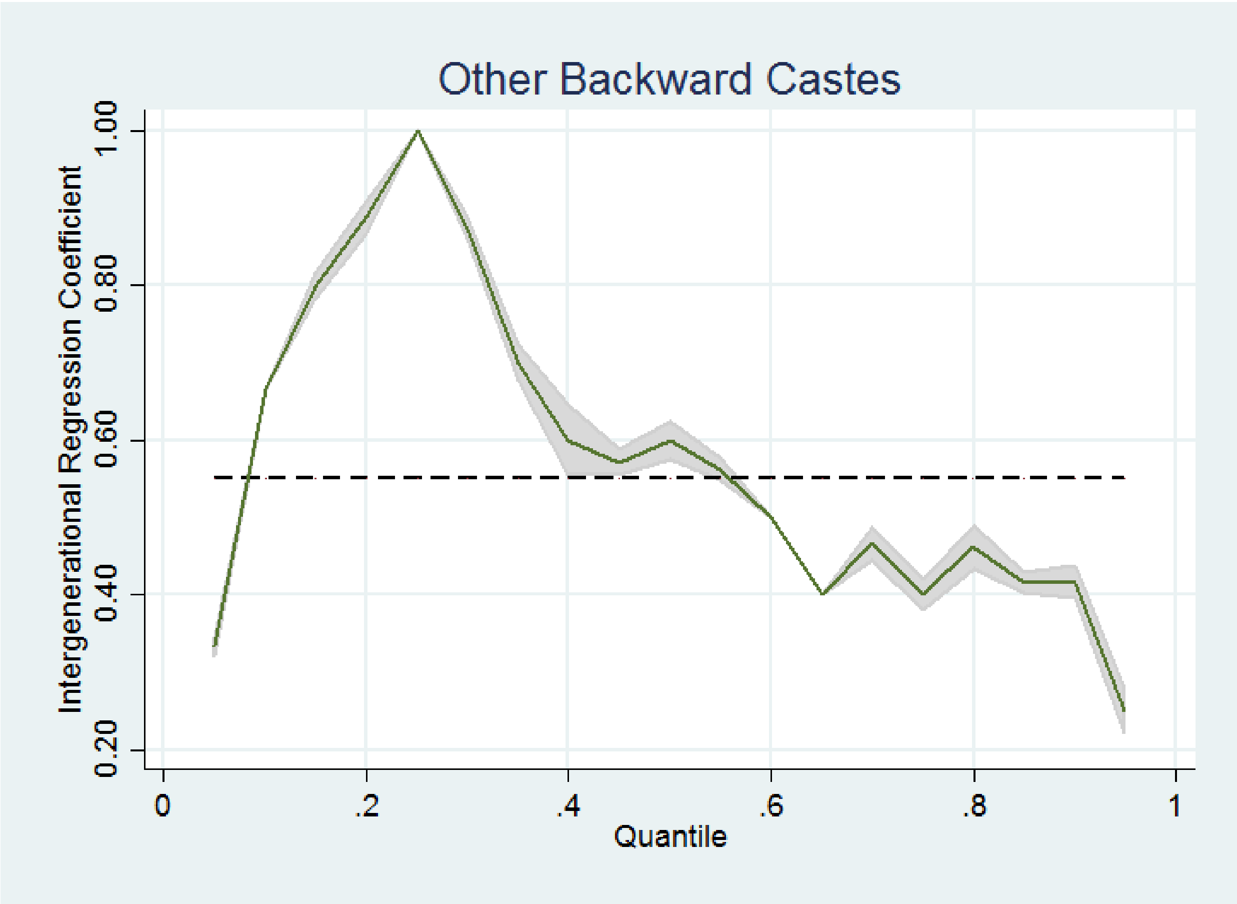

Figure B.7. *Quantile Regression IGRCs (Other Backward Castes)*

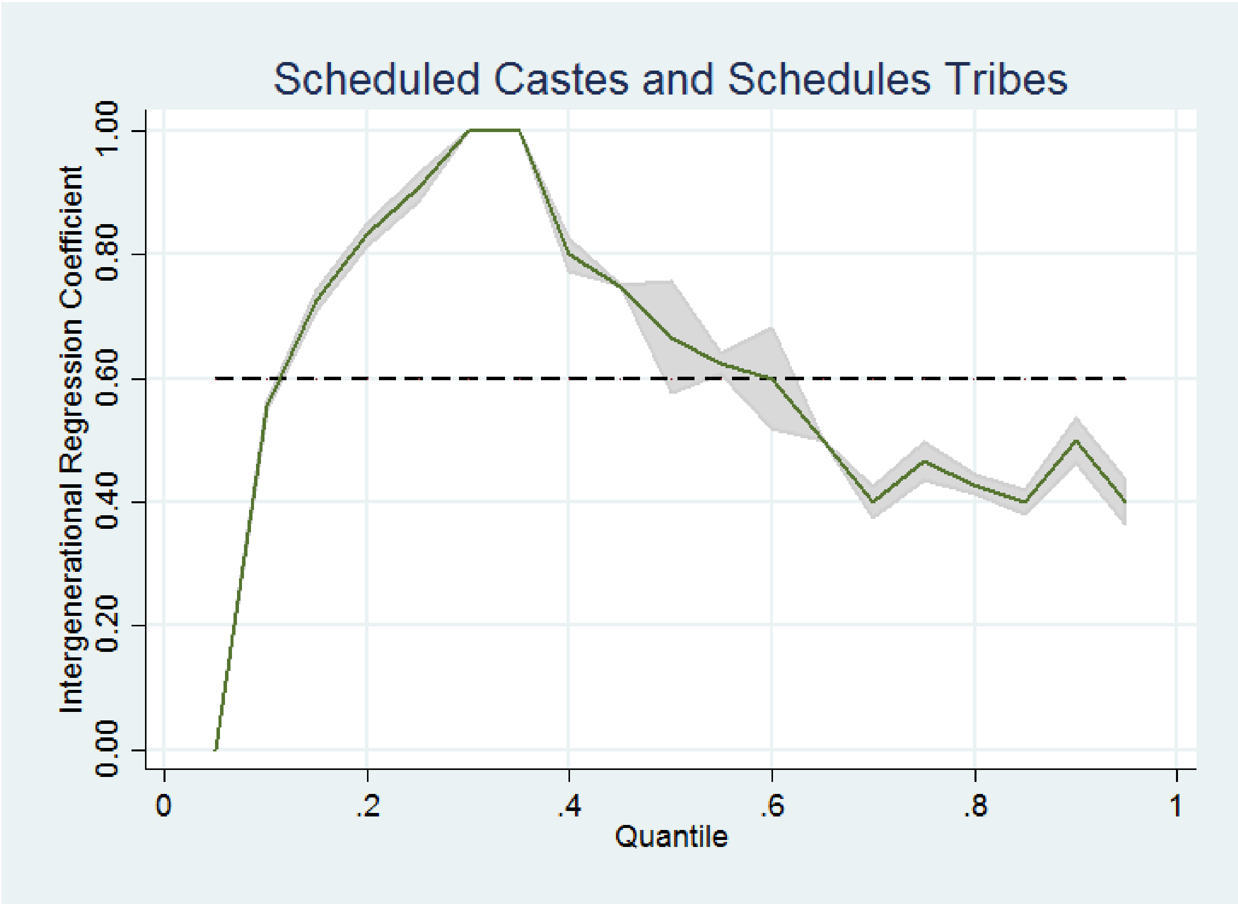

Figure B.8. *Quantile Regression IGRCs (Scheduled Castes and Scheduled Tribes)*

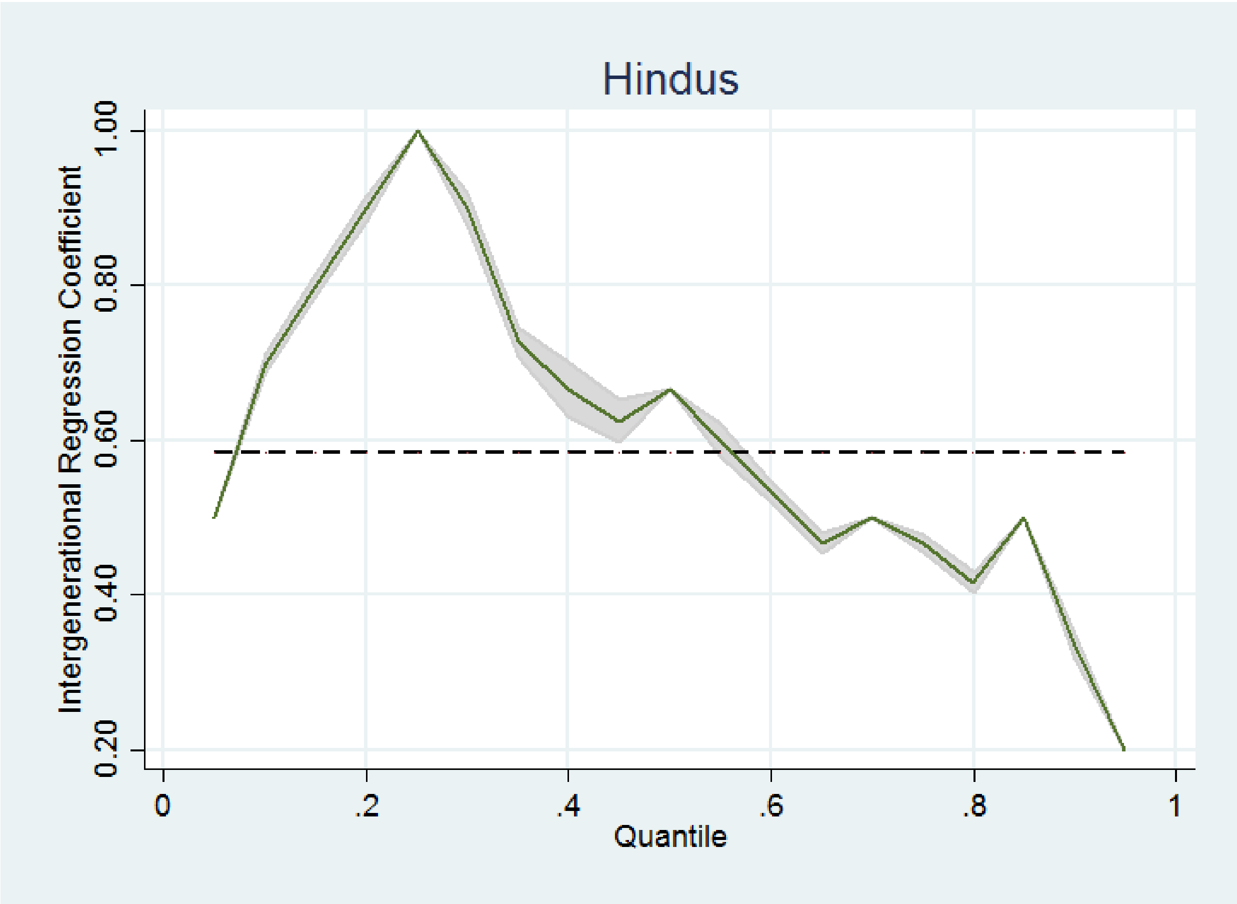

Figure B.9. *Quantile Regression IGRCs (Hindus)*

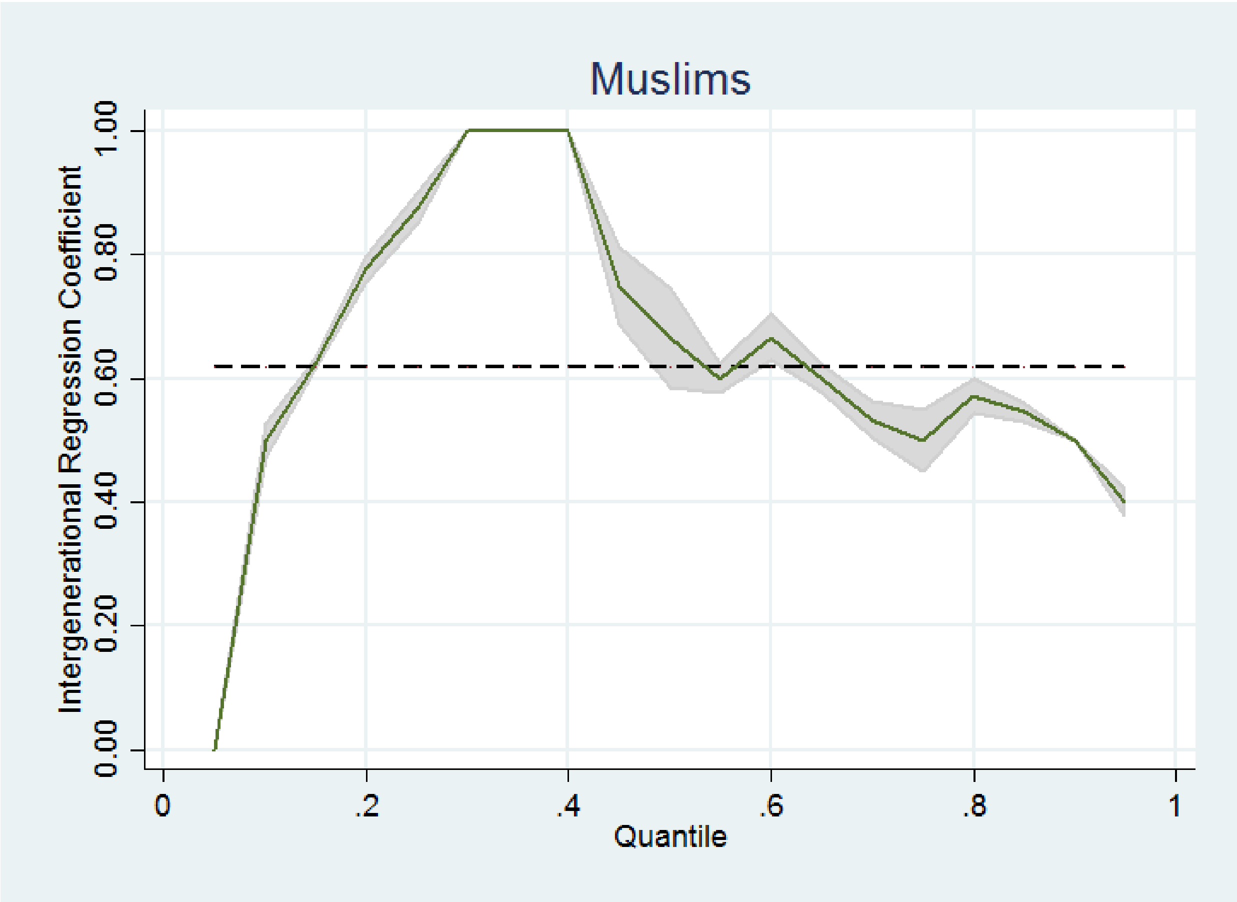

Figure B.10. *Quantile Regression IGRCs (Muslims)*

Appendix C

Table C. 1

Comparison of Educational Transitions between Urban Population and Rural Population

Urban India				
Educational Levels		Son's Education		
		Illiterate	At least Secondary	At least Graduation
Father's Education	Illiterate	23.14	37.17	6.71
	Primary		59	14.16
	Secondary			32.52
	Higher Secondary			48.2
	At least Graduation			70.62
Rural India				
Educational Levels		Son's Education		
		Illiterate	At least Secondary	At least Graduation
Father's Education	Illiterate	37.39	25.26	3.03
	Primary		47.23	7.57
	Secondary			19.85
	Higher Secondary			26.75
	At least Graduation			51.09

Table C. 2

Comparison of Educational Transitions across various Caste Groups

Brahmins + Other Upper Castes				
Educational Levels		Son's Education		
		Illiterate	At least Secondary	At least Graduation
Father's Education	Illiterate	25.17	37.61	5.86
	Primary		61.05	14.49
	Secondary			33.65
	Higher Secondary			49.05
	At least Graduation			70.27
Other Backward Castes				
Educational Levels		Son's Education		
		Illiterate	At least Secondary	At least Graduation
Father's Education	Illiterate	32.31	27.85	3.72
	Primary		50.23	9.04
	Secondary			22

	Higher Secondary			30.8
	At least Graduation			59.52

Schedules Castes and Scheduled Tribes				
Educational Levels		Son's Education		
		Illiterate	At least Secondary	At least Graduation
Father's Education	Illiterate	40.05	23.57	3.19
	Primary		44.11	7.25
	Secondary			18.91
	Higher Secondary			28.36
	At least Graduation			57.31

Table C. 3

Comparison of Educational Transitions across various Religions

Hindus				
Educational Levels		Son's Education		
		Illiterate	At least Secondary	At least Graduation
Father's Education	Illiterate	32.49	29.55	4.16
	Primary		53.6	11.2
	Secondary			27.64
	Higher Secondary			39.56
	At least Graduation			67.15
Muslims				
Educational Levels		Son's Education		
		Illiterate	At least Secondary	At least Graduation
Father's Education	Illiterate	42.94	19.07	2.76
	Primary		39.53	6.29
	Secondary			23.74
	Higher Secondary			40.46
	At least Graduation			54.63
Christians, Sikhs, and Others				
Educational Levels		Son's Education		
		Illiterate	At least Secondary	At least Graduation
Father's Education	Illiterate	28.19	33.7	4.51
	Primary		55.02	6.95
	Secondary			24.55
	Higher Secondary			42.42
	At least Graduation			61.02

Table C. 4

Comparison of Educational Transitions between the Youngest and the Oldest 10-year Age Cohort

Age Cohort 25-34				
Educational Levels		Son's Education		
		Illiterate	At least Secondary	At least Graduation
Father's Education	Illiterate	23.56	35.27	5.1
	Primary		55.35	9.73
	Secondary			28.27
	Higher Secondary			41.37
	At least Graduation			62.78
Age Cohort 55-64				
Educational Levels		Son's Education		
		Illiterate	At least Secondary	At least Graduation
Father's Education	Illiterate	43.41	19.87	2.75
	Primary		47.91	10.91
	Secondary			29.76
	Higher Secondary			35
	At least Graduation			73.28

The matrices divided along regional lines (urban vs rural) (Table C.1) point to higher educational mobility for the urban population as compared to the rural folk. In the urban sample, 37.17% of the sons with illiterate fathers, 59% of those whose fathers completed primary schooling went on to complete secondary level of education. The same numbers languish at 25.26% and 47.23% respectively in the case of the rural population. Even among sons with relatively better-educated fathers (e.g. fathers who completed secondary education or higher secondary education), the upward mobility is more pronounced in urban areas than rural areas.

The disadvantage of being born as a scheduled caste or in a scheduled tribe shows vividly among the education transition matrices categorized by castes (Table C.2). For SCs and STs, the persistence is highest at the lowest levels of education (illiterates) and lowest at the highest level of schooling (graduates and above) when compared to the upper castes and the OBCs. Upward mobility conditional on lower levels of fathers' education (below primary and primary) is also least for SCs and STs. Even the OBCs only do marginally better. This trend of "Upper castes better off than OBCs better off than SCs and STs" continues even in cases where sons of fathers with secondary and higher secondary education go on to complete the highest levels of education.

Coming to categorizations done by religions (Table C.3), the education transition matrices show a clear position of disadvantage for Muslim offspring, whereas the advantage is divided between respective sons of Hindus and other religions (Christians, Sikhs, Jains, etc.). To cite an instance, educational persistence is highest at the lowest level of education and lowest at the highest level of education for Muslims when compared with all others. Between Hindus and other religions, while persistence is highest at the highest level of education for Hindus (67.15% vs 61.02% for other religions), it is the lowest at the lowest level of education for Christians, Sikhs, Jains, etc. (28.19% vs 32.49% for Hindus). The propensity for sons of fathers at low educational levels (below primary and primary) to reach the highest education levels (secondary and above) is the least for Muslims. The same numbers are much better for Hindus and other religions with Hindus at a slightly worse off position than members of other religions.