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Nonlinearity, and the Great Gatsby Curve

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Abstract

The paper explores 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. Through appropriate cohort analysis, we find that there is still a high degree of intergenerational persistence in education. However, the same is decreasing steadily over time. We detect nonlinearity in the relationship between fathers' and sons' schooling outcomes across the education distribution through quantile regressions. 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.

Keywords: Intergenerational mobility, education, nonlinearity, quantile regression, Great Gatsby Curve, economic growth, education spending

JEL Classification: H52, I21, I24, J62

1. Introduction

A couple of reasons can be broadly ascribed to inequality in society – one, a disparity in efforts of individuals, and two, differences in predetermined circumstances outside the locus of control of individuals. The former is essential in society to promote merit and provide incentives for individuals to work hard. However, inequality due to differences in predetermined circumstances is unfair as it manifests into inequality of opportunity where the relative socioeconomic status of an individual's parents or ancestors determines her life chances. Collectively, such transmission of relative (dis)advantage from one generation to the next indicates the intergenerational persistence prevalent in society. Conversely, intergenerational mobility is a marker of the opportunity for a generation to move beyond its social origins (Fox et al., 2016).

This paper explores the aspects and channels of intergenerational mobility in India by analyzing the association between parent's and adult child's educational outcomes. Education is one of the significant vehicles of transmission of opportunity from parents to children. It plays out through the direct mechanism of having more educated parents. Other indirect channels include cultural and social reproduction, teaching practices within a household, parental economic ability and resulting investment, and positive externalities emerging from social connections (Becker & Tomes, 1979; Benabou, 1996; Hertz et al., 2007; Bussolo et al., 2019).

We choose education as a lens to study intergenerational mobility as it is less prone to errors than income in terms of measurement. In developing countries such as India, data on educational outcomes is primarily available, unlike data on earnings and income, conspicuous by their absence in a typical household survey (Azam & Bhatt, 2015). Formal education gets fixed once individuals reach their mid-twenties. Hence, life cycle biases are accounted for as educational attainment is a stable measure among adults at a point in time, compared to measures of earnings or income which vary across years (Haider & Solon, 2006; Black & Devereux, 2011). Finally, Tilak (2002) envisaged a "*strong linear relationship between education and earnings*" (p. 192), and per Torche (2019), educational attainment has stood as the primary determinant of earnings in contemporary societies.

Much of the current crop of literature in the Indian context has dealt with the estimation of descriptive intergenerational mobility measures[1] (Jalan & Murgai, 2008; Maitra & Sharma, 2009; Hnatkovska et al., 2013; Azam & Bhatt, 2015; Emran & Shilpi, 2015). Different households have different endowment levels and hence experience varying resource and expenditure thresholds. It appears plausible that a parent's educational achievement explains the child's educational attainment differently for a child lying at the top of the children's conditional educational distribution compared to a child at the bottom of the distribution. From a policy point of view, evaluating the effects of parents' educational attainments at the tails of children's conditional educational achievement distribution seems particularly relevant.

It is also vital to understand the factors that play an essential role in promoting or inhibiting the intergenerational education association. Incorporating the human capital approach to inequality, Becker and Tomes (1979) establish determinants of intergenerational mobility through their model. Per the model, 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. Further, other factors such as economic growth rate, tax subsidy, public expenditure systems, and discrimination against minorities sometimes have surprising implications on intergenerational transmission of advantage. Literature focusing on the

[1] Various descriptive intergenerational mobility measures include intergenerational regression coefficient, intergenerational correlation coefficient, and sibling coefficient.

correlates of intergenerational mobility, including macro-level factors such as public spending on education and economic growth, is limited in the developing countries context.

This paper employs the latest round (2011-2012) of Indian Human Development Survey (IHDS-II) data. We 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. We make two main contributions to the literature on intergenerational mobility in India. One, we explore the nonlinearities in the intergenerational education relationship. Two, we check if the ‘Great Gatsby Curve’ phenomenon, i.e., a negative relationship between income inequality and intergenerational mobility, comes to pass in the case of *education inequality - intergenerational education mobility* association in India. We also estimate the effect of economic growth and public spending on education in strengthening or weakening the intergenerational transmission of educational advantage.

2. Empirical Evidence on Intergenerational Mobility

Most of the early empirical studies on intergenerational mobility deal with computation of precise estimates of correlations and elasticities between the socioeconomic status of parents and their adult children for either a cross-section of countries (Corak, 2006; Jäntti et al., 2006; Hertz et al., 2007; Blanden, 2009) or individual countries – Sweden and US (Björklund & Jäntti, 1997), Germany (Couch & Dunn, 1997), United Kingdom (Dearden et al., 1997), Canada (Corak & Heisz, 1999). 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). Lately, there has been a shift in favor of investigating the causal mechanisms 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 an individual's childhood environment.

Using sibling correlation as a measure of intergenerational mobility, Björklund et al. (2010) delineate the effect of shared parental and neighborhood factors on an individual's IQ, and hence her abilities. By estimating the standard intergenerational regression models separately for Korean-American adopted children and their non-adopted American siblings, Sacerdote (2007) finds evidence supporting the thesis that genetics and infant endowments matter more than nurture in influencing the educational outcomes of individuals. Adopting the IV approach, Oreopoulos et al. (2008) use the father's displacement from work as a source of variation in his income, unrelated to any other characteristics, to find the effect on children's outcomes. Employing the Canadian Administrative panel, they detect a nine percent difference in annual earnings in favor of sons whose respective fathers were not displaced 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. These strategies tend to focus on separate parts of the socioeconomic status distribution, i.e., while twins are spread evenly across the status distribution, adopted children generally belong to the higher end of the distribution, and employment shocks, on average, affect those belonging to the lower end of the distribution (Holmlund et al., 2011). Thus, we attempt to explore the extent of such differences in the intergenerational education relationship across the education distribution in India.

2.1. The Indian Setting

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

Jalan and Murgai (2008) employ two rounds of the National Family Health Survey (NFHS) from 1992-93 and 1998-99 to study inequality in educational attainments and its persistence across generations for different population groups in India. Their results reflect significant and consistent improvements in education mobility and decreasing education gaps between various caste groups. Maitra and Sharma's (2009) investigation of the intergenerational transmission of human capital using data from the Indian Human Development Survey (IHDS-I) in 2004-05 affirms the results obtained by Jalan and Murgai (2008). On the contrary, Azam and Bhatt (2015) observe a high degree of intergenerational stickiness in educational attainment. Their sample construction design harnessed the retrospective information provided by IHDS-I on the father's (or husband's) educational attainment of the head of the household. The final sample circumvented the 'co-resident only' son-father pair constraint (encountered in the use of other large sample datasets in the earlier studies). It consisted of son-father matched pairs representative of the adult male population of India. Concurrently, 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, unchanged over the time of the study.

The studies on intergenerational education mobility in India have differed over the choice of measures and data sources. Although a consensus does not emerge, some studies agree upon improvements in education mobility in India and attribute various reasons to the process ranging from structural changes following liberalization to positive discrimination policies. However, there is a lack of literature in the Indian context to ascertain the channels underlying the transmission of advantage from one generation to the next. We investigate the effect of a few macro-level factors on intergenerational education mobility in this paper.

3. Methods and Data

We commence by conducting a baseline analysis of the trends in intergenerational education mobility by dividing the sample of individuals into the youngest and the oldest ten-year birth cohorts and estimating the following model:

$$S_i = \beta_0 + \beta_1 F_i + x_i' \theta + \epsilon_i \qquad (1)$$

where S_i denotes the number of years of schooling of the i^{th} son, F_i is i^{th} father's completed years of schooling, x_i' is a vector of control variables, and ϵ_i encapsulates the unobserved elements. β_1 is the primary variable of interest and is termed Intergenerational Regression Coefficient (IGRC). β_1 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.

Equation 1 can be further estimated by adopting either the co-resident household approach or the two-sample instrumental variables approach (Mohammed, 2019). The three major sample surveys in India – NSSO, NFHS, and IHDS – amply facilitate the co-resident household approach. However, considering 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 Motiram and Singh (2012) averred, 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. The downward bias[2] due to such truncation is explained through a simple Emran et al. (2018) model.

To carry out the analyses, we employ IHDS-II conducted in 2011-12. IHDS is a collaborative project between the National Council of Applied Economic Research (NCAER) and the University of Maryland. The survey is nationally representative and covers 42,152 households in 1420 villages and 1042 urban neighborhoods across India and includes household information on education, health, employment, economic status, social capital, fertility, etc.

We start by preparing a dataset aligned with Azam and Bhatt's (2015) approach. The dataset is unique because, besides matching father-son data based on the "Relationship to head of household" field in the household questionnaire that links the co-resident pairs, we also use the retrospective question[3] on the household head's educational attainment. The final sample consists of 44,532 observations of individuals (males) aged between 25 and 64 (as of 2012) with matched information on their respective father's educational attainment.

Per the convention in literature, apart from IGRC, we also report Intergenerational Correlation (IGC). IGC is a standardized measure of intergenerational persistence that removes the cross-sectional variability in educational attainment in the successive generations from consideration. The following expression operationalizes it –

$$IGC = \beta_1 \left(\frac{\sigma_F}{\sigma_C}\right) \tag{2}$$

where σ_F and σ_C are the standard deviations of educational attainment of the father's and son's generation, respectively.

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[2] The downward truncation bias in IGRC, as established in Emran, Greene, and Shilpi (2018), is inversely proportional to the extent of co-residency rates observed in the data.

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

4. Baseline Analysis and Trends

Table 1 presents the OLS estimation results for the overall sample. For the base specification, the estimated IGRC 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.

[Insert Table 1 here]

Next, we apply controls to account for factors that could have a bearing on the schooling achievements of individuals. Once the control variables are accounted for, the degree of persistence decreases, underlining the importance of caste, state, and religion in the inequality of opportunity debate. We employ the Wald test to check for the equality of the coefficients on fathers' educational attainment across all specifications. We fail to reject the null hypothesis of the equality between any two IGRCs in Table 1 at a 10% significance level.

4.1. Intergenerational Education Mobility across Cohorts

Caste and religion play in determining socioeconomic outcomes and status in India. Hence, 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.

[Insert Table 2 here]
[Insert Table 3 here]

Within all categorizations in tables 2 and 3, there is a marked improvement in education mobility across the 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 favor of SCs and

STs, the improvement in their education mobility has happened faster than the upper castes and the OBCs. IGRC for SCs and STs has fallen by 33.28% over 30 years compared to 25.29% for OBCs and 29.19 percent for the upper castes. Our arguments align with the general narrative (Jalan & Murgai, 2007; Hnatkovska et al., 2013).

Apropos of grouping by religion, Hindus have held precedence over Muslims in the 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 that for Muslims (18%). The status of Muslims continues to be majorly hindered by their previous generations.

5. 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 given credit market imperfections, differences in intra-family altruism, the indivisibility of investment in human capital, and neighborhood effects (Becker & Tomes, 1979, 1986; Galor & Zeira, 1993; Grawe, 2004; Jantti et al., 2006; Bratsberg et al., 2007).

Building on the work of Becker and Tomes (1986), Bratsberg et al. (2007) place importance on 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 education relationship. In Figure 1, we fit a Lowess curve representing the functional form between sons' and fathers' educational attainments.

[Insert Figure 1 here]

The Lowess plot 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 Becker and Tomes' (1986) conjecture of concavity in the face of imperfect capital markets. Thence, we infer that the credit constraints impact the poorest fathers and render them incapable of borrowing against their sons' future income/human capital potential in India. In turn, the fathers in the lower end of the earnings spectrum are unable to make optimum investments in their sons. In the absence of redistributive education policies that ensure basic education irrespective of socioeconomic status, a disadvantaged Indian son experiences strong intergenerational persistence.

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

$$\mathrm{Q}_{\theta}(\mathrm{S_i}/F_i) = \beta_0 + \beta_{\theta} F_i + (\text{cohort effects}) + \epsilon_i \qquad (3)$$

where $\mathrm{Q}_{\theta}(\mathrm{S_i}/F_i)$ represents θth centile of the distribution of the sons' educational attainment conditional on the fathers' years of schooling. The .10, .20, .50 (or median), .75, .90, and .95 quantiles listed in tables 4 and 5 broadly correspond to 0 years (no education), five years (completed primary education), eight years (completed middle-school education), ten years (completed secondary-school education), 12 years (completed higher secondary-school education), and 15 years (completed some tertiary education) of schooling, respectively, for the sons' educational distribution in our sample.

[Insert Table 4 here]

[Insert Table 5 here]

It is clear from Table 4 and Table 5 that the effect of a father's education on his son's schooling is not linear[4] across the sons' schooling attainment distribution as IGRCs estimated at different conditional centiles of the distribution are not equal. Apropos of the regressions for each subsample, we observe a vaguely similar general trend. If we exclude sons with zero educational attainments and thus restrict the sample to between the 20th and 95th centile of son's educational distribution, intergenerational mobility in education (= 1 – IGRC) displays an increasing trend. However, in some cases, the increase is non-monotonic. For the overall sample, mobility stands at a value of 0.1 at the 20th percentile. It 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 bound by their circumstances (conditional on their background). Even for the rest of the subsamples (rural, urban, Hindus, Muslims, etc.), this holds, albeit to different extents.

Rural inhabitants are often impeded by the lack of economic and educational opportunities compared to their urban counterparts. As evident in the second and third panels of Table 4, urban areas promote greater education mobility compared to rural regions. Finally, from the bottom two panels of Table 4, we can safely contend that there has been a marked improvement in educational mobility over the years at almost all points of the education distribution. We also note that 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

[4] 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. The use of Quantile Regression is justified.

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 the scope of this paper. Nonetheless, we shall attempt to shed some light on certain factors that are possibly intrinsic to the intergenerational education relationship in the next section.

The quantile regression results are comparable to those estimated in Eide and Showalter (1999) (for the USA) and Grawe (2001) (for the USA, Canada, Malaysia, Nepal, and Peru). The results underscore that a son's background characterized by his father's educational outcome is the more important explanatory variable for the son's life chances at the bottom of the son's conditional education distribution than at the top. Such a "fanning in" pattern of intergenerational association suggests that the dispersion in sons' educational attainment is wider at lower compared to higher levels of fathers' schooling distribution. It means there is a higher probability of sons of highly educated fathers staying homogenously well-educated than the likelihood of sons of less-educated fathers staying homogenously less educated (Torche, 2013).

6. 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 persistence in the next generation for countries worldwide (Krueger, 2012; Corak, 2013). The curve implies that the persistence in the circumstances handed over by parents to their children depends on the economic inequality prevalent in the said region during parents' time. 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 (dis)advantage 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. 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 individuals while growing up shape their outcomes and life chances. Suppose inequality in human capital levels among families is high for a given generation. In that case, the subsequent inequality of investment in children's education, directly and indirectly, conserves the status quo and impedes mobility. However, the countervailing forces of education spending by the government (Mayer & Lopoo, 2008; Aizer, 2014), and economic growth (Maoz & Moav, 1999; Hassler & Mora, 2000), work towards neutralizing the advantage due to better family background and further intergenerational mobility.

Going further, we consider children in the age group 6-18 as differences in mobility rates between two populations are induced by factors that affect individuals in their formative years (Chetty et al., 2014). Given the IHDS-II data, we examine adult sons (aged 25 and above as of 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 a proportion of Gross State Domestic Product (GSDP) per capita* and *year on year per capita GSDP growth* for 1992-93[5]. Information on the education expenditure variable is obtained from the *CMIE States of India* Statistical Compendium. For GSDP growth rates, we refer *to EPWRF India Time Series* economic indicators. Finally, Gini of the educational attainment of fathers of individuals in the birth cohort 1974 - 1986 is constructed to denote education inequality in fathers' generation. These state-level variables are slow-moving, i.e., they remain relatively

[5] 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.

stable across time. Thus, following Chetty et al. (2014), we estimate cross-sectional relationships rather than employ panel data methods.

Figure 2 plots the relationship between education inequality in fathers' generation and IGRC for the birth cohort (1974 – 1986) for various Indian states. The cross-state relationship between the variables of interest in the figure corroborates the Great Gatsby Curve connection for education in India.

[Insert Figure 2 here]

Next, we empirically test the hypothesis of a positive relationship between inequality and intergenerational persistence. We also 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. The following model based on Neidhöfer (2019) is employed.

$$S_{is} = \beta_0 + \beta_1 F_{is} + \gamma_1 * F_{is} * G_s + \delta_1 G_s + \gamma_2 * F_{is} * E_s + \delta_2 E_s + \gamma_3 * F_{is} * R_s + \delta_3 R_s + \theta_s + \epsilon_{is} \tag{4}$$

where the subscript s denotes individual i's state of residence, G_s depicts the education Gini coefficient 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. γ_1, γ_2, and γ_3 are the coefficients of interest.

[Insert Table 6 here]

In Table 6, the IGRCs are reported in the top row. The coefficients of the interaction between fathers' education outcome and the channels under consideration are presented in rows two to five. There are three main findings. First, we obtain a confirmation of a positive relationship between education inequality and intergenerational education persistence. Evidently, in India's case, inequality subjects an individual's life chances to majorly depend on his background and lessens the role of hard work. It means that a son of an educationally advantaged father has access to better schools, an opportunity to study further, and better networks than 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. Per Corak (2013), the Great Gatsby Curve phenomenon is also fuelled by an increase in returns to education for the highly educated. The positive association between inequality and education immobility hints at an imperfect capital market situation and substantial heterogeneity in returns to higher education in India. Such a scenario calls upon a redistributive education policy (Bratsberg et al., 2007), rational wage settings institutions, a more functional welfare system, and better capital markets.

Secondly, the negative and statistically significant interaction effect of economic growth with fathers' education on son's education points towards a positive relationship between economic growth and intergenerational mobility. This result conforms with the economic models proposed in Maoz and Moav (1999) and Hassler and Mora (2000), where growth and mobility reinforce each other. 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. However, the result is not always statistically significant. Higher government spending on education may not always translate into 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.

7. 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 educational outcomes. We explore the nonlinearity in the relationship between educational outcomes of successive generations for various cohorts and regions by employing quantile regressions. We also analyze the role of specific 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.

We find that education mobility is not linear across the conditional distribution of the educational attainment of individuals. For the overall sample and 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' conditional education distribution. 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 affect intergenerational education mobility positively.

For equality of opportunity to improve in society, public institutions need to play a significant role and devise policies to offset the disadvantage faced by the lowly endowed sections of the population. Given the high degree of education persistence at the primary and middle school levels across all sub-groups, the government must look in the following directions. First, designing redistributive education policies that ensure primary and secondary education irrespective of socioeconomic status. Secondly, considering the spatial differences in mobility between urban and rural regions across the entire education distribution, it is essential to improve accessibility and the quality of education in rural areas of the country. Thirdly, it is crucial, in the face of inequality, to improve 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. Finally, enhancing the access 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. 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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Tables

Table 1. Intergenerational Regression Coefficients (All India)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Son's years of schooling						
Father's YoS	0.588***	0.544***	0.534***	0.582***	0.529***	0.570***	0.522***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Constant	5.318***	7.131***	7.325***	5.456***	7.233***	6.684***	8.140***
	(0.027)	(0.083)	(0.162)	(0.029)	(0.082)	(0.145)	(0.165)
Correlation (IGC)	0.519	0.479	0.470	0.514	0.466	0.503	0.460
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	44,532	44,411	44,411	44,532	44,411	44,532	44,411
Adj. R-sq.	0.270	0.287	0.306	0.276	0.299	0.296	0.316

Notes: Father's YoS – Father's Years of Schooling; Standard errors clustered at household level in parentheses; * p<0.05, ** p<0.01, *** p<0.001

Table 2. Cohort trends in Intergenerational Regression Coefficient by Caste (Dependent Variable – Son's years of schooling)

	(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
Father's YoS	0.422***	0.596***	0.449***	0.601***	0.447***	0.670***
	(0.013)	(0.019)	(0.012)	(0.022)	(0.015)	(0.038)
Constant	9.190***	6.870***	8.511***	4.372***	7.549***	5.134***
	(0.357)	(0.450)	(0.612)	(0.691)	(0.431)	(1.146)
Correlation (IGC)	0.483	0.517	0.445	0.420	0.399	0.396
State Controls	Yes	Yes	Yes	Yes	Yes	Yes
Religion Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	4,042	2,217	5,919	2,931	4,313	1,882
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 3. Cohort trends in Intergenerational Regression Coefficient by Religion (Dependent Variable – Son's years of schooling)

	(7)	**(8)**	**(9)**	**(10)**
	Hindu		Muslim	
	25-34	55-64	25-34	55-64
Father's YoS	0.426***	0.599***	0.533***	0.650***
	(0.008)	(0.015)	(0.024)	(0.045)
Constant	8.595***	7.592***	7.159***	3.338***
	(0.326)	(0.492)	(0.404)	(0.498)
Correlation (IGC)	0.440	0.441	0.472	0.476
Caste Controls	Yes	Yes	Yes	Yes
State Controls	Yes	Yes	Yes	Yes
N	11,700	5,858	1,899	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

Table 4. Intergenerational Regression Coefficients across the distribution of sons' years of schooling (Dependent Variable – Son's years of schooling)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Quantile (.10)	Quantile (.20)	Quantile (Median)	Quantile (.60)	Quantile (.75)	Quantile (.90)	Quantile (.95)
			All India				
Father's YoS	0.667***	0.900***	0.600***	0.500***	0.467***	0.375***	0.200***
Constant	0	0	5***	7***	9***	12***	14***
N				44,532			
			Rural Sample				
Father's YoS	0.600***	0.800***	0.556***	0.500***	0.400***	0.375***	0.375***
Constant	0	0	5***	6.500***	8.182***	10***	12***
N				28,138			
			Urban Sample				
Father's YoS	0.750***	0.800***	0.500***	0.467***	0.400***	0.223***	0.091***
Constant	0	0.714***	7***	8***	10***	13***	15***
N				16,394			
			Age Cohort: 25-34				
Father's YoS	0.714***	0.800***	0.455***	0.438***	0.467***	0.333***	0.111***
Constant	0	1***	7***	8***	9***	12***	14.78***
N				14,529			
			Age Cohort: 55-64				
Father's YoS	0.667***	0.938***	0.733***	0.700***	0.533***	0.600***	0.500***
Constant	0	0	4***	5***	8***	10***	12***
N				7,138			

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

Table 5. Intergenerational Regression Coefficients across the distribution of sons' years of schooling (Dependent Variable – Son's years of schooling)

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
	Quantile (.10)	Quantile (.20)	Quantile (Median)	Quantile (.60)	Quantile (.75)	Quantile (.90)	Quantile (.95)
			Brahmins and Other Upper Castes				
Father's YoS	0.75***	0.833***	0.500***	0.467***	0.400***	0.300***	0.100***
Constant	0	1.667***	7.5***	8.267***	10***	12.6***	15***
N				13,124			
			Other Backward Castes				
Father's YoS	0.667***	0.833***	0.500***	0.428***	0.416***	0.375***	0.25***
Constant	0	1***	7***	8***	9.334***	12***	13.75***
N				17,981			
			SCs and STs				
Father's YoS	0.555***	0.800***	0.600***	0.500***	0.400***	0.400***	0.400***
Constant	0	0.8***	6***	7.5***	9***	12***	13***
N				12,702			
			Hindus				
Father's YoS	0.700***	0.900***	0.555***	0.500***	0.461***	0.375***	0.167***
Constant	0	0.8***	6.667***	8***	9.461***	12***	14.334***
N				36,369			
			Muslims				
Father's YoS	0.500***	0.777***	0.667***	0.600***	0.500***	0.500***	0.416***
Constant	0	0	5***	6.4***	8.5***	10.5***	12.25***
N				5,910			

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

Table 6. The Great Gatsby Curve and other channels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	yrssch	yrssch	yrssch	yrssch	yrssch	yrssch	yrssch	yrssch
Father's YoS	0.498***	0.487***	0.322***	0.282***	0.269***	0.269***	1.385***	2.206***
	(0.006)	(0.006)	(0.045)	(0.047)	(0.053)	(0.054)	(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					-0.014***	-0.015***		
					(0.003)	(0.004)		
channel1b_int							-0.12***	-0.21***
							(0.016)	(0.022)
channel2_int						-0.0027		-0.04***
						(0.007)		(0.008)
State FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes
N	18,934	18,934	18,934	18,934	18,323	18,286	18,323	18,286
Adj. R-sq	0.251	0.278	0.253	0.278	0.280	0.279	0.281	0.281

Notes: Standard errors clustered at household level in parentheses; * p<0.05, ** p<0.01, *** p<0.001. We control for the son's age in all regressions and report only the pertinent coefficients. *GGC_int* is the slope coefficient of the interaction between Gini of Educational attainment in fathers' generation and IGRC. *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); *channel2_int* is the slope coefficient of the interaction between Government expenditure on education and IGRC. The definition of Government expenditure on education is - Per Capita Expenditure on Education, sports, art & culture as a proportion of GSDP per Capita (Average from 1990-91 to 1994-95) (in %).

Figures

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

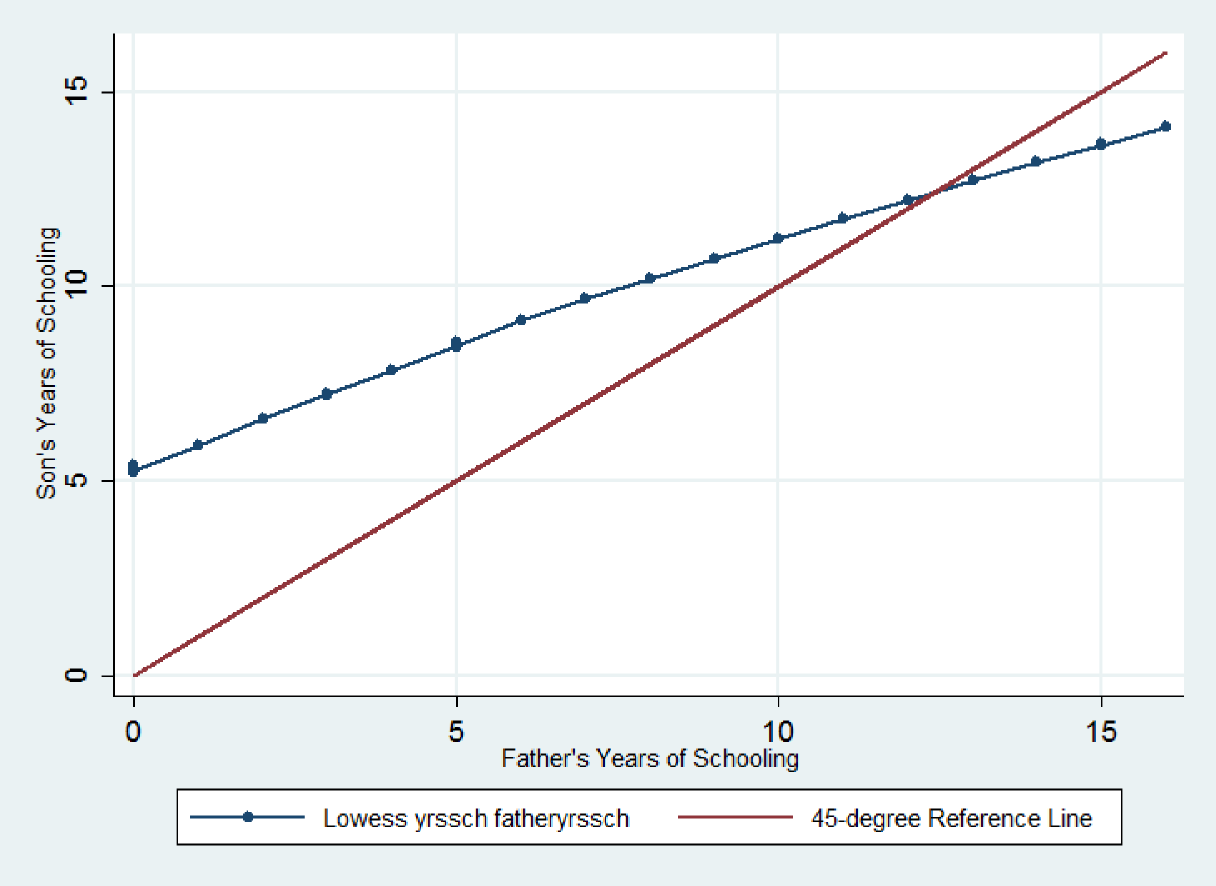

Figure 2. Intergenerational Regression Coefficient vs. Education Gini