

Intergenerational Mobility in India: New Methods and Estimates Across Time, Space, and Communities*

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Abstract

We study intergenerational educational mobility in India over time, across groups, and across space. We show that the modern set of rank-based mobility measures can be at best partially identified with education data. We introduce a new measure, bottom half mobility, which generates tight bounds and is valid for studying subgroup mobility, unlike prior measures. We find that population intergenerational mobility has been constant and low since before liberalization. Among boys, rising mobility for Scheduled Castes is almost exactly offset by declining mobility among Muslims, a comparably sized group with few constitutional protections. Among girls, mobility is lower and less variable over time, but the gender gap is heterogeneous across space and social group. Muslim disadvantage cannot be explained by occupational patterns, fertility, differential returns to education, or location. However, affirmative action appears to be important for mobility; we exploit a natural experiment that reclassified members of some Scheduled Caste groups, finding that the effect of affirmative action on Scheduled Castes may be large enough to explain all of the Muslim–Scheduled Caste gap. We generate high-resolution geographic measures of intergenerational mobility across 5600 rural subdistricts and 2300 cities and towns. On average, children are most successful at exiting the bottom of the distribution in places that are southern, urban, or have higher average education levels. Our measures are relevant for the study of mobility in poorer countries and in historical contexts.

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1 Introduction

There are two widely held narratives regarding access to opportunity in India. On the one hand, economic liberalization, rapid economic growth, and urbanization have vastly expanded the set of opportunities available to Indians, leading to the emergence of a large middle class. The political sphere has also opened, with the emergence of a wide range of parties organized around caste, region, and ideology. Decades of affirmative action programs have targeted government benefits at historically disadvantaged groups. On the other hand, some of India's entrenched inequalities seem as persistent as ever. Marriage across religious, caste, and class lines is exceedingly rare. Elites in business, government and civil society are still largely from upper classes and castes. Inequality has risen, and religious cleavages may be deepening.

In this paper, we shed light on changing access to opportunity in India by studying the intergenerational transmission of economic status (Solon, 1999; Black and Devereux, 2011; Chetty et al., 2014a; Chetty et al., 2017). We focus on the estimation of upward mobility, describing its variation in India over time, across social groups, and across geography. To do so, we develop a set of methods that makes it possible to apply modern rank-based measurements of upward mobility in contexts where coarse educational outcomes are the only viable measure of socioeconomic status that can be linked across generations. Our methods may be useful in studies of intergenerational mobility in other developing countries, as well as in historical contexts in richer countries.

Because of data quality and availability, as well as the challenge of measuring individual income in households with joint production, studies of intergenerational mobility in developing countries (and in historical contexts) often use education as a proxy for social status.¹ A key challenge in the measurement of educational mobility is that education data is often coarsely measured; for instance, for the 1960–69 birth cohort in India, over 50% of fathers and 80% of mothers report a bottom-coded level of education. This makes it difficult to use recent rank-based measures of mobility, such as

¹In developing countries or in historical data, education may in fact be a better proxy for lifetime income than wages, which are measured with significant error and life-cycle bias. Linked parent-child education data are also much more widely available than linked income data. Recent studies of intergenerational mobility focusing on education and occupation include Black et al. (2005), Güell et al. (2013), Wantchekon et al. (2015), Card et al. (2018), Deroncourt (2018), and Alesina et al. (2019). More are summarized in Black and Devereux (2011).

absolute mobility, which require observing parents at specific percentiles in the socioeconomic status distribution.² Studies of educational mobility have instead focused on estimators like the correlation coefficient between parents’ and children’s educational outcomes. These linear estimators have several limitations (discussed in Section 3.1), the most important of which is that they are not meaningful for subgroup analysis, because they measure individuals’ progress only against other members of their own group (Hertz, 2005).^{3,4}

In this paper, we show that with education data, the new generation of rank-based estimators of intergenerational mobility can at best be partially identified. Intuitively, when income mobility estimators are applied directly to educational mobility, they do not account for the loss of information associated with coarse measurement of ranks; they instead rely on implicit and untested assumptions about the latent rank distribution.⁵ We treat the estimation of child outcomes conditional on latent parent ranks as an interval data problem; for each mobility measure, we calculate the *set* of values that are consistent with a latent conditional expectation function that generates the coarsely observed moments.⁶

We introduce a new measure of upward mobility, *bottom half mobility*, which is the expected rank of a child born to a parent in the bottom half of the education distribution. Bottom half mobility has a similar interpretation to other measures of upward mobility, but it can be bounded tightly even in contexts with extreme interval censoring.⁷ In contrast, once prior measures (absolute

²Chetty et al. (2014a) define absolute mobility at percentile i as the expected income rank of a child, conditional on that child being born to a parent at the i th income percentile.

³For example, the parent-child rank-rank gradient among U.S. Blacks is nearly identical to that among U.S. Whites, even though Black children obtain considerably worse outcomes in expectation than White children at every percentile of the parent income distribution (Chetty et al., 2018).

⁴Similarly, a regression of child years of education on parent years of education conflates changes in the distribution of education with changes in the persistence of ranks across generations (Chetty et al., 2014a).

⁵The notion of a latent distribution of education ranks arises directly out of the standard human capital model (Card, 1999); individuals who are close to the margin of obtaining the next discrete level of education are those with high latent ranks in each bin. Note that because we use education as a proxy for socioeconomic status, the latent education rank is the parameter of interest rather than the precise number of years of education obtained. We discuss this concept further in Section 3.3.

⁶We use a standard approach to interval data established by Manski and Tamer (2002) and extended to the problem of estimating outcomes conditioning on coarse education ranks in Novosad et al. (2020). We generate this set by using best- and worst-case assumptions about the underlying data generating process that are consistent with the data we do observe.

⁷Bottom half mobility describes the expected outcome of children conditional on having a parent in the bottom half of the distribution. Absolute upward mobility Chetty et al. (2014a) is similar, except it conditions on the *median* parent in the bottom half of the distribution. If the conditional expectation function is linear in parent rank, the two measures are identical. If the CEF is concave, then bottom half mobility puts more weight on the outcomes of

upward mobility and the rank-rank gradient) are adjusted to account for the underlying uncertainty associated with interval data, their bounds are too wide to be meaningful. This paper thus relaxes the hidden assumptions underlying most mobility estimators in settings with education data and still obtains precise (if partially-identified) mobility estimates. To our knowledge, bottom half mobility is the first measure of intergenerational educational mobility that can be meaningfully compared across time and space, across countries, and across population subgroups.⁸

We apply our measure to India, using data from the 2012 India Human Development Survey (IHDS), and the 2012 Socioeconomic and Caste Census (SECC).⁹ We document trends in educational mobility from the 1950–59 to the 1985–89 birth cohorts.¹⁰ We focus on measuring mobility from fathers to sons/daughters; mobility from mothers to children cannot be bounded tightly because the bottom-coding of mothers’ education is so severe.

We present three main findings. First, upward mobility has remained constant for the past several decades, despite dramatic gains in average levels of education and income. An Indian son born in the bottom half of the parent education distribution in 1985–89 (our youngest cohort) can expect to obtain the 37th percentile; a daughter obtains percentile 35.5.¹¹ A similar child in the U.S., which has low intergenerational mobility by OECD standards, on average attains education percentile 41.7.^{12,13} This suggests that India’s decades of economic growth may best be described as an order-preserving

the least privileged children. Note that the linear parent-child income rank CEF in the United States is an exception rather the rule; in most countries, these CEFs are non-linear (Bratsberg et al., 2007; Boserup et al., 2014; Bratberg et al., 2015; Connolly et al., 2019).

⁸Hertz (2008) provides a decomposition of intergenerational mobility that permits comparisons across subgroups. Like work before Chetty et al. (2014), this is a linear estimator that is difficult to use with interval-censored data.

⁹The former is a sample survey, and the latter is a socioeconomic census with high geographic resolution covering all individuals in the country.

¹⁰Our main estimates include data from both children living with their parents and children who have moved out, mitigating concern about coresidence bias. Our geographically precise estimates are restricted to coresident father/son pairs due to data limitations; we restrict this sample to sons aged 20–23 and show that the sample selection bias for this group is likely to be very small.

¹¹Following convention (Chetty et al., 2014b; Chetty et al., 2018), we always rank children in the own-gender distribution.

¹²In a society where children’s outcomes are independent of parents (i.e. total mobility), a child born in the bottom half of the distribution obtains the 50th percentile on average. In a society with no upward mobility, (i.e. where all children obtain the same percentile as their parents) the same child attains the 25th percentile.

¹³All of our mobility estimates are robust to different data construction methods, and we show that survivorship bias, migration, or bias in estimates from coresident parent-child households do not substantially affect our results. We also show that unobserved changes in the latent rank distribution of population subgroups within education bins cannot drive the secular changes that we document.

shift in socioeconomic outcomes; while people are better off at every point in the distribution, the likelihood of moving to a higher *rank* across generations has not changed on average.

Second, we show that there are significant changes in the cross-group distribution of upward mobility over time, particularly among boys. We divide the population into Scheduled Castes (SCs), Scheduled Tribes (STs), Muslims, and Forwards/Others.¹⁴ Consistent with prior work (Hnatkowska et al., 2012; Emran and Shilpi, 2015), we find that boys from India’s constitutionally protected marginalized groups, the Scheduled Castes and Tribes, have closed respectively 50% and 30% of the mobility gap to Forwards/Others. In contrast, upward mobility for Muslim boys has steadily declined from the 1960s to the present. The expected educational rank of a Muslim boy born in the bottom half of the parent distribution has fallen from between 31 and 34 to a dismal 29. Muslim boys have considerably worse upward mobility today than both Scheduled Castes (38) and Scheduled Tribes (33), a striking finding given that STs tend to live in much more remote and low mobility areas than Muslims. The comparable figure for U.S. Black men is 34.¹⁵ Higher caste groups have experienced constant and high upward mobility over time, a result that contradicts a popular notion that it is increasingly difficult for higher caste Hindus to get ahead.

Our measures for father-daughter mobility are less precise, but the subgroup patterns appear to be different. Girls from poor Muslim, SC, and ST households all have persistently lower mobility than Forwards/Others, and there is minimal convergence over the sample period.

Third, we describe substantial variation in upward mobility across 5,600 rural subdistricts and 2,000 cities and towns. Paralleling results from Chetty et al. (2014b), we find substantial heterogeneity even within small geographic regions. Upward mobility is highest in urban areas, and in places with high consumption, education, school supply, and manufacturing employment, which are broad correlates of development. High mobility is inversely correlated with caste segregation and land

¹⁴We include non-Muslim OBCs in the “Others” category. Measuring OBC mobility is challenging because OBC definitions are less stable over time, are sometimes inconsistently classified between federal and state lists, and may be reported inconsistently by the same individual over time. These concerns apply to SC and ST groups, but at a considerably smaller scale. The very small number of Muslim SC/STs are categorized as Muslims; reclassifying them as SCs or STs, or excluding Sikhs, Jains and Christians from the “others” category do not affect our results.

¹⁵This was calculated using the methodology in this paper and education data from Chetty et al. (2018). Bottom half *income* mobility for U.S. Black men is 39 (Chetty et al., 2018).

inequality. Geography-subgroup interactions are important; for instance, girls have higher mobility than boys in urban areas, but lower in rural areas.

The final section of the paper examines several potential mechanisms for the divergence of Scheduled Castes from Muslims over the last 25 years. We show that this divergence cannot be explained by differential returns to education, occupational patterns, geography, or differential fertility. However, the basket of affirmative action policies targeted to India’s scheduled groups appears to have had a substantial impact on their mobility. Following Cassan (2019), we exploit a natural experiment that added many castes to the Scheduled Caste lists in 1977. We show that when a social group (jati) gets assigned to Scheduled Caste status, it experiences a 7–8 rank point increase in upward mobility over the next twenty years. This is the same size as the rank mobility gap that has opened between Muslims and Scheduled Castes over the same period. This finding is consistent with the possibility that educational quotas, government job reservations, and other affirmative action policies (which benefited Scheduled Castes but not Muslims) are a key driver of the growing upward mobility gap between Scheduled Castes and Muslims.

Our paper’s contributions are both methodological and empirical. Bottom half mobility is the first educational mobility measure that is valid for comparing population subgroups across different contexts. Prior researchers have used CEF-based mobility measures to examine subgroup outcomes, but the coarse measurement problem has forced them to use inconsistent measures over time and across contexts. For example, Card et al. (2018) and Deroncourt (2018) define upward mobility in the 1920s as the 9th grade completion rate of children whose parents have 5–8 years of school (or approximately parent percentiles 30–70) — they then compare this measure with absolute upward mobility (i.e. children of parents at the 25th percentile) in the present. Alesina et al. (2019) define upward mobility in Africa as the likelihood that a child born to a parent who has not completed primary school manages to do so. While this measure captures the ability of poor children to exceed the education levels of their parents, it does not distinguish between average educational gains and changes in the ability of individuals to move up the socioeconomic distribution in *relative* terms,

an essential component of mobility.¹⁶ In contrast, our measure precisely isolates individuals' ability to move up in the rank distribution across generations, holding parent rank constant.

Empirically, we present several previously unknown facts about upward mobility in India. Our most striking finding is that Muslims are losing substantial ground in intergenerational mobility, and currently have lower mobility than either Scheduled Castes or Scheduled Tribes. Despite a population share comparable to Scheduled Castes, Muslims are often overlooked by the economic literature on marginalized groups in India.¹⁷ We also present causal evidence that the combination of affirmative action policies targeting Scheduled Castes has increased their intergenerational mobility.

Our findings imply that virtually all of the upward mobility gains in India over recent decades have accrued to Scheduled Castes and Tribes, groups that have constitutional protections, reservations in politics and education, and who have been targeted by many development policies. There is no evidence that any of these gains have come at the expense of higher caste groups.

These patterns have to our knowledge not been identified because earlier studies have either (i) focused on absolute outcomes (such as consumption), which are rising for all groups due to India's substantial economic growth (Maitra and Sharma, 2009; Hnatkowska et al., 2013); or (ii) compared subgroups using the parent-child outcome correlation or regression coefficient, which describes the outcomes of subgroup members relative to their own group, rather than to the national population (Hnatkowska et al., 2013; Emran and Shilpi, 2015; Azam and Bhatt, 2015).¹⁸ Studies on affirmative action in India have identified improvements in SC/ST access to higher education but have not examined impacts on Muslims (Frisancho Robles and Krishna, 2016; Bagde et al., 2016); our findings point to the importance of studying the effects of such policies on a wider set of marginalized groups.¹⁹

¹⁶This measure also conditions on substantially different parts of the education distribution in different times and places; this measure corresponds to, for example, $E(y > 52 | x \in [0, 76])$ in Mozambique (where 76% of parents and 48% of children have not completed primary), but to $E(y > 18 | x \in [0, 42])$ in South Africa, where y is child rank and x is parent rank. See Section 3.5 for more detail.

¹⁷Notable exceptions include Khamis et al. (2012) and Bhalotra and Zamora (2010), who note poor education outcomes among Muslims. The Sachar Committee Report (2006) and Basant et al. (2010) summarize some recent research on Muslims on India, none of which addresses intergenerational mobility.

¹⁸Note that there is a parallel literature examining the persistence of income within an individual lifetime in India; this is sometimes described as *income* or *economic mobility*. That literature is focused largely on measurement error in income over the course of an individual's lifetime and is thus not directly related to our work (Azam, 2016; Li et al., 2019).

¹⁹In an analogous finding, Bertrand et al. (2010) find that when Indian colleges intentionally select lower caste students, they end up admitting fewer women.

Our paper proceeds as follows. Section 2 provides background on India's social groups. Section 3 describes our methodological innovation in the context of prior measures of intergenerational educational mobility. Section 4 describes the data sources. Section 5 presents results on national and cross-group mobility trends, the geographic distribution of intergenerational mobility, and our analysis of mechanisms. Section 6 concludes.

2 Context on Scheduled Castes, Scheduled Tribes, and Muslims

While intergenerational mobility is of interest around the world, India's rapid economic transformation, caste system, and high levels of inequality make it a particularly important setting for understanding access to opportunity. Indian society has undergone a massive transformation over the last forty years. Economic liberalization, starting in the 1980s, dismantled many parts of the India's post-Independence socialist experiment. Decades of sustained economic growth have resulted in a massive decrease in poverty and the rise of a large middle class.

India's caste system is characterized by a set of informal rules that inhibit intergenerational mobility by preventing individuals from taking up work outside of their caste's traditional occupation and from marrying outside of their caste. Since independence in 1947, the government has systematically implemented policies intended to reduce the disadvantage of communities that are classified as Scheduled Castes or Scheduled Tribes. These groups are targeted by a range of government programs and benefit from reservations in educational and political institutions.

India's Muslims constitute a similar population share as the Scheduled Castes and Scheduled Tribes (14% for Muslims vs. 17% for SCs and 14% for STs). While Muslim disadvantage has been widely noted, including by the well-known federal Sachar Report (2006), there are few policies in place to protect them and there has not been an effective political mobilization in their interest. On the contrary, a large scale social movement (the Rashtriya Swayamsevak Sangh, or RSS) and several major political parties have rallied around pro-Hindu platforms and policies which arguably discriminate against Muslim religious, economic, and cultural practices. Violent anti-Muslim riots have been closely tied to political parties and political movements (Wilkinson, 2006; Berenschot, 2012; Blakeslee, 2018).

The last 30 years have seen tremendous growth in market opportunities in India as well as in

educational attainment. While some have argued that economic growth is making old social and economic divisions less important to the economic opportunities of the young, caste remains an important predictor of economic opportunity (Munshi and Rosenzweig, 2006; Ito, 2009; Hnatkowska et al., 2013; Mohammed, 2019). Understanding how mobility has changed for these population groups is thus an essential component of understanding secular trends in intergenerational mobility in India. Whether economic progress can overcome traditional hierarchies of social class and religion is a central question for both India and the broader world.

3 Methods: Measuring Mobility in Developing Countries

When intergenerational mobility is low, the social status of individuals is highly dependent on the social status of their parents (Solon, 1999). In more mobile societies, individuals are less constrained by the circumstances of their birth. A growing literature, facilitated by new administrative datasets, has documented differences in intergenerational mobility across countries, across groups within countries, and across time.²⁰

In this section, we present a brief background on the measurement of intergenerational mobility in various contexts. We then present the key challenge for using modern mobility measures in developing country contexts. We then propose a novel measure of upward mobility, *bottom half mobility*, which can provide much tighter estimates of upward mobility than conventional measures.²¹

3.1 Background: Measurement of Intergenerational Mobility

The first generation of intergenerational mobility studies summarized the joint parent-child outcome distribution with a single linear parameter, such as the correlation coefficient between children's earnings and parents' earnings (Solon, 1999; Black and Devereux, 2011). Such gradient measures are easy to calculate and interpret and they form the basis of studies in dozens of countries. These measures have two main limitations: (i) they do not distinguish between changes in opportunity

²⁰See Hertz et al. (2008) for cross-country comparisons, and Solon (1999), Corak (2013), Black and Devereux (2011), and Roemer (2016) for review papers.

²¹Code and documentation to generate all the measures used in this paper are available at <https://github.com/paulnov/nra-bounds/>.

at the top and the bottom of the distribution;²² and (ii) they are not well-suited for between-group comparisons. The parent-child outcome gradient in a population subgroup effectively compares children’s outcomes against more advantaged members of their own group. A subgroup can therefore have a lower gradient (suggesting higher mobility) and yet worse outcomes at every point in the parent distribution. For a striking example, see Chetty et al. (2018), who show that the parent-child income rank gradient is virtually identical for Whites and Blacks; Black boys suffer the same large rank disadvantage at every point in the parent rank distribution.

More recent studies have analyzed the entire joint parent-child income distribution, and in particular, the conditional expectation function of child rank given parent rank (Boserup et al., 2014; Chetty et al., 2014a; Bratberg et al., 2015; Hilger, 2016). Studying transitions in ranks is useful because it holds constant any changes in average income levels or inequality over time, isolating individuals’ relative movement in the social hierarchy. The most widely used measure in the new generation of studies is *absolute upward mobility*, defined as the expectation of a child’s income rank, conditional on having a parent at the 25th income percentile, or $p_{25} = E(y|x=25)$, where y is the child rank and x is the parent rank. Proposed by Chetty et al. (2014a), this measure describes the expected rank of a child born to the median parent in the bottom half of the parent rank distribution.²³

Unlike the gradient estimators, absolute upward mobility (henceforth p_{25}) is valid for cross-group comparisons: with p_{25} , we can compare outcomes of children in different population subsets who are born to parents at the same income percentile. It is also comparable across contexts or countries with different levels of income or income inequality. However, as we discuss below, methodological challenges have made it difficult to use this measure in developing countries.

²²This weakness is consequential only if the conditional expectation of the child outcome given the parent outcome is non-linear. But many studies find non-linear CEFs (Bratsberg et al., 2007; Boserup et al., 2014; Bratberg et al., 2015; Connolly et al., 2019); the linearity of the income rank CEF described by Chetty et al. (2014a) is an exception. The Indian education rank CEF that we study below is clearly non-linear.

²³Chetty et al. (2014a) use the term “absolute mobility” because this measure does not depend on the value of the CEF at any other point in the parent rank distribution, distinguishing it from the rank-rank correlation which they describe as a *relative* mobility measure. Other authors use the term “absolute mobility” to describe the set of mobility measures which use child levels as outcomes rather than child ranks. To avoid confusion, we use the term “absolute mobility” only when making reference to the specific measure used by Chetty et al. (2014a).

3.2 Educational Mobility and Income Mobility

In the study of upward mobility in developing countries, education is often a better proxy of social status than income, for three reasons. First, matched parent-child education data are more widely available than matched income data. Because education is fixed early in life and parents' education is generally known by the next generation, it is possible to record matched parent-child education data even when the parent is no longer alive. Second, income is subject to significant measurement error in developing countries. Transitory incomes are noisy estimates of lifetime income, especially in agriculture, and depend on an individual's place in the life cycle. Subsistence consumption is difficult to measure, and many individuals report zero income. Measurement error in income is consequential because it biases mobility estimates upward (Zimmerman, 1992). In contrast, education levels are measured more precisely than income, and rarely change in adulthood, mitigating life-cycle bias.

Third, individual permanent income is difficult to assign in households with joint production processes, like many of the rural poor. When these households span multiple generations, it is virtually impossible to distinguish between parent income and child income. Education, in contrast, is directly ascribed to an individual.

For these reasons, studies of intergenerational mobility in developing countries, as well in historical periods in developed countries, have focused on the intergenerational persistence of social status as measured by educational attainment (Solon, 1999; Güell et al., 2013; Wantchekon et al., 2015; Card et al., 2018; Derenoncourt, 2018; Alesina et al., 2019). But studies of educational mobility have thus far not come up with a satisfactory analog to rank-based measures like absolute upward mobility.

The key challenge is that the coarse measurement of educational completion makes it impossible to identify a parent at a precise education percentile. This challenge is demonstrated in Figure 1A, which shows the average child education rank in each parent education rank bin, for two Indian birth cohorts: 1960–69 (circles) and 1985–89 (x's).²⁴ The solid and dashed vertical lines respectively show the boundaries for the bottom-coded education bin in the two cohorts. In the 1960–69 birth cohort, a full 57% of fathers report a bottom-coded education level; in the 1985–89 cohort, this figure is 36%. How

²⁴Data are from the Indian Human Development Survey (2012), described in Section 4.

does one identify the expected child rank given a parent at the 25th percentile in these birth cohorts?²⁵

Figure 1B shows two conditional expectation functions that are both perfectly consistent with the 1960–69 moments. The data available cannot distinguish between these two functions, but they have very different implications for upward mobility: the flatter of the two functions implies a much higher expected rank for a child growing up at the bottom of the distribution. This example demonstrates that the CEF of child rank given parent rank can be at best partially identified from education data; Section 3.3 below shows that we can nevertheless recover useful estimates of upward mobility from the data.

Coarse measures of parental status like these are extremely common in the mobility literature. In older generations in developing countries, bottom-coding rates in excess of 50% are widespread (Narayan and Van der Weide, 2018) and researchers encounter a similar problem when studying older generations in richer countries. Internationally comparable censuses often report education in as few as four or five categories. Income mobility is also often based on censored estimates; in the well-known British Cohort Study, one income bin contains more than 30% of the data. Table 1 reports the number of parent education bins used in a set of recent studies of intergenerational mobility from several rich and poor countries. Many studies observe education in fewer than ten bins; the population share in the bottom bin is often above 20%, and in many developing countries it is above 50%.

Comparing transition matrices over time poses a similar problem to that of estimating p_{25} : when education bin boundaries are changing over time (due to changes in the education distribution), transition matrix cells cannot be directly compared in different years. Using a quantile transition matrix would resolve the problem of comparability, but calculating the quantile transition matrix from coarsely binned rank data poses exactly the same challenge as calculating p_{25} .

²⁵The graph makes self-evident why we cannot assume that the expected child rank given a parent at the 25th percentile is equivalent to the expected child rank given a parent in the bottom education bin. The size of the bottom bin is a function of the granularity of the education coding and the national distribution of education; when this bin is smaller, children in that bin are more negatively selected and will have mechanically lower education. In the case of Figure 1A, the path traced by the CEFs of the two birth cohorts look highly similar in rank space, but the expected child rank in the bottom bin is mechanically lower in the 1985–89 birth cohort because of the smaller bin size.

3.3 Estimating Bounds on a CEF with Censored Rank Data

In this section, we describe our approach to bounding the conditional expectation function of child rank given parent rank (henceforth the CEF), when rank data are binned as in the case of education. Our approach can also be used to bound functions of the CEF, like absolute upward mobility and the rank-rank gradient. We will show that one function of the CEF, which we call bottom half mobility, has particularly tight bounds. The partial identification approach is based on Novosad et al. (2020), which is concerned with identifying $E(y|x=i)$, where y is adult mortality and x is adult education rank. The methodological contribution of this paper is to use these partial identification tools to solve the problem of measuring intergenerational educational mobility.

Formally, our goal is to measure $E(y|x=i)$, where y is a child outcome (primarily the child education rank in this paper) and x is a parent rank. We observe only that x lies within some interval $[x_k, x_{k+1}]$, where k indexes bins. The mean value of $E(y|x)$ in bin k is observed.

We require only two substantive assumptions to derive bounds on $E(y|x)$. First, we assume that there is a latent continuous parent education rank; this implies a meaningful but unobserved ranking of parent educations *within* each observed education category. Formally:

$$E(y|x=i) \text{ has support for all values of } i \in [0,100]. \quad (\text{Assumption 1})$$

This assumption arises directly from a standard human capital model where observed differences in education levels reflect individual differences in costs and benefits of seeking education (Card, 1999). The latent education rank x reflects the amount that the marginal benefit or cost of obtaining the next level of education (e.g., “Middle School”) would need to change in order for a given individual to progress to the next level. Individuals who are at the margin of obtaining the next level of education (*i.e.* they would need only a small increase in marginal benefit in order to do so) have the highest educational ranks within their rank bin. Individuals who would not advance further even if the net benefit changed a great deal have the lowest ranks in the bin. Alternatively, x represents what an individual’s education rank would be if education choices were fully continuous and observed as such.

The latent rank thus reflects the underlying factors that shift individuals’ demand for education, which can be expected to be correlated with socioeconomic status (Card, 1999).^{26,27} Assumption 1 implies that the calculation of $E(y|x=i)$ can be treated as an interval censoring problem (Manski and Tamer, 2002; Novosad et al., 2020).

Our second assumption is that the expectation of a child’s education level is weakly increasing in the latent parent education rank. In other words, having a more advantaged parent cannot make a child worse off. Formally:

$$E(y|x) \text{ must be weakly increasing in } x. \quad (\text{Assumption 2})$$

Empirically, average socioeconomic outcomes of children are strongly monotonic in parent socioeconomic outcomes across many socioeconomic measures and countries (Dardanoni et al., 2012). Average child education is also monotonic in parent education across nearly all of the subgroup-cohorts that we study in India (see Appendix Table A1).²⁸ Note that the conventional linear estimation of educational mobility also implicitly imposes monotonicity.

Given Assumptions 1 and 2, we can obtain sharp bounds on the child CEF. The analytical formulation of the bounds is derived in Novosad et al. (2020) and presented in Appendix B for the context of upward mobility.

Figure 2A shows the bounds on the Indian CEF for the 1960–69 and the 1985–89 birth cohorts. While the bounds are tight in parts of the CEF where the education bins are small, they are very wide in the bottom half of the distribution where the data is heavily interval-censored. Note that

²⁶Note that like other papers on intergenerational educational mobility, we use education strictly as a *proxy* for socioeconomic status. Our interpretation of the latent rank holds even if individuals at different latent ranks within the same bin have obtained *exactly* the same number of years of education. All things equal, the individual with a higher latent rank is understood in expectation to have socioeconomic advantages in dimensions other than years of education.

²⁷While the transformation of income to income rank is common, the same transformation in education has been rare, perhaps because of the coarse data problem that we identify in this paper. See, for example, Rosenbaum et al. (2000).

²⁸In practice, when education data are highly granular, non-monotonicity may emerge from monotonic distributions due to sampling error. While this occurs for a minority of subgroup-cohorts in our data, it only occurs at the very top of the distribution where bins are very small. These non-monotonicities do not affect our calculations of upward mobility, which only use information from bins adjacent to the bottom half of the parent distribution. To use our analytical method in cases where non-monotonicity is likely to result from sampling error, we advise pooling small bins into larger bins until monotonicity is restored.

absolute upward mobility (p_{25}) can be read directly from this graph by examining the bounds of the CEF at the 25th percentile (i.e. where $x=25$). In this case, they are far too wide to be meaningful for either the 1960–69 or the 1985–89 cohort.

We can obtain tighter bounds by imposing a constraint on the curvature of the CEF; this is equivalent to assuming that a marginal change in parent education rank cannot result in a discontinuous change in the slope or level of the CEF. Figure 2B shows bounds on the CEF under a conservative curvature constraint.²⁹ The bounds are tighter, but the bounds on p_{25} remain too wide to be meaningful even with constrained curvature. Tightening the curvature constraint to its limit results in a linear estimation that is equivalent to calculating the rank-rank gradient, which in this case is a poor fit to the data. There is therefore no curvature constraint that both fits the data and generates tight bounds on p_{25} . Because the bounds on our primary mobility measures are only marginally improved by the curvature constraint, we take a parsimonious approach and present all results below with unconstrained curvature.

We can take a similar approach to bound a function of the CEF. We focus on two functions in particular. The first is the slope of the best linear approximator to the CEF (or the rank-rank gradient), which is analogous to the linear estimator used in the bulk of the prior educational mobility literature. The second is a new function, which we call *bottom half mobility*, defined as $\mu_0^{50} = E(y|x \in [0,50])$. This measure describes the expected outcome of a child born to parents in the bottom half of the parent distribution. Bottom half mobility is thus similar to absolute upward mobility, the latter of which describes the expected outcome of a child born to the median parent in the bottom half of the parent distribution.³⁰

In Appendix B.2, we provide a formal statement of analytical bounds on μ_a^b (derived in Novosad et al. (2020)). We calculate bounds on the rank-rank gradient using a numerical optimization, described in Appendix B.3.

²⁹These bounds are calculated numerically following Novosad et al. (2020); the procedure and choice of constraint are described in Appendix B.

³⁰If the CEF is linear, p_{25} is equal to μ_0^{50} ; if the CEF is concave at the bottom of the parent distribution, then Jensen’s Inequality implies that μ_0^{50} will be lower than p_{25} , reflecting the greater persistence of bad outcomes at the bottom of the distribution. For non-linear CEFs, μ_0^{50} thus effectively puts more weight on outcomes at the very bottom of the parent distribution than p_{25} .

3.4 Comparing Bounds on Different Functions of the CEF

Panels A through C of Figure 3 respectively show bounds on the rank-rank gradient (denoted β), absolute upward mobility (p_{25}), and bottom half mobility (μ_0^{50}) for the 1960–69 and the 1985–89 birth cohorts. As benchmarks, we also show mobility estimates for USA and Denmark.³¹

The bounds on the conventional measures β and p_{25} are not informative either in levels or in changes; they are consistent with both major declines and major increases in mobility from 1960–85. In contrast, μ_0^{50} can be bounded tightly in the 1960s and can be nearly point estimated in the 1980s. On the basis of μ_0^{50} , we can clearly distinguish upward mobility in India from the U.S. and Denmark (India is about as far below the U.S. as the U.S. is below Denmark), and we can reject substantial changes in upward mobility over the sample period.

The figure shows the key advantage of bottom half mobility: it can be tightly bounded even with severely interval-censored rank data. For intuition behind the tight bounds on μ_0^{50} , note that μ_a^b is point-identified when a and b correspond to rank boundaries in the data. If $X\%$ of parents are in the bottom-coded rank bin, then μ_0^X is the expected child rank, conditional on having parents in the bottom-coded bin, and is point identified. In general, μ_a^b is tightly bounded when a and b are close to bin boundaries in the data, by virtue of the continuity of the CEF and uniformity of the rank distribution. In contrast, absolute mobility at percentile i ($E(y|x=i)$) cannot be point identified for any value of i . For further clarification, Figure 4 presents a graphical example demonstrating how these relatively tight bounds in μ_0^{50} are obtained.

Note that the wide uncertainty around changes in mobility as measured by β and p_{25} are not weaknesses of our partial identification approach, but strengths. When rank data are highly censored, we should indeed have less certainty over the ability of individuals to move up from the bottom of the rank distribution. By delivering precise point estimates regardless of the coarseness of the data, conventional methods use hidden assumptions (such as linearity of the CEF, in the case of the rank-rank gradient) and convey excess precision. Nevertheless, without a measure such as μ_0^{50} which is tightly

³¹The rank-rank gradients are benchmarked against educational mobility estimates from Hertz et al. (2008). For p_{25} and μ_0^{50} , we use income mobility estimates from Chetty et al. (2014a).

bounded, the interval censoring problem would make it difficult to study intergenerational mobility.

The rank-rank gradient, absolute mobility, and bottom half mobility are all scalar statistics that capture different characteristics of the intergenerational persistence of rank, and they may all be of independent policy interest. However, only bottom half mobility can be measured informatively given the type of education data typically available in developing countries. To our knowledge, bottom half mobility is thus the first measure of intergenerational educational mobility that can be compared meaningfully across population subgroups, across countries, and across time. We therefore use this measure in our analysis below.

3.5 Comparison with Other Approaches

In this section, we briefly contrast our approach to measuring intergenerational educational mobility with several other recent approaches in the literature.

Card et al. (2018) and Derenoncourt (2018) use education data to compare geographic patterns in upward mobility between the 1920s and the 1980s. They define upward mobility in the 1920s as the 9th grade completion rate of children whose parents have 5–8 years of school, whom they describe as “roughly in the middle of the parental education distribution” — they then compare this measure with p_{25} for a birth cohort in the 1980s. Translating this into our framework, where x is a parent rank and y is a child outcome, these papers are comparing $E(y \geq 50 | x \in [30, 70])$ in the 1920s to $E(y | x = 25)$ in the present. This approach has the disadvantage of comparing upward mobility from the middle class in the 1920s to upward mobility from a considerably lower class in the present. The 1920s measure is chosen because it corresponds to bin boundaries in the education data. Our approach makes it possible to consistently measure $\mu_0^{50} = E(y | x \in [0, 50])$ in both periods (or μ_a^b for any a, b), regardless of the bin boundaries available in the data.

Alesina et al. (2019), who study intergenerational mobility across Africa, face the same problem. They define upward mobility as the probability that a child born to a parent who has not completed primary school manages to do so. Both the x and the y variables represent different ranks in each country and time. In rank terms, this measure is approximately capturing $E(y > 52 | x \in [0, 76])$ in Mozambique (where 76% of parents and 48% of children have not completed primary school) and

$E(y > 18 | x \in [0, 42])$ in South Africa. Using this measure implies comparing outcomes at very different points of the socioeconomic distribution in different countries and across time. These measures also do not distinguish between aggregate increases in education and the ability of individuals to rise to a new rank; these phenomena are independently interesting and our approach makes it possible to distinguish between them.

Finally, when constructing transition matrices from data that are not subdivided by exact quantiles, researchers often take the ad hoc approach of randomly reassigning individuals across bins to create the desired quantile bins. This approach is taken by the World Bank’s recent flagship report on intergenerational mobility (Narayan and Van der Weide, 2018).³² While this approach may seem innocuous, it in fact implicitly assumes that the CEF is a step function with zero slope between bin boundaries. This can result in biased estimates that are misleadingly precise. For example, Narayan and Van der Weide (2018) find virtually identical outcomes for children growing up in the bottom three quartiles of the parent distribution in Ethiopia — this result is a mechanical artifact of over 80% of parents reporting the bottom-coded education level.

4 Data

We draw on two datasets that report matched parent-child educational attainment.

First, the India Human Development Survey (IHDS) is a nationally representative survey of 41,554 households, with rounds in 2004–05 and 2011–12. The IHDS identifies religion and Scheduled Tribe or Scheduled Caste status. We classify SC/ST Muslims, who make up less than 2% of SC/STs, as Muslims. About half of Muslims are Other Backward Castes (OBCs); we classify these as Muslims. We do not consider OBCs as a separate category in this paper because OBC status is inconsistently reported across surveys, due to both misreporting and changes in the OBC schedules. Analysis of mobility of OBCs will therefore require detailed analysis of subcaste-level descriptors and classifications which are beyond the scope of the current work. We pool Christians, Sikhs, Jains and Buddhists, who collectively make up less than 5% of the population, with higher caste Hindus

³²A similar approach is taken in Bound et al. (2015) and by Coile and Duggan (2019) to study mortality change in education quantiles.

(*i.e.* forward castes and OBCs); we describe this group as “Forward/Other.” We find broadly similar results if we exclude these other religions from the sample.

Crucially, the IHDS solicits information on the education of parents of the majority of respondents, even if those parents have died or are not resident in the household. This is important for studying mobility of all but the youngest cohorts, because parent-child coresidence rates decline rapidly with child age, as shown in Appendix Figure A1. Estimating mobility using only coresident parent-child pairs is thus likely to be biased. Appendix Figure A2 shows the extent of this bias—the difference between bottom half mobility estimated using only coresident parent-child pairs and the same measure estimated using the full information on the parents of non-coresident children. The bias rises substantially for boys over age 25 and girls over the age of 18. When looking at older cohorts, it is thus essential to include children who no longer live with their parents; earlier Indian mobility estimates based on coresident children as old as 40 should be treated with caution.

We estimate mobility in the past by studying children from older birth cohorts, also in the 2011–2012 IHDS. We address potential survivorship bias by showing that our results are consistent with an analysis of the *same* birth cohorts using the 2004–05 IHDS, described in Section 5.1. We pool the data into 10-year birth cohorts for 1950–69, and 5-year birth cohorts for 1970–1989 where we have more power. The data do not contain links for mothers or daughters for the 1950–59 birth cohort.

The sample size of the IHDS is too small to study geographic variation in any detail. We therefore draw on the 2011–12 Socioeconomic and Caste Census (SECC), an administrative socioeconomic database covering all individuals in the country that was collected to determine eligibility for various government programs. The household roster describes age, gender, education, and Scheduled Caste or Scheduled Tribe status. Assets and income are reported at the household rather than the individual level, and thus cannot be used to estimate mobility. Religion and subcaste were recorded but not included with the publicly posted data, and are therefore not available in the geographic analysis.³³

The SECC allows us to construct parent-child links only when parents and children reside in the same household. To minimize bias from exclusion of non-coresident children, we limit our analysis of

³³Additional details of the SECC and the scraping process are described in Asher and Novosad (2019) and in Appendix D.

the SECC to sons aged 20 to 23, a set of children for whom schooling is largely complete, but parent coresidence rates are still high. We do not study daughters using the SECC, because many girls have already left home at ages when other girls are still completing their education.³⁴ The SECC sample thus consists of 31 million young men and their fathers. For the coresident father-son pairs that are observed in both datasets, IHDS and SECC produce similar point estimates for upward mobility.

Given the strengths and limitations of each dataset, we use the SECC to study cross-sectional geographic variation in mobility, and we use the IHDS to study mobility differences across groups and across time.

Education is reported in seven categories in the SECC.³⁵ IHDS records completed years of education. To make the two data sources consistent, we recode the SECC into years of education, based on prevailing schooling boundaries, and we downcode the IHDS so that it reflects the highest level of schooling completed, *i.e.*, if someone reports thirteen years of schooling in the IHDS, we recode this as twelve years, which is the level of senior secondary completion.³⁶ The loss in precision by downcoding the IHDS is minimal, because most students exit school at the end of a completed schooling level.

The oldest cohort of children that we follow was born in the 1950s and would have finished high school before the beginning of the liberalization era in the 1980s. The cohorts born in the 1980s would have completed much of their schooling during the liberalization era. The youngest cohort in this study was born in 1989; cohorts born in the 1990s may not have completed their education at the time that they were surveyed and are therefore excluded.

Details on construction of parent-child links, as well as additional data sources and information on variables used in the geographic analysis, can be found in Appendix D.

³⁴Appendix Figure A2 shows that upward mobility estimates of girls living with their fathers are already biased upward by 5 rank points—the mobility difference between the U.S. and Finland—by age 20.

³⁵The categories are (i) illiterate with less than primary; (ii) literate with less than primary (iii) primary; (iv) middle; (v) secondary (vi) higher secondary; and (vii) post-secondary. These are standard categories used in many of India’s surveys, including the National Sample Surveys.

³⁶We code the SECC category “literate without primary” as two years of education, as this is the number of years that corresponds most closely to this category in the IHDS data, where we observe both literacy and years of education. Results are not substantively affected by this choice.

5 Results: Intergenerational Mobility in India

5.1 National Estimates

Figure 5 shows our main measure of upward mobility (bottom half mobility, or $E(y|x \in [0,50])$, where y is the child education rank). Panel A shows the father-son relationship. Upward mobility has been largely static over time, moving from [36.6,39.0] in 1960–69 to [37.5,37.9] for the 1980–85 birth cohort.³⁷ The bounds on the 1950–59 estimates are wider, leaving open the possibility of some gains from the 1950s to the 1960s birth cohorts.³⁸ The comparable measure for the 1980s birth cohort in the United States is 41.7, which is low by OECD standards.³⁹

Panel B of the same figure describes mobility from fathers to daughters. This sample does not go back to the 1950s since there are no respondents from that birth cohort in the women’s surveys. We cannot reject a broadly similar pattern to the father-son results, though the bounds in the 1960s are wider than for sons, leaving open the possibility of mobility losses over this period. In fact, mobility for daughters has fallen by about half a percentage point from the 1970–79 birth cohort to the 1980–84 and 1985–89 birth cohorts. In the youngest birth cohort, father-daughter mobility is 35.6, about two rank points lower than father-son mobility. Daughters are thus less likely to escape low socioeconomic status than sons.

Obtaining informative mobility estimates for the mother-child relationships is more difficult, because the distribution of women’s education is much more left-skewed (and thus censored in rank terms). Among mothers of the 1960s birth cohort, 82% had less than two years of education. For the 1985–89 birth cohort, this number was 65%. Under such severe censoring, we cannot estimate μ_0^{50} with any precision. Even in the most recent 1985–89 birth cohort, we estimate bottom half mobility to be [37.5,41.4]

³⁷The measures are very tightly bounded for the more recent birth cohorts, because there is a rank boundary close to 50 in the parent distribution. When the distance between upper and lower bounds is less than 0.3, we report the midpoint as a point estimate.

³⁸Appendix Figure A3 shows that these results are unlikely to be affected by survivorship bias. We estimate upward mobility for the same birth cohorts using the IHDS 2004–05; if mobility estimates for older cohorts were affected by differential mortality of high mobility groups, we would find different estimates from the earlier data, but the bounds are highly similar and show the same lack of change over time.

³⁹Source: our calculations using μ_0^{50} , based on data from Chetty et al. (2018). There is not yet a wide set of internationally comparable estimates of rank-based educational mobility, in part because of the methodological challenges described and addressed in this paper.

for sons and [33.8,39.1] for daughters.⁴⁰ We thus focus on estimates of mobility based on fathers.

We can also calculate μ_0^{50} with child education *levels* as the y variable. For example, $E(\text{child years} \geq 12 | x \in (0,50))$ describes the likelihood that a child attains high school or greater, conditional on having a parent in the bottom half. Panels C and D of Figure 5 show this measure for father-son and father-daughter links respectively. The graphs also show $E(\text{child years} \geq 12 | x \in (50,100))$, which is the likelihood of child high school attainment conditional on having a parent in the top half of the education distribution.⁴¹ These graphs show the secular increase in high school attainment over time for children from privileged and underprivileged backgrounds. Girls from bottom half families have experienced the least gains, while girls born in the top half of the distribution have almost closed the gap with well-off boys. For both boys and girls, gains in high school attainment have accrued almost entirely to children from the top half of the distribution, a reflection of the stagnant overall upward rank mobility seen in panels A and B. However, these estimates confound mobility with aggregate increase in education, which is why we focus on μ_0^{50} in rank terms.

To summarize, children born to less privileged families in post-liberalization India have very similar prospects for moving up in the rank distribution as they did in the pre-liberalization era. To be clear, living standards have improved for individuals across the rank distribution; it is the probability of making progress in rank terms which is unchanged. This result thus contradicts the narrative of India becoming a land of greater churn in terms of relative social status.

5.2 Changing Mobility Across Social Groups

We next examine how these levels and trends differ across groups. Figure 6 presents results analogous to those above but subdivided into Muslims, Scheduled Castes, Scheduled Tribes, and all others. Panel A shows bottom half mobility (μ_0^{50}) from the 1950s to the 1980s for father-son pairs, revealing substantial trend differences across groups. As noted by other researchers, upward mobility for Scheduled Tribes, and especially for Scheduled Castes, has improved substantially (Hnatkovska et al., 2012; Emran and Shilpi, 2015). SCs born in the bottom half of the parent distribution in the

⁴⁰Appendix Figure A4 shows the admittedly uninformative graph of this measure over time.

⁴¹This measure is similar in meaning to Chetty et al. (2014a)'s absolute downward mobility, or $p_{75} = E(y|x=75)$.

1960s could expect to obtain between the 33rd and 35th percentile; the comparable group born in 1985–89 obtains the 38th percentile, closing approximately half of the mobility gap with upper castes. Upward mobility for members of Scheduled Tribes rises from [29,31] to 33 over the same period.

In contrast with SCs and STs, Muslim intergenerational mobility declines substantially, falling from [31,34] in the 1960s to 29 in the 1985–89 birth cohort. These changes not only constitute a major decline in mobility, but make Muslim men the least upwardly mobile group in modern India. Mobility for Muslim boys is lower even than for ST boys, who are often thought of as having benefited very little from Indian industrialization. The fact that a Muslim boy born to a family in the bottom half of the distribution can expect to obtain the 29th percentile implies almost no reversion to the national mean among this group. Finally, the “Forward/Others” group, which predominantly consists of higher caste Hindus, shows little change, with mobility shifting from [42,44] to 42. The static trend in upward mobility for boys can therefore be decomposed into gains for SCs and STs and losses for Muslims.

Panel B shows downward mobility (μ_{50}^{100}) for father-son links over the same period; this measure reflects the persistence of high status among each group. We see a small amount of convergence between the three marginalized groups and the Forward/Others group, chiefly from the 1970s to the 1980s birth cohort. But there is no sign of the dramatic divergence between SCs and Muslims that was found for upward mobility.⁴²

Panels C and D of Figure 6 show the same results for father-daughter pairs. Among daughters, with the exception of recent minor gains for SCs from top half families, none of the marginalized groups have made substantial gains relative to Forwards/Others. There is also little sign of the divergence between SCs and Muslims that was observed among boys. Table 2 summarizes the changes over time for the full sample and all the population subgroups, along with bootstrap confidence sets for partially identified data calculated following Chernozhukov et al. (2007). Table 3 shows confidence sets for static mobility differences between groups for the youngest (1985–89) birth cohort.⁴³

⁴²Appendix Figure A5 shows analogous results to Figure 6, but with education levels (at least primary, and at least high school) as outcomes, rather than education ranks. The results are consistent with the rank-based estimates, confirming that the separation between Scheduled Caste and Muslim boys is not driven by unobserved changes in latent ranks for children from these groups. The upward trend in the levels graphs reflects the overall rise in educational attainment seen in Figures 5C and 5D.

⁴³The confidence sets are wider than mobility confidence intervals from prior studies because they reflect both

To summarize, we observe a sharp divergence between upward mobility for boys from Scheduled Caste and Muslim groups. Muslim boys from poor families have declining mobility and very little opportunity to improve their relative social status. This low mobility may also adversely affect female Muslims, since marriage is nearly universal in India and almost entirely within subgroup, and female labor force participation is very low. Understanding how marriage ties interact with the upward mobility of boys and girls would be valuable, but is beyond the scope of the present paper.

5.3 Upward Mobility Across Geographic Areas

We next describe the geographic variation in upward mobility. The limited sample size of the IHDS only allows us to examine geographic patterns of subgroup mobility at a low resolution. Appendix Figure A6 shows bottom half mobility, disaggregated by child gender, social group, and rural-urban status. Mobility is systematically higher in urban areas, but subgroup disadvantage varies substantially by geography. The urban-rural gap is much higher for girls than for boys, such that urban girls in fact have about five rank points higher upward mobility than urban boys. Muslims and SCs on average have higher mobility in cities, but their relative position in cities with respect to Forwards/Others is worse.

The remainder of this section uses the SECC, whose large sample makes it possible to generate mobility estimates in very small geographic areas. However, in the SECC, we cannot measure mobility for Muslims (because religion is not recorded) or for father-daughter pairs (because our SECC sample is limited to coresident 20–23 year old boys, as described in Section 4). Finally, we do not explore time series patterns across geography, because we do not observe where children grew up, only where they are in 2011–12.

We first map the distribution of upward mobility across India. Figure 7A presents a heat map of upward mobility across 4000 subdistricts and 2000 major towns across all of India. The graph shows the midpoint of the bounds; in 99% of cases, the bound width is less than two rank points.⁴⁴

statistical variation and uncertainty due to coarse measurement of education, the latter of which has not been addressed by prior studies. Nevertheless, the cross-group differences in the present are all highly significant, as is the trend difference between SCs and Muslims.

⁴⁴There are 8000 towns in the 2011 Population Census, on which the SECC is based. While our coverage of rural areas is almost complete, the data posted online described only 2000 of the towns. The town sample is broadly representative of the urban population in demographics and income.

The geographic variation is substantial. Upward mobility is consistently highest in southern India—Tamil Nadu and Kerala—and is also noticeably high in the mountainous states of the North. Parts of the Hindi-speaking belt—especially the state of Bihar—and the Northeast are among the lowest mobility parts of India. Gujarat is noteworthy as a state with high economic growth but relatively low mobility.

In broad regions of high mobility, there are low mobility islands, such as the rugged region between Andhra Pradesh and Karnataka. Cities and towns for the most part stand out as islands of higher mobility. However, there is not a single subdistrict or town in Bihar with higher average mobility than the southern states.

There is substantial variation in mobility based on neighborhood of residence even within a single city. Figure 7B shows a ward-level mobility map of Delhi.⁴⁵ The highest mobility wards have upward mobility that is 38% higher than the lowest mobility wards. Children in the dense and industrial areas of Northeast Delhi have the least opportunity; the average child from a bottom half family in this area can expect to obtain the 32nd percentile nationally. Children from similarly-ranked families in Southwest Delhi, about 5km away, can expect to obtain the 44th percentile.

To explore some of the potential drivers of geographic variation in upward mobility, Figure 8 presents the association between bottom half mobility and several correlates identified by the earlier literature on India and other countries. Panel A presents bivariate correlations between upward mobility and location characteristics across all rural subdistricts in India. Panel B presents analogous results for the town sample. The indicators cover four broad areas: subgroup distribution (specifically, presence of SCs and STs, and the residential segregation of SCs and STs); inequality (consumption and land inequality); development (manufacturing jobs per capita, average consumption, average education, and remoteness); and local public goods (schools, paved roads, and electricity). All of the measures are standardized to mean zero and standard deviation one for meaningful comparison.⁴⁶

At the rural level, the traditional markers of economic development — monthly consumption, and

⁴⁵See <http://www.dartmouth.edu/~novosad/mobility-delhi.html> for an interactive version of this map with higher resolution.

⁴⁶All of these variables are defined in Appendix D.

average levels of education — are the strongest correlates of upward mobility. Local public goods and manufacturing employment are also positively correlated with upward mobility. Interestingly, availability of primary schools is the least important of these, but availability of high schools is highly correlated with mobility. Surprisingly, the share of SCs and STs is positively correlated with upward mobility. Segregation and land inequality are negatively correlated with upward mobility, a parallel result to that found in the United States (Chetty et al., 2014a).

Turning to urban places, we find that upward mobility is higher in towns that have (i) higher population; (ii) more SCs; (iii) more educated populations; and (iv) more high schools per capita. As in rural areas, SC/ST segregation is negatively associated with mobility. By contrast, consumption inequality is positively associated with mobility.

These local mobility estimates have two limitations. First, they are based on the educational outcomes of children born between 1989 and 1992, the majority of whom finished their education by 2010. They therefore reflect the circumstances that drove education choices in the period 2000–2010, which may be different in the present. Second, the estimates do not account for migration, as we do not observe respondents’ location of birth. Low mobility in Northeast Delhi could in part be the effect of immigration from poor parts of rural North India. The more local the mobility estimate, the greater is the potential bias from migration. Ideally, we would have local surveys that record both location of origin and parental education; to our knowledge, there are no such surveys with high geographic precision. The rural (subdistrict-level) estimates are less likely to be biased by migration, because permanent migration in rural areas in India is extremely low.⁴⁷

The picture that emerges is one where place of residence appears to be highly important to upward mobility. Cities have higher mobility for all groups, but the effect of geography may be different for individuals of different genders and population subgroups. We leave additional exploration of these patterns for future research.

⁴⁷Foster and Rosenzweig (2007) find decadal rural-to-urban migration rates for 15–24 year old males of about 3% in 1961–2001; Munshi and Rosenzweig (2016) present confirmatory evidence in IHDS and the DHS.

5.4 Potential Mechanisms for Subgroup Mobility Differences

In this section, we explore a series of mechanisms that could potentially explain the upward mobility differences and changes across social groups in India, with a focus on the growing mobility gap between Scheduled Castes and Muslims. We examine the extent to which these group differences can be explained by: (i) affirmative action for Scheduled Castes; (ii) differential fertility across social groups; (iii) patterns in location of residence; and (iv) different occupational patterns causing differential returns to education. These analyses are suggestive, but they point toward affirmative action as a key mechanism for the SC/Muslim divergence, and largely reject the other three mechanisms.

5.4.1 Mechanisms: Affirmative Action for Scheduled Groups

First, we consider the hypothesis that the basket of programs and policies targeted to Scheduled Castes and Scheduled Tribes has driven the increase in upward mobility of SCs and STs relative to Muslims since the 1950s. To estimate the causal effect of affirmative action on bottom half mobility, we exploit a change in the population groups eligible for Scheduled Caste status that was made in 1977, previously studied by Cassan (2019). Between 1956 and 1977, the list of social groups that was eligible for Scheduled Caste status varied across regions within states; this inconsistency was left over from the reorganization of states along linguistic lines in 1956. In 1977, a federal law caused these lists to be harmonized within states, arbitrarily moving many additional groups into the SC designation, making them eligible for SC-targeted benefits. As shown by Cassan (2019), this policy change makes it possible to examine the impact of Scheduled Caste status, while controlling for a group's ethnicity, historical experience, and narrow geographic region.⁴⁸

To test for the impact of affirmative action on upward mobility, we divide SCs into two groups: (i) those classified as SCs at the time when states were reorganized on linguistic lines in 1956 (whom we call early SCs); and (ii) a group which obtained protected status only in 1977 (whom we call late SCs). Following Cassan (2019), we assume that individuals needed to be 6 or younger in 1977

⁴⁸Looking primarily at educational outcomes, Cassan (2019) finds that newly scheduled groups experience literacy and schooling gains, but these accrue mostly to boys.

to benefit in terms of education from the change in status.⁴⁹ We therefore treat individuals born later than 1970 as being in the late SC group.

We assign individuals to early and late SC groups using jati-level group identifiers in the IHDS.⁵⁰ Figure 9 demonstrates the upward mobility trajectory of the early and late SC groups, showing bounds on μ_0^{50} over time. In the 1950s and 1960s, the early SC group experiences rapid relative increases in mobility and diverges from the late-SC group, which has not yet obtained protected status. Beginning with the 1970 birth cohorts when the late SC group obtains protected status, it begins to close the mobility gap. The mobility gap peaks right before the late SC group gains SC status and the gap then steadily closes through the remainder of the sample period.

We can formally estimate the impact of SC status in a regression based on the specification of Cassan (2019):

$$Y_{i,j,r,c} = \beta_0 + \beta_1 \text{LateSC}_{j,r} + \beta_2 \text{post}_c + \beta_3 (\text{post}_c \times \text{LateSC}_{j,r}) + \nu_{j,r} + \eta_{r,c} + \zeta_{j,c} + \epsilon_{i,j,r,c}, \quad (5.1)$$

where $Y_{i,j,r,c}$ is the education rank of child i in jati j , region r , and birth cohort c . We include fixed effects for jati \times region (ν), region \times cohort (η), and jati \times cohort (ζ). These fixed effects exploit the fact that the same jati group could be an early-SC or a late-SC depending on its region within a state. The coefficient of interest, β_3 , therefore compares individuals in late SC groups born after 1970 to those born earlier in the same narrow social group and the same region, controlling for outcomes of individuals from early SC groups in the same region, and for outcomes of members of the same jati group in other regions. Regressions are clustered at both the jati and the region level.

Using bottom half mobility as a Y variable in this specification is challenging because for each group it can at best be bounded. Instead, we proxy bottom half mobility by restricting the sample to a set of father ranks that is close to the bottom half and can be held almost constant across the different decades. The Y variable is thus equivalent to μ_0^{59} in the 1950s birth cohort, μ_0^{57} in the 1960s, and μ_0^{58} in the 1970s and 1980s.

⁴⁹We find similar results if we use a cutoff of 11 or younger, also used in Cassan (2019).

⁵⁰A jati is a caste identifier that is more granular than the broad Scheduled Caste category, which includes many jatis.

The result of this regression is shown in Table 4. Column 1 shows the specification above. The cohorts exposed to the basket of affirmative action policies experience an eight rank point change in upward mobility. Column 2 shows robustness to a specification where we limit the sample to sons of fathers with less than two years of education in all years instead of the sons of fathers in the approximate bottom 60% as noted above. The point estimate is similar. Column 3 (using the same sample as Column 1) shows that both the 1970s and 1980s birth cohorts of late SCs benefited relative to the earlier cohorts.

These results show that affirmative action has had a large effect on upward mobility for Scheduled Caste groups. The rank point gain of late SCs is comparable in magnitude to the upward mobility gap in the 1980s between Muslims and SCs, and it emerged over only 20 years of affirmative action. Note that this specification does not directly test for the effect of affirmative action on SCs as a whole vis-a-vis Muslims. However, if these treatment effects for early and late SCs are externally valid for the potential effect of affirmative action on Muslims, then affirmative action could explain the entire modern mobility gap between Scheduled Castes and Muslims.

5.4.2 Group Differences and Fertility

Muslims on average have higher fertility than either Scheduled Castes, Scheduled Tribes, or Forward Castes and other groups. In this section, we consider whether higher fertility could cause lower mobility for Muslims, perhaps through a household expenditure channel where children with many siblings received fewer educational inputs. We explore this question in a regression framework. We estimate the number of siblings of each individual based on their mothers' responses to the IHDS women's survey, which has a question about the number of births. This variable differs from total fertility by excluding children who have died. We only have information on mothers' fertility for children who live with their mothers; we therefore focus on boys under the age of 30, for whom the coresidence rate is highest.⁵¹ The average number of siblings for Muslims is 5.5, compared with 4.3 for SCs and STs, and 4.2 for Forwards/Others.

⁵¹For girls, coresidence begins to fall rapidly as soon as schooling is finished, leaving too little sample to estimate mobility among coresiders. Restricting the sample to individuals aged 20–23 as we did for the SECC would cut our sample too much to obtain informative estimates.

As in Section 5.4.1, we require a point estimate of upward mobility to use in a regression. We use μ_0^{51} , which can be point estimated as the education of children whose fathers completed two or fewer years of education.⁵² We regress this mobility measure on a set of group indicators (Muslim, SC, ST), an urban indicator, and a set of state fixed effects, showing the results in Table 5. Column 1 shows the Muslim mobility gap in the full sample and Column 2 shows the same gap in the set of boys whose coresident mother answered the women’s survey. An additional sibling is associated with 2.4 fewer ranks in the outcome distribution. The Muslim upward mobility disadvantage is 12 rank points, without adjusting for fertility. Column 3 adds a control for the number of siblings, which brings the Muslim mobility gap down by 25%.

High fertility can thus explain at most 25% of the Muslim mobility disadvantage relative to SCs. This is likely to be an upper bound, because household income is a direct cause of both children’s education and parental fertility (Schultz, 2003). Higher fertility can thus explain at most a small share of the present-day mobility disadvantage experienced by Muslims.

5.4.3 Geography and Subgroup Differences

To describe the extent to which Muslim disadvantage in upward mobility can be explained by geography, we examine here whether Muslims live in low mobility places, or whether they have low mobility after conditioning on place. Because the SECC does not record religion, we use the IHDS and explore cross-state and cross-district variation.

SCs, STs and Muslims are unevenly distributed across the country; the 25th-percentile district in SC population is only 8% SC. The equivalent numbers for STs and Muslims (0.4% and 2.7%) reflect the greater geographic concentration of these groups.

To examine the relationship between place and subgroup outcomes, we regenerate father and son education ranks within states and within districts. Mobility estimates generated in this way thus describe the ability of disadvantaged children to increase their relative rank within their own district. If low overall mobility for Muslims is a function of living in districts where everyone has low opportunity, then their within-district mobility gap with Forwards / Others should be substantially

⁵²We find similar estimates if we use children of fathers with strictly less than 2 years of education.

smaller than the national mobility gap. We focus on the static father-son mobility gap for the most recent birth cohort, corresponding to individuals born in 1985–89.

The results are shown in Figure 10. The first set of bars shows the relative mobility gap to Forwards / Others for the three marginalized groups using national education ranks; these gaps correspond to the differences between groups in Figure 6A in the 1985–89 birth cohort. For simplicity, we show the midpoint of the bounds; the width of the bounds is less than one percentage point in all cases. Upward mobility for the Forward / Others reference group is 42.

The following two sets of bars show the same gaps for within-state and within-district ranks. The extent to which group disadvantages in upward mobility can be explained by location differ substantially by group. District of residence explains about 18% of the Muslim upward mobility gap, 44% of the Scheduled Caste upward mobility gap, and 60% of the Scheduled Tribe mobility gap.⁵³ The result for Scheduled Tribes is consistent with the fact that STs disproportionately live in remote areas of the country with low levels of public goods and educational attainment. Given the uneven distribution of SCs and Muslims throughout India, the unimportance of district as an explanation for their mobility differences is worthy of note. Muslim disadvantage cannot be explained by the broad regions in which Muslims live. However, these results do not rule out the possibility that finer geographic definitions (such as urban neighborhoods) could explain a greater share of the mobility gap; unfortunately, higher resolution analysis is not possible with the data available at this time. To be clear, these results show that location is not a major mediator of Muslim disadvantage; the prior section (Section 5.3) shows that location is an important predictor of mobility in the aggregate.

5.4.4 Occupations, Returns to Education, and Subgroup Differences

We next examine whether occupational choices and returns to education can explain the low and falling upward mobility of Muslims. Muslims are more likely to work as small-scale entrepreneurs than the other major social groups (Figure 12A). If the returns to education are lower in entrepreneurship than in wage work, the low education outcomes of Muslim children born into poor families would

⁵³IHDS districts are not representative so these results should be treated with caution; however, the ordering of the changes is the same when we use only within-state ranks—the middle set of bars in Figure 10.

reflect a different expected career path but not necessarily a lack of opportunity.

To evaluate this hypothesis, we first examine the Mincerian returns to education for the different social groups. Figure 11 shows point estimates from Mincerian return regressions for each social group, calculated in three ways: (i) household log income on household head education (IHDS); (ii) individual log wages on individual education (NSS); and (iii) household log consumption on household head education.⁵⁴ Across all three measures, there is no evidence that Muslims have lower returns to education than Scheduled Castes or Tribes. The point estimates for Muslims are higher than for SCs in all cases, though both Muslims and SCs have lower returns to education than Forward/Others. Mincerian returns may not reflect the causal effect of education on income and consumption, but there is no evidence here that Muslims are choosing less education because their returns are lower.

Even if returns to education for Muslims are not lower overall, they could be low for Muslims who choose to run small businesses. The data rejects this hypothesis as well. Figure 12B divides the IHDS sample into individuals who own their own business (right panel) and individuals who do not (left panel). We pool SCs and STs for this graph because very few SCs and STs own businesses, leading to small samples. The divergence in upward mobility between SC/STs and Muslims is sustained and of similar magnitude both among business- and non-business owning families.

In conclusion, the evidence does not support the idea that the decline in Muslim upward mobility is an artifact of Muslim occupational choice or returns to education.

5.5 Robustness to Alternate Assumptions

5.5.1 Non-Uniform Within-Bin Subgroup Distributions

Our bounds on the full sample CEF $E(y|x)$ (explained in Section 3.3) use the uniformity of the rank distribution, which is given when working with the national sample. However, when working with population subsamples (e.g. Muslims), uniformity is not guaranteed. Take the example of the 1960s, where 57% of fathers are in the lowest education bin. Conditional on being in the bottom

⁵⁴In each case, we regress the outcome variable on individual years of education, age, and age squared. We restrict the data to men aged 18–64 to avoid concerns about selection into labor markets. Results are similar if we restrict to young ages (reflecting education of the youngest birth cohorts), if we include women and men, and if we include additional controls.

bin, the distribution of latent ranks of Muslim fathers is not necessarily uniform.

In Appendix C.1, we perform an empirical exercise to determine the extent to which non-uniform within-bin latent rank distributions could bias our mobility estimates. We fit a range of parametric distributions to the binned subgroup education data, and then draw continuous data from these distributions. Effectively, we simulate a continuous education distribution which would not suffer from the same problem. We then examine the dispersion of subgroup ranks within the bins where they are censored in the real data. We find that under worst-case assumptions, at most 10% of the growing gap between Muslims and SCs can be explained by changes in latent parent ranks within education bins.

Intuitively, this bias would be large if one social group was entirely concentrated at the bottom of the distribution. But while Scheduled Castes and Muslims are certainly disadvantaged on average, their education distributions are largely overlapping with higher caste Hindus. Further, SCs and Muslims have similar parent education distributions, so within-bin variation is unlikely to affect our comparisons of these two groups against each other.

5.5.2 Interval Censoring of Child Ranks

In our results thus far, we have assumed that child ranks are directly observed and are equal to the midpoint of each child’s rank bin. Child ranks are also interval-censored in our context. Note first that the censoring problem for child ranks is much smaller than the censoring problem for parent ranks, because children are on average more educated than their parents. This makes their education bins more evenly distributed. In the 1960–69 birth cohort, the bottom child education bin (and the largest) contains 26.5% of the population; in 1985–89, it contains only 9%. The bias from censored child ranks is thus expected to be considerably smaller than that from censored parental ranks, where the largest bins can contain 60% of the data.

Second, note that when we use uncensored measures of child outcomes, such as primary or high school completion (in Figures 5C, 5D, and Appendix Figure A5), we continue to find substantial divergence of SCs and Muslims from bottom half families, as well as the relative lack of progress of individuals from the bottom half as a whole.

Nevertheless, in Appendix C.2 we provide two approaches to estimate the bias in our main

estimates from son censoring. First, we estimate the maximal extent of this bias by examining the effects of the best- and worst-case assumptions regarding the latent child rank distribution on our mobility estimates. This puts an upper bound on the potential bias from latent child ranks. Second, we impute these latent ranks using data on children’s wage ranks within education bins; doing so, we find virtually the same mobility estimates as in our results above, suggesting the actual bias is small.⁵⁵ These results suggest that using the midpoint of a child’s rank bin is capturing most of the meaningful variation in child ranks.

6 Conclusion

In this paper, we present a set of tools that are well-suited to measuring intergenerational educational mobility in developing countries and other contexts where high quality income data are unavailable and education is coarsely binned. Our partial identification approach takes seriously the loss of information when a very large share of the population reports a bottom-coded education level. We have shown that bottom half mobility is a measure that is easy to calculate, analogous to the popular absolute upward mobility measure, and informative regarding intergenerational mobility even when education data are very coarse. Bottom half mobility is also the first measure of intergenerational educational mobility that is meaningful for cross-group analysis across contexts; the absence of such a measure has prevented researchers from studying subgroup mobility in developing countries.

Despite enormous economic and political changes, bottom half mobility in India has barely changed from the 1950s to the 1980s birth cohorts. This lack of change overall can be decomposed into substantial gains for SC/STs and substantial losses for Muslims, a growing disparity which can be explained at least in part by the basket of affirmative action policies that have targeted SC/ST disadvantage since Indian independence. The falling mobility of Muslims has not previously been noted in part because there has previously been no methodology for creating comparable rank bins across cohorts.

Our work has only begun to describe the wide geographic and cross-group variation in intergenerational mobility in India. As in the U.S., location is a very strong predictor of intergenerational

⁵⁵Specifically, we define an individual’s rank *within* an education bin based on their wages, yielding a continuous distribution. Results are similar if we use household income.

mobility, even if cross-group differences are nearly universal across locations for Muslims and SCs. Individuals growing up in different parts of India, even conditional on similar economic conditions in the household, can expect vastly different opportunities and outcomes throughout their lives. Future work describing the geographic variation in mobility in more detail, and moving toward causal estimates of the impact of place, will be an important basis for policies that create opportunities for those who are currently being left behind in India and in other developing countries around the world.

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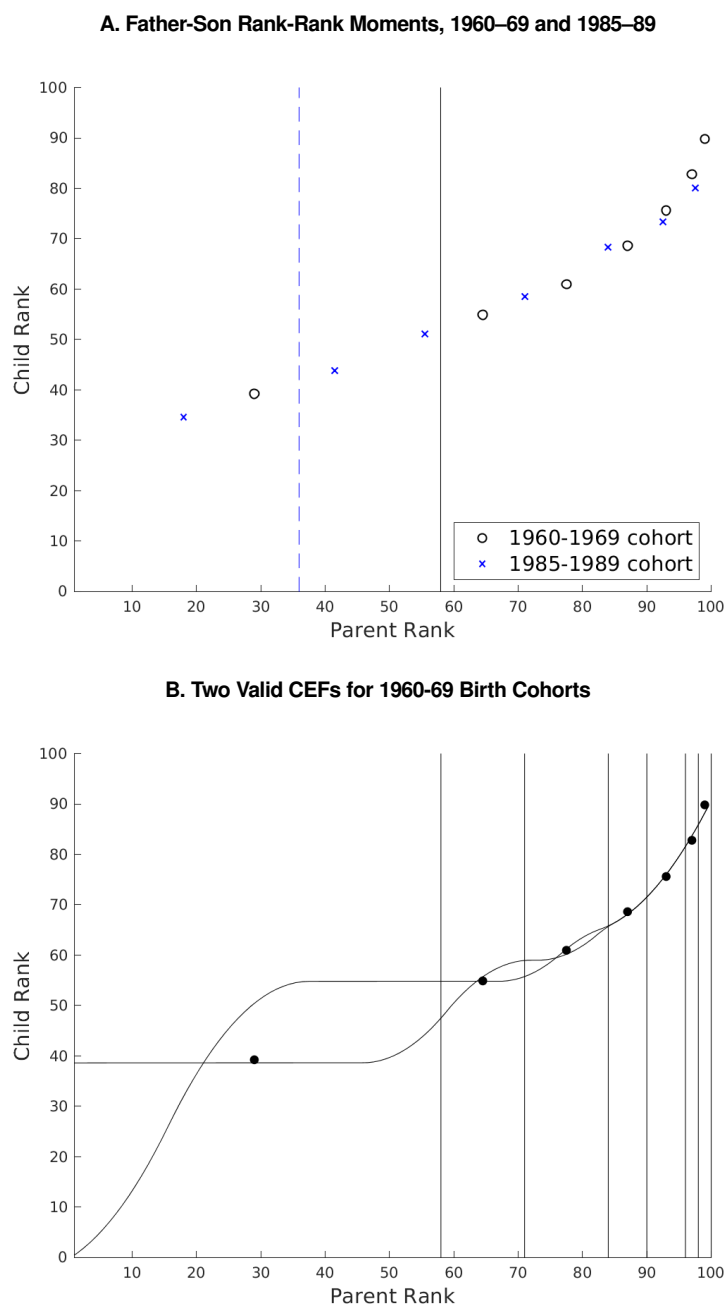
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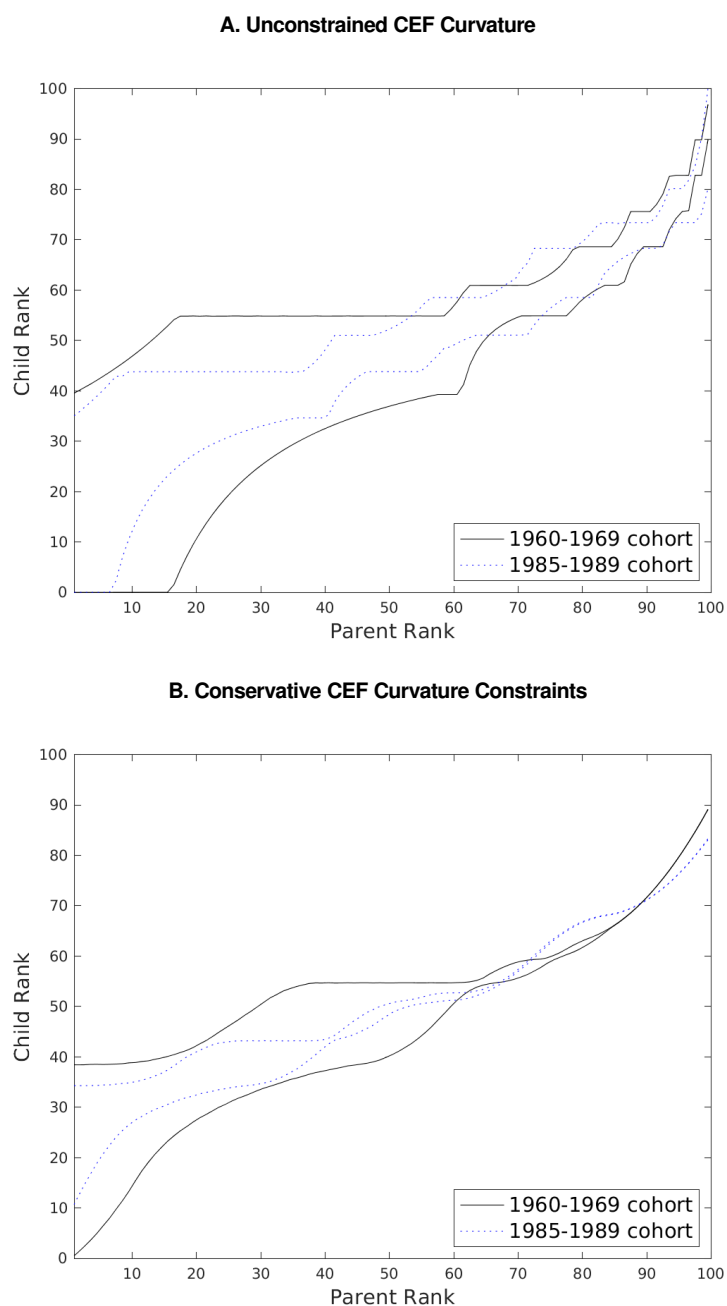
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Figure 1
 Father-Son Mobility: Raw Moments and Example CEFs



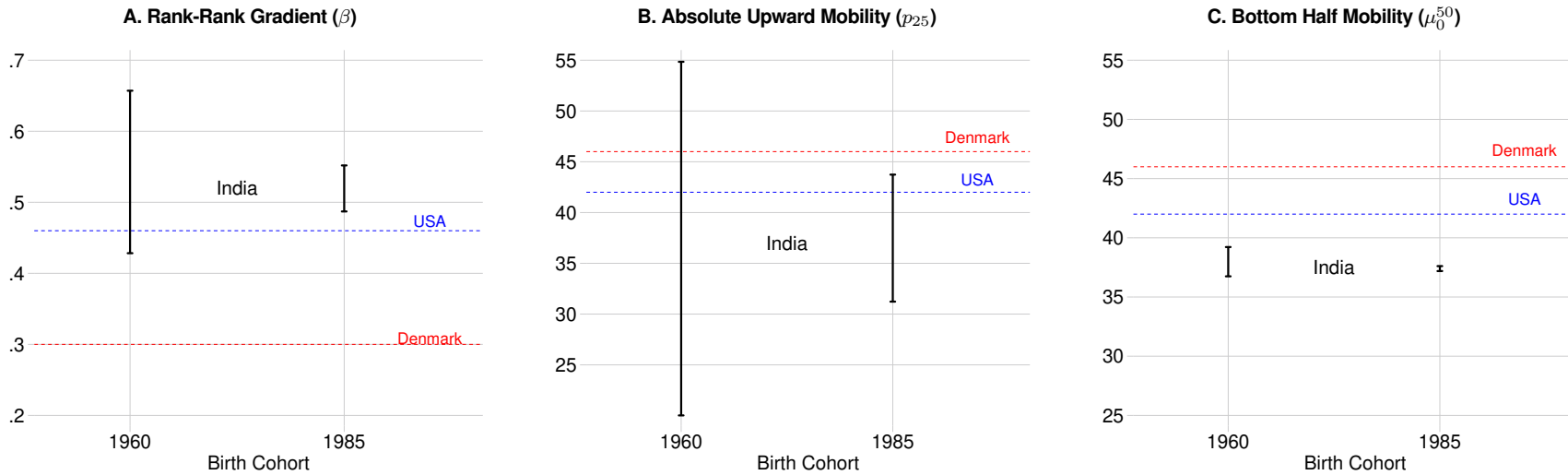
Panel A of the figure shows the average child education rank in each parent education rank bin for the 1960–69 and 1985–89 birth cohorts. The vertical lines show the boundaries for the bottom parent bin, which corresponds to less than two years of education. The solid line corresponds to the 1960–69 birth cohort and the dashed line to the 1985–89 birth cohort. Points are displayed at the midpoint of each parent rank bin. Panel B shows the 1960–69 moments again, along with two simulated conditional expectation functions which are equally good fits to the moments. Source: IHDS 2012.

Figure 2
 Bounded Father-Son Rank CEFs:
 1960–69 and 1985–89 Birth Cohorts



The figure presents the change over time in the rank-rank relationship between Indian fathers and sons born in the 1960–69 and the 1985–89 birth cohorts. The graph shows bounds on the expected child education rank, given a parent at a given rank in the parent education distribution. Panel A shows bounds on father-son CEFs with unconstrained curvature. Panel B shows bounds using a conservative curvature constraint equal to double the maximum curvature of parent-child *income* rank-rank CEFs from Sweden, Denmark, Norway, and the United States (Chetty et al., 2014b; Boserup et al., 2014; Bratberg et al., 2015). Source: IHDS 2012.

Figure 3
 Bounds on Mobility Measures in India:
 1960–69 and 1985–89 Birth Cohorts



The figure shows bounds on three mobility statistics for the 1960–69 and 1985–89 birth cohorts, estimated on father-son pairs in India. For reference, we display estimates of similar statistics from USA and Denmark. Data on rank-rank education gradients for USA and Denmark are from Hertz et al. (2008). For p_{25} and μ_0^{50} , the USA and Denmark references are *income* mobility estimates from Chetty et al. (2014a). The Indian measures are all based on education data. The rank-rank gradient is the slope coefficient from a regression of son education rank on father education rank. p_{25} is absolute upward mobility, which is the expected rank of a son born to a father at the 25th percentile. μ_0^{50} is bottom half mobility, which is the expected rank of a son born to a father below the 50th percentile. Source: IHDS 2012.

Figure 4
Sample Calculation of μ_0^{50} for 1960–69 Birth Cohort

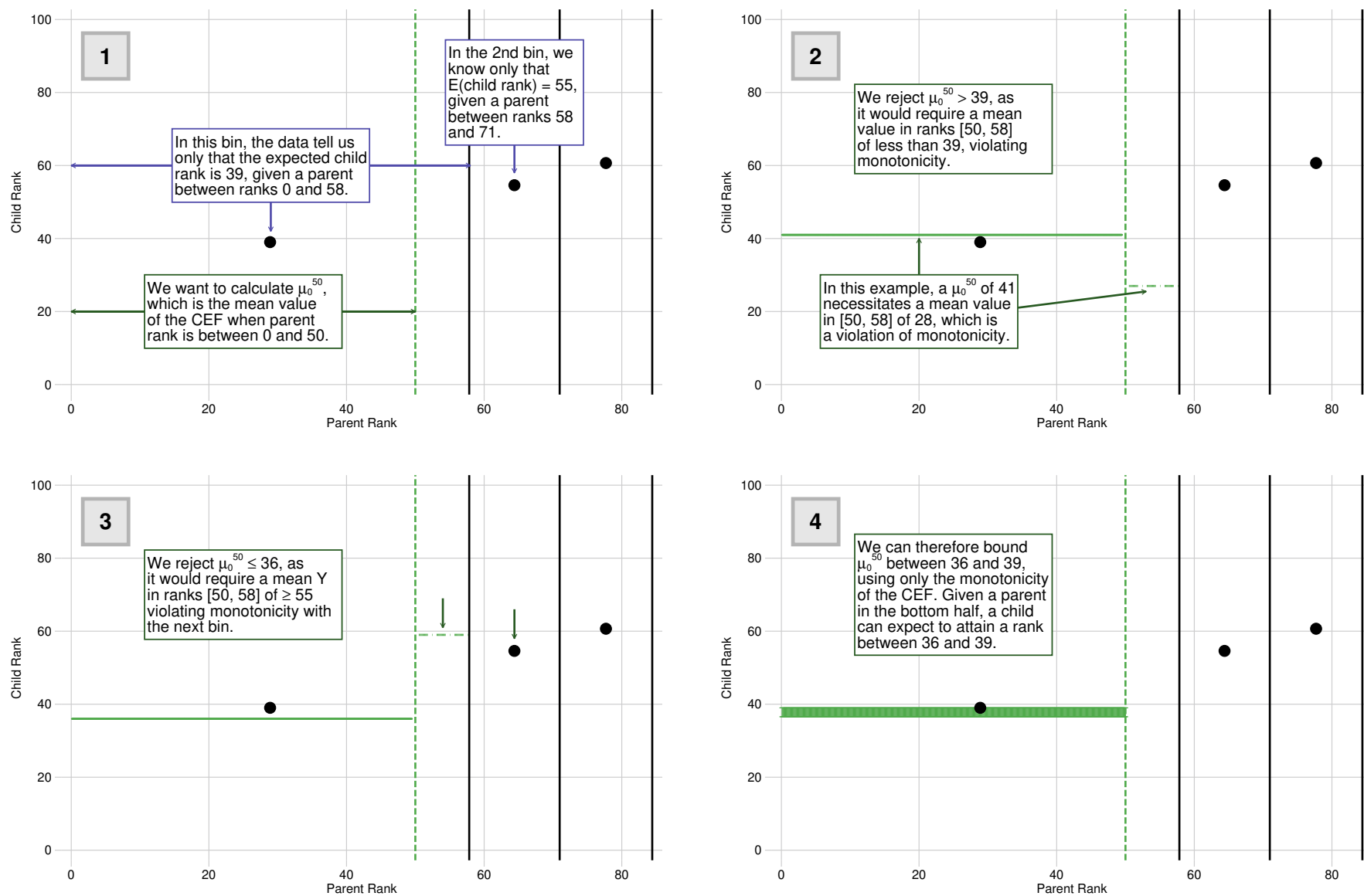


Figure 4 walks through the process of calculating bounds on $\mu_0^{50} = E(y|x \in (0,50))$ using data from the 1960–69 birth cohort in India. Source: IHDS (2012).

Figure 5
Bottom Half Mobility, Fathers to Sons and Daughters

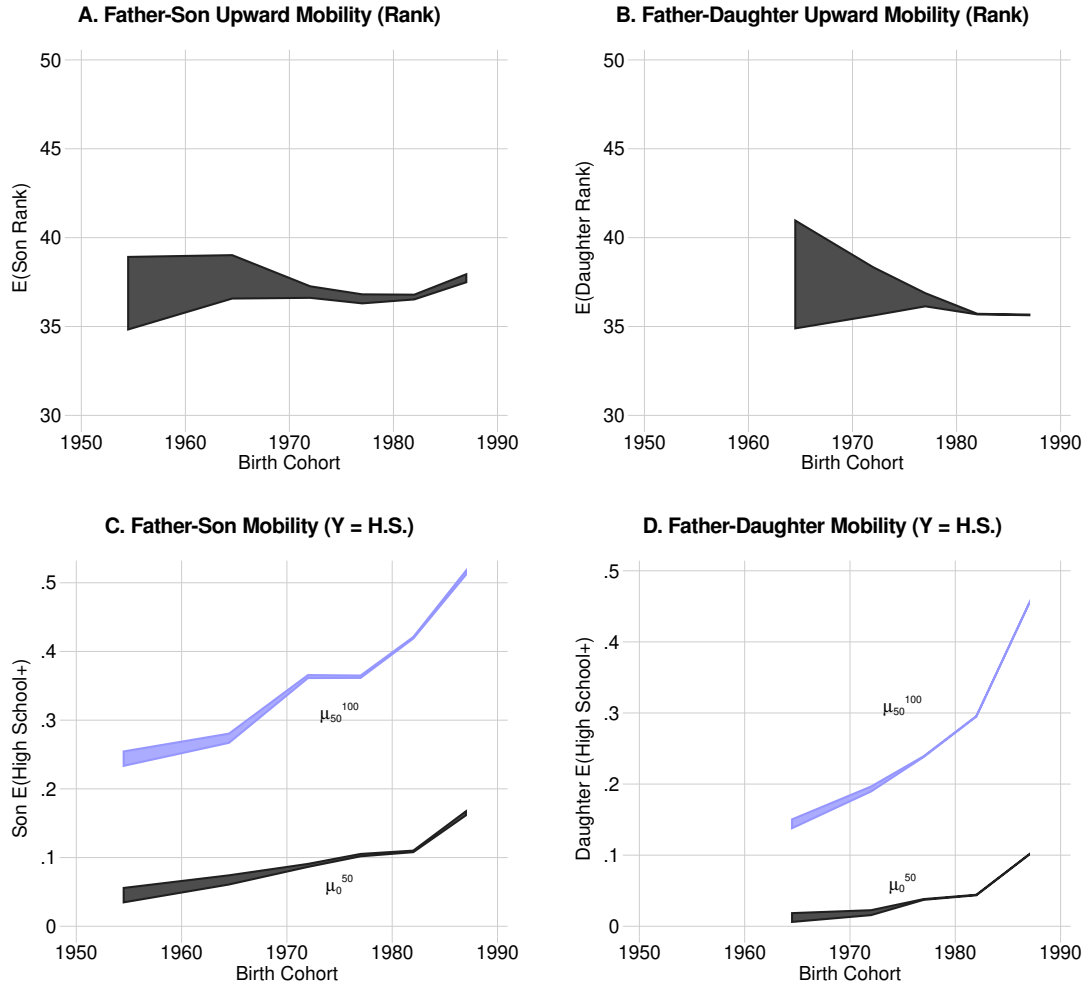


Figure 5 presents bounds on national intergenerational mobility, using cohorts born from 1950 through 1989. Panels A and B show bottom half mobility ($\mu_0^{50} = E(y|x \in [0,50])$), where x is parent rank and y is child rank. This is the average rank attained by children born to parents who are in the bottom half of the education distribution, respectively for sons and daughters. Panels C and D show an analogous measure, $E(HS|x \in [0,50])$ (gray) and $E(HS|x \in [50,100])$ (blue). The first (gray) is the share of children completing high school, conditional on having parents in the bottom half of the education distribution. The second (blue) is the share of children completing high school, conditional on parents in the top half of the parent distribution. Source: IHDS 2012.

Figure 6
Trends in Mobility by Subgroup, 1950–1989 Birth Cohorts

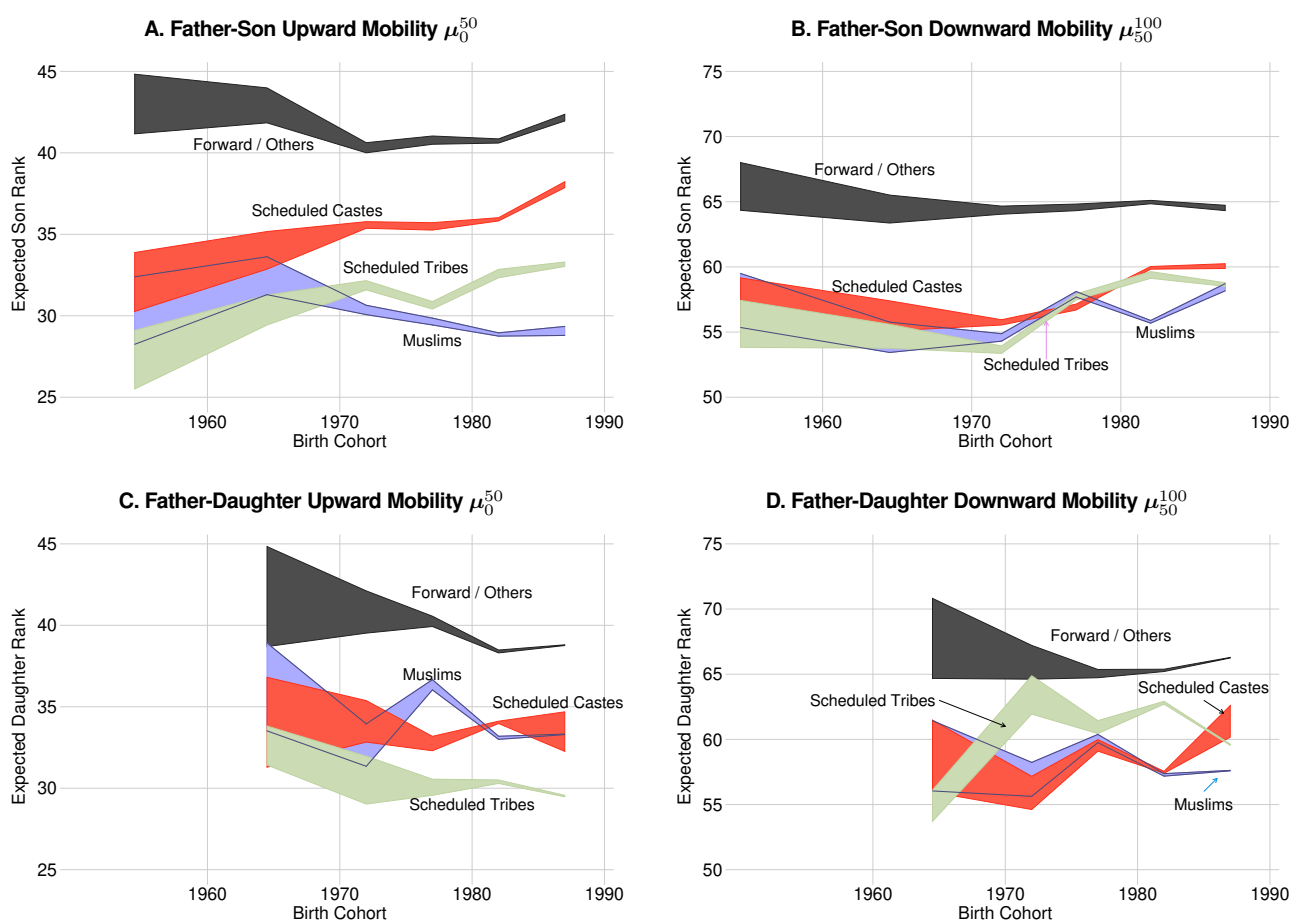


Figure 6 presents bounds on trends in intergenerational mobility, stratified by four prominent social groups in India: Scheduled Castes, Scheduled Tribes, Muslims, and Forward Castes/Others. The mobility measure in Panels A and B is bottom half mobility (μ_0^{50}), or the average rank among children born to fathers in the bottom half of the father education distribution. The measure in Panels C and D is top half mobility (μ_{50}^{100}), or the average rank among children born to fathers in top half of the father education distribution. Linked father-daughter education data are not available for the 1950–59 birth cohort. Source: IHDS 2012.

Figure 7

Upward Mobility by Geographic Location: National and Neighborhood Estimates

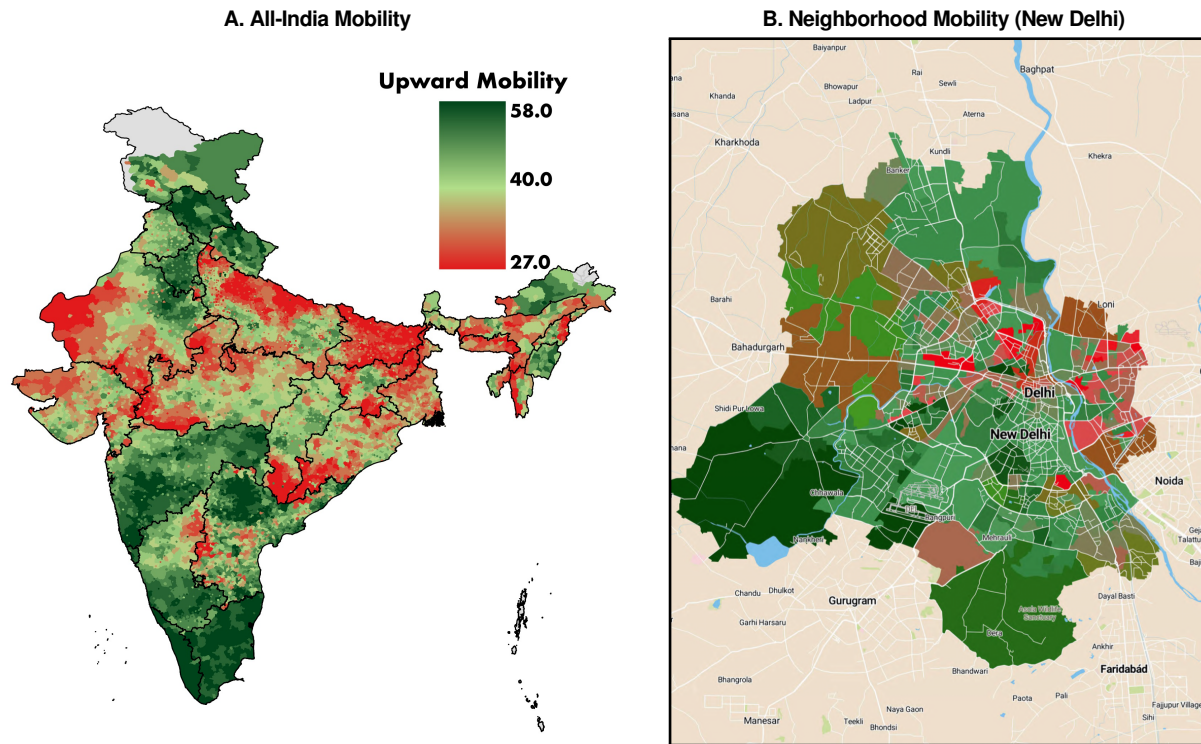


Figure 7 Panel A presents a map of the geographic distribution of upward mobility across Indian subdistricts and towns. Panel B shows a map of the geographic distribution of upward mobility across the wards of Delhi. Upward mobility (μ_0^{50}) is the average education rank attained by sons born to fathers who are in the bottom half of the father education distribution. Green areas have the highest mobility and red areas the lowest. The heat map legend applies to both panels of the figure. Source: SECC 2012.

Figure 8
Correlates of Upward Mobility, 1985–1989 Birth Cohort

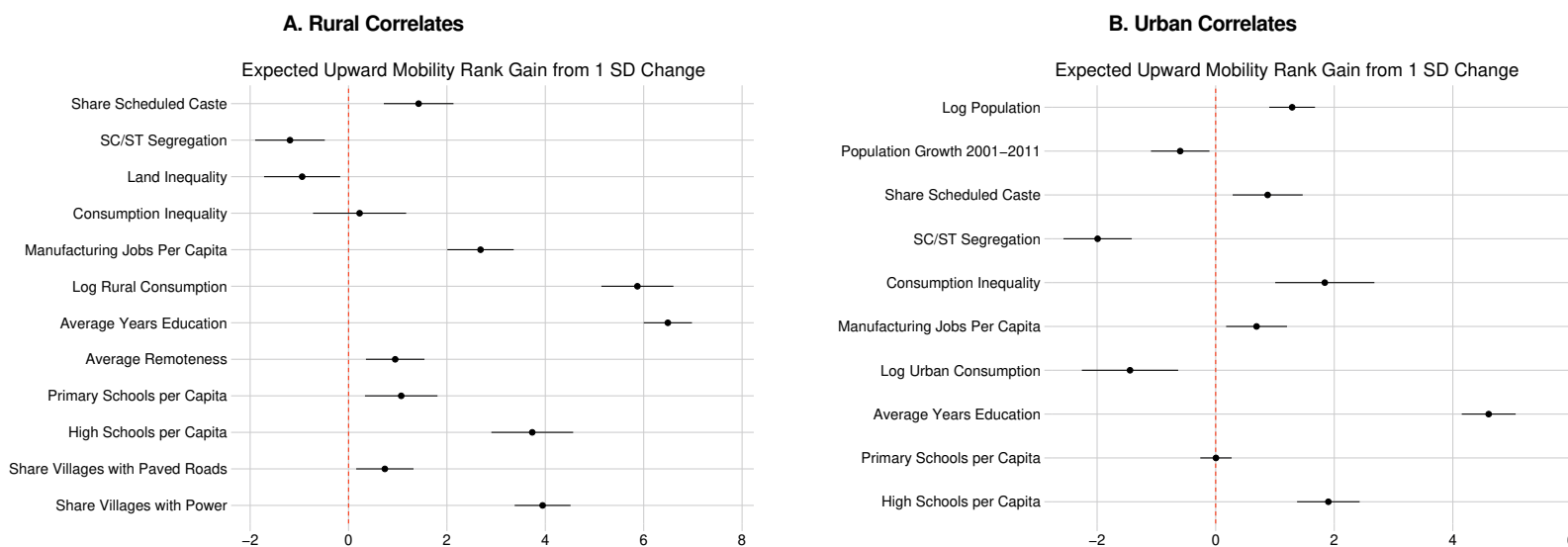


Figure 8 shows the cross-sectional relationship between local upward mobility and various characteristics of locations. Bottom half mobility (μ_0^{50}) is the average rank attained by sons born to fathers who are in the bottom half of the education distribution. Each point in the graph is a coefficients from a bivariate regression of bottom half mobility on the standardized variable on the Y axis. The Y variables are standardized to mean 0 and standard deviation 1 to make them comparable. Source: SECC 2012.

Figure 9
Jati Redesignation and Intergenerational Mobility

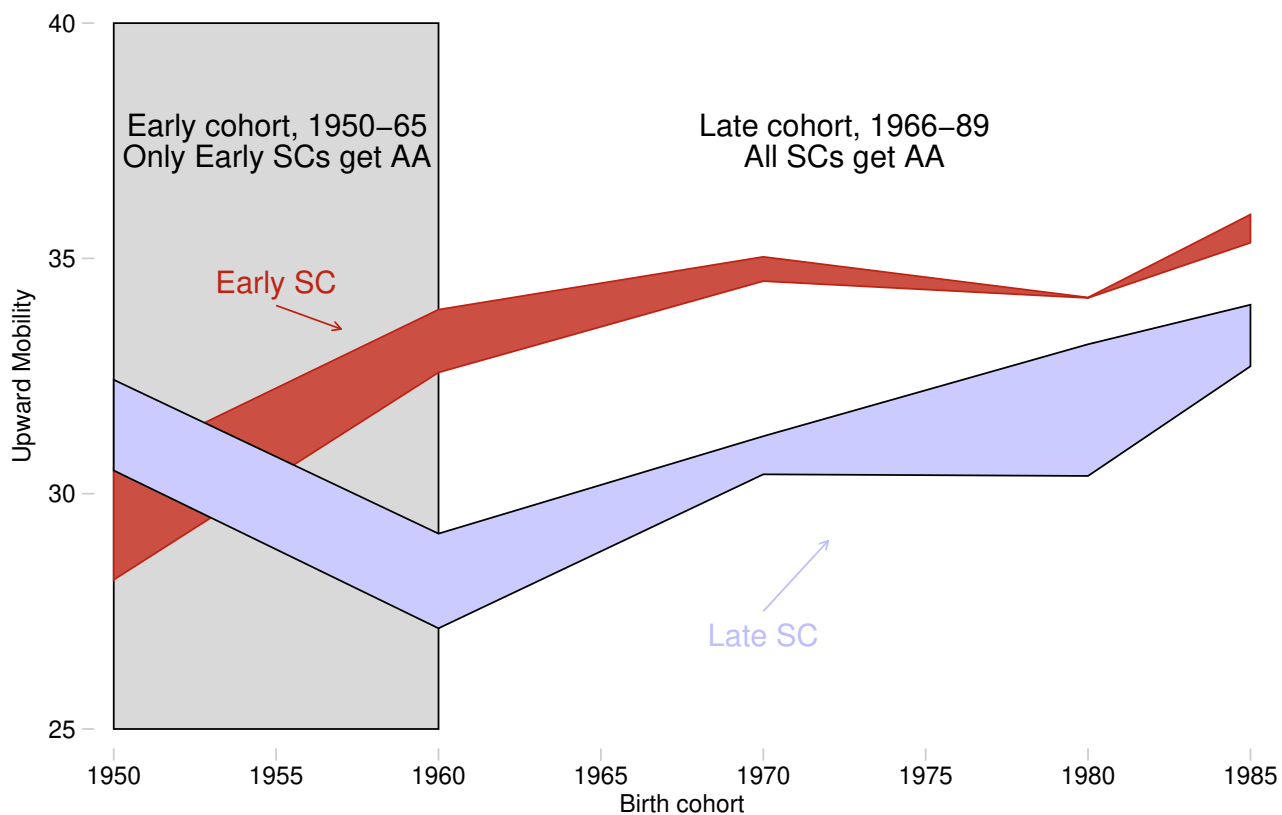


Figure 9 shows bounds on bottom half mobility μ_0^{50} for two social groups in India. The dark red series shows upward mobility for groups that were designated as Scheduled Castes beginning in the 1950s. The black series shows upward mobility for groups that were not designated as Scheduled Castes until 1977; birth cohorts later than 1970 (outside the grey box) are those who were young enough to benefit. Source: IHDS 2012.

Figure 10
Within-State and Within-District Social Group Mobility Gaps

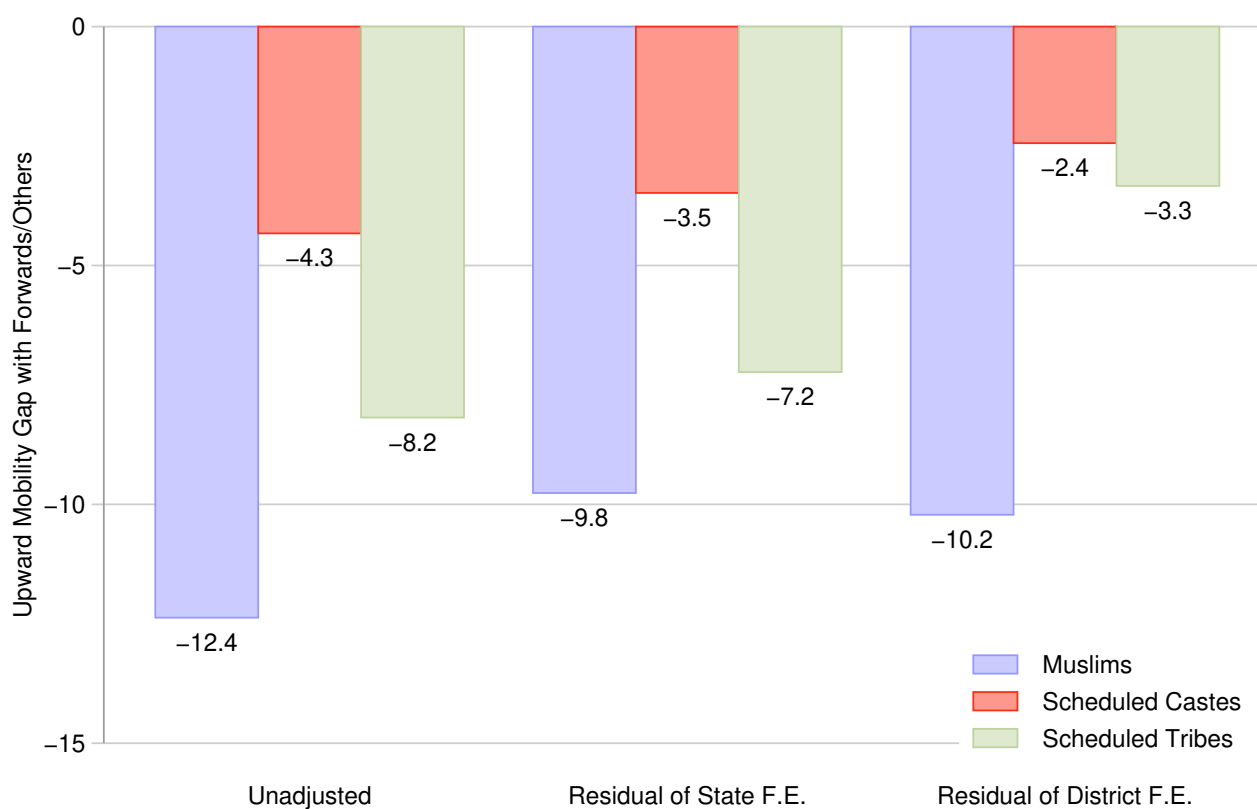


Figure 10 presents the upward mobility disadvantage relative to Forwards/Others faced by Muslims, Scheduled Castes and Scheduled Tribes. The first set of bars shows the aggregate mobility disadvantage of each group in rank terms. The second set of three bars shows the gaps calculated using within-state father and son education ranks. The third set shows gaps calculated using within-district father and son education ranks. Upward mobility in all cases is defined as $\mu_0^{50} = E(y|x \in [0,50])$, where x is parent rank and y is child rank. Upward mobility is partially identified; for simplicity, we show the midpoint of the bounds, which in all cases span less than a single rank. Source: IHDS 2012.

Figure 11
Mincerian Returns for Different Social Groups

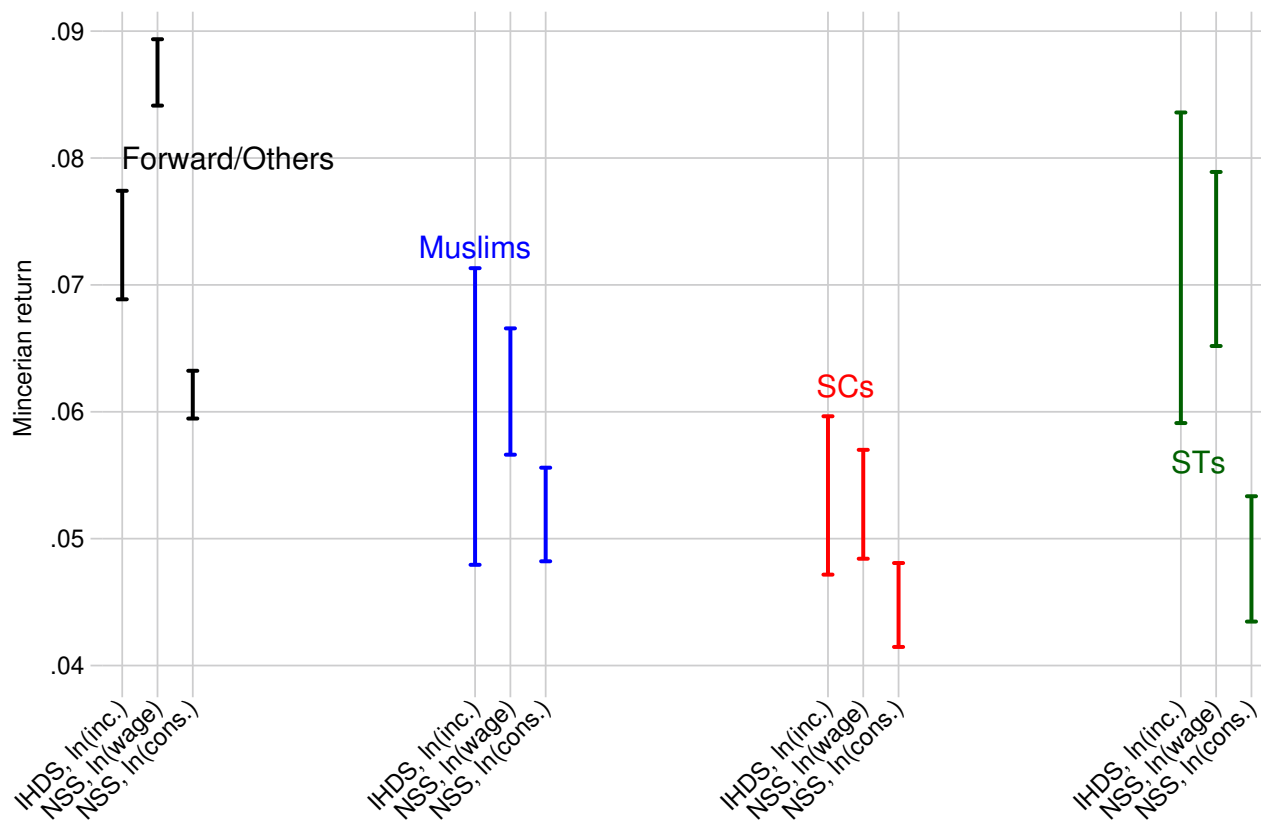
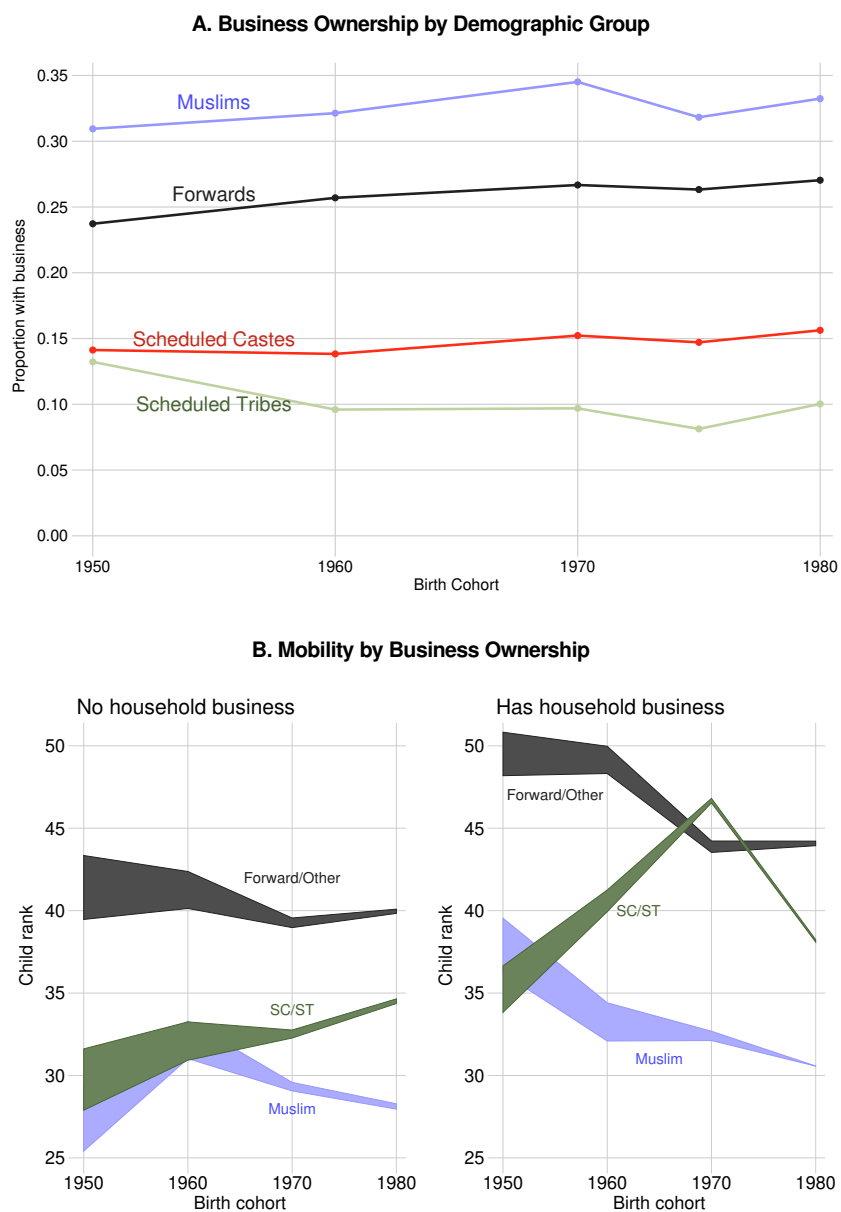


Figure 11 shows Mincerian returns to education for each major social group. Each band shows 95% confidence intervals for the Mincerian return to household log income (IHDS 2012), individual log wages (NSS 2012), and household log per capita income (NSS 2012).

Figure 12
Business Ownership and Intergenerational Mobility



Panel A of Figure 12 shows the share of individuals who report that they work in their own business, by social group and time. Source: NSS (2012). Panel B shows bottom half mobility (μ_0^{50}) for the major social groups, separated by individual business ownership. Scheduled Castes and Tribes are pooled to increase power, since few members of either group own businesses.

Table 1
Bin Sizes in Studies of Intergenerational Mobility

Study	Country	Birth Cohort of Son	Number of Parent Outcome Bins	Population Share in Largest Bin
Alesina et al. (2019)	Many countries in Africa ⁵⁶	1960–2005	5	83%
Card et al. (2018), Derenoncourt (2018)	USA	1920s	5	41% ⁵⁷
Dunn (2007)	Brazil	1972–1981	> 18	20% ⁵⁸
Emran and Shilpi (2011)	Nepal, Vietnam	1992-1995	2	83%
Güell et al. (2013)	Spain	~ 2001	9	27% ⁵⁹
Guest et al. (1989)	USA	~ 1880	7	53.2%
Hnatkovska et al. (2013)	India	1918-1988	5	Not reported
Knight et al. (2011)	China	1930–1984	5	29% ⁶⁰
Lindahl et al. (2012)	Sweden	1865-2005	8	34.5%
Long and Ferrie (2013)	Britain	~ 1850	4	57.6%
	Britain	~ 1949-55	4	54.2%
	USA	~ 1850-51	4	50.9%
	USA	~ 1949-55	4	48.3%
Piraino (2015)	South Africa	1964–1994	6	36%

Table 1 presents a review of papers analyzing educational and occupational mobility. The sample is not representative: we focus on papers where interval censoring may be a concern. The column indicating number of parent outcome bins refers to the number of categories for the parent outcome used in the main specification. The outcome is education in all studies with the exception of Long and Ferrie (2013) and Guest et al. (1989), where the outcome is occupation.

⁵⁶Many countries are studied; the table shows illustrative statistics for Ethiopia, one of the largest countries in the sample.

⁵⁷Source: Census Bureau (1940).

⁵⁸Includes all people born after about 1990.

⁵⁹Includes all people born after about 1960.

⁶⁰This is the proportion of sons in 1976 who had not completed one year of education — an estimate of the proportion of fathers in 2002 with no education, which is not reported.

⁶¹Estimate is from the full population rather than just fathers.

⁶²This reported estimate does not incorporate sampling weights; estimates with weights are not reported.

Table 2
Changes in Upward Mobility Over Time

A. Father/son pairs					
	All groups	Forward/Others	Muslims	SCs	STs
1960–1969	[36.6, 39.0] {35.7, 39.8}	[41.8, 44.0] {40.6, 45.2}	[31.3, 33.6] {29.4, 35.5}	[32.9, 35.2] {31.5, 36.6}	[29.4, 31.3] {27.1, 33.6}
1980–1989	[37.1, 37.2] {36.4, 37.9}	[41.3, 41.3] {40.2, 42.4}	[28.9, 29.0] {27.5, 30.3}	[36.9, 37.0] {35.4, 38.6}	[33.1, 33.1] {31.1, 35.1}
Change over time	[-1.9, 0.6] {-2.9, 1.6}	[-2.7, -0.5] {-4.4, 1.1}	[-4.7, -2.3] {-7.1, 0.1}	[1.8, 4.1] {-0.4, 6.3}	[1.8, 3.7] {-1.3, 6.8}
Fraction overlapping bounds	0.818	0.322	0.050	0.102	0.118
B. Father/daughter pairs					
	All groups	Forward/Others	Muslims	SCs	STs
1960–1969	[34.9, 41.0] {34.1, 41.8}	[38.7, 44.8] {37.6, 46.0}	[33.5, 38.9] {31.7, 40.7}	[31.3, 36.8] {29.8, 38.3}	[31.4, 33.8] {29.0, 36.2}
1980–1989	[35.4, 35.5] {34.6, 36.2}	[38.0, 38.2] {36.8, 39.3}	[32.0, 33.5] {31.0, 34.6}	[32.9, 34.2] {31.6, 35.5}	[30.4, 30.5] {28.4, 32.4}
Change over time	[-5.6, 0.6] {-6.7, 1.7}	[-6.9, -0.5] {-8.5, 1.1}	[-6.9, -0.0] {-8.9, 2.0}	[-3.9, 2.9] {-5.9, 4.9}	[-3.4, -0.9] {-6.5, 2.1}
Fraction overlapping bounds	0.802	0.244	0.446	0.982	0.344

Table 2 shows estimates of full sample and subgroup bottom half mobility (μ_0^{50}) for the 1960–69 and 1980–89 birth cohorts for father-son (Panel A) and father-daughter (Panel B) pairs. We show both bounds (in square brackets) and 90% confidence sets (in curly braces) on those bounds. The table also reports the bounds and 90% confidence sets on the change in bottom half mobility between these two time periods. We obtain confidence sets by generating 1,000 bootstrap draws, estimating bounds on each bootstrap draw, and following the framework in Chernozhukov et al. (2007) to form 90% confidence sets from bootstrapped bounds. Because these are confidence sets rather than confidence intervals, instead of p -values we show the fraction of bootstraps in which the 1960–69 and 1980–89 bounds are overlapping. Source: IHDS (2012).

Table 3
Group Differences in Upward Mobility

	F/O minus SC	F/O minus Muslim	SC minus Muslim
Father/son (μ_0^{50})	[4.6, 5.0] {2.8, 6.9}	[11.6, 12.1] {9.8, 13.9}	[6.9, 7.3] {4.5, 9.7}
Fraction overlapping bounds	0.000	0.000	0.000
Father/daughter (μ_0^{50})	[4.2, 4.5] {1.8, 6.9}	[5.1, 5.5] {3.0, 7.6}	[0.8, 1.1] {-2.1, 4.0}
Fraction overlapping bounds	0.000	0.000	0.509
Father/son (μ_{50}^{100})	[4.6, 5.0] {3.2, 6.5}	[11.6, 12.1] {5.7, 18.1}	[6.9, 7.3] {0.7, 13.4}
Fraction overlapping bounds	0.000	0.000	0.012
Father/daughter (μ_{50}^{100})	[4.2, 4.5] {0.9, 7.8}	[5.1, 5.5] {1.3, 9.3}	[0.8, 1.1] {-2.6, 4.5}
Fraction overlapping bounds	0.000	0.000	0.329

Table 3 shows estimates of cross-group differences in bottom half mobility (μ_0^{50}) and top half mobility (μ_{50}^{100}) in the 1980–89 birth cohorts. We show both bounds (in square brackets) and 90% confidence sets (in curly braces) on those bounds. We obtain confidence sets by generating 1,000 bootstrap draws, estimating bounds on each bootstrap draw, and following the framework in Chernozhukov et al. (2007) to form 90% confidence sets from bootstrapped bounds. Because these are confidence sets rather than confidence intervals, instead of p -values we show the fraction of the bounds for the two social groups that are overlapping. For example, the value of 0.509 in the final column indicates that 50.9% of the bootstraps generate overlapping bounds for the two groups. Source: IHDS (2012).

Table 4
Effect of Caste Redesignation on Scheduled Caste Upward Mobility

	(1)	(2)	(3)
Post * Late SC	8.432*** (1.794)	6.764*** (1.555)	
1970-79 * Late SC			6.739** (2.025)
1980-89 * Late SC			9.649*** (2.580)
N	4502	3746	4502
r2	0.32	0.34	0.32

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4 shows estimates from Equation 5.1, which describes the impact of Scheduled Caste redesignation on upward mobility. The dependent variable is the child education rank. The sample consists of SC sons of fathers with less than two years of education in the 1960s and 1970s, and SC sons of fathers with 2 or fewer years of education in the 1980s. The dependent variable thus corresponds to μ_0^{59} in the 1950s birth cohort, μ_0^{57} in the 1960s, and μ_0^{58} in the 1970s and 1980s. Late SC is an indicator for jati groups that were added to Scheduled Caste lists in the caste redesignation of 1977. All estimations control for region*cohort, jati*region, jati*cohort, and birth year, and are clustered at the jati and the region levels. Source: IHDS (2012).

Table 5
Relationship Between Fertility and Subgroup Upward Mobility

	(1)	(2)	(3)
Muslim	-13.476*** (0.976)	-12.338*** (1.697)	-9.287*** (1.721)
Scheduled Caste	-4.163*** (0.749)	-2.608** (1.281)	-1.901 (1.268)
Scheduled Tribe	-9.075*** (1.076)	-8.040*** (1.851)	-8.291*** (1.829)
Urban	3.881*** (0.782)	3.812*** (1.276)	3.514*** (1.261)
Number of Siblings			-2.359*** (0.304)
N	6345	2347	2347
r2	0.11	0.15	0.18

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 shows estimates from regressions of child education rank on social group indicators and an individual's number of siblings, a proxy for mother's fertility. The sample is limited to individuals born in 1985–89 to fathers with two or fewer years of education. The outcome variable thus corresponds to μ_0^{51} , a close analog of bottom half mobility (μ_0^{50}). Column 1 shows the estimation without the fertility measure for the full sample. Column 2 limits the data to the set of individuals for whom mother's fertility can be measured, and Column 3 adds the fertility variable. The effect of fertility on subgroup mobility gaps is understood as the change in the subgroup coefficient from Column 2 to Column 3. All regressions control for state fixed effects. Source: IHDS (2012).

A Appendix A: Additional Tables and Figures

Figure A1
Coresidence Rates by Age and Gender

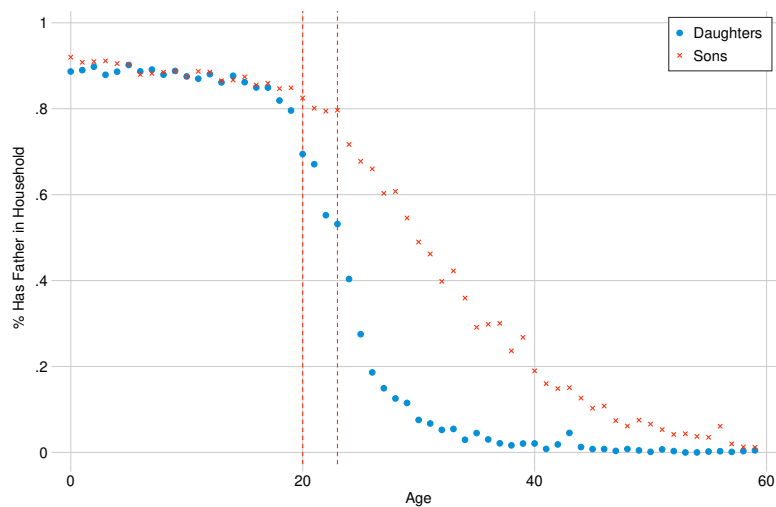


Figure A1 shows the share of individuals who live in the same household as their father as a function of gender and age. Source: IHDS (2012).

Figure A2
Bias in Mobility Estimates When Sample is Limited to Coresident Pairs

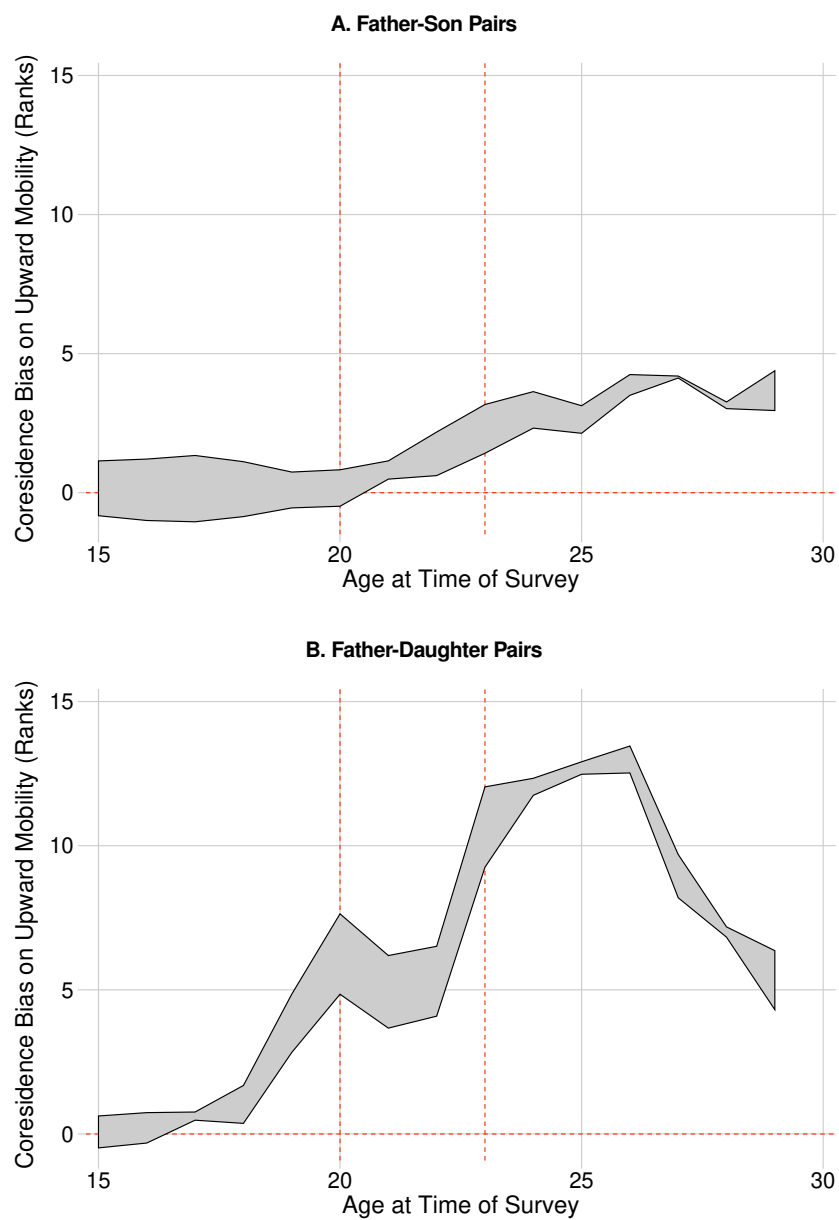


Figure A2 shows the bias in a measure of upward mobility when children who do not live with their parents are excluded. The bias is shown as a function of child age. The mobility measure is bottom half mobility (μ_0^{50}), which is the expected child rank conditional on being born to a parent in the bottom half of the education distribution. Bias is calculated as the coresident-only measure minus the full sample measure. Source: IHDS (2012).

Figure A3
Robustness of Upward Mobility to Survivorship Bias

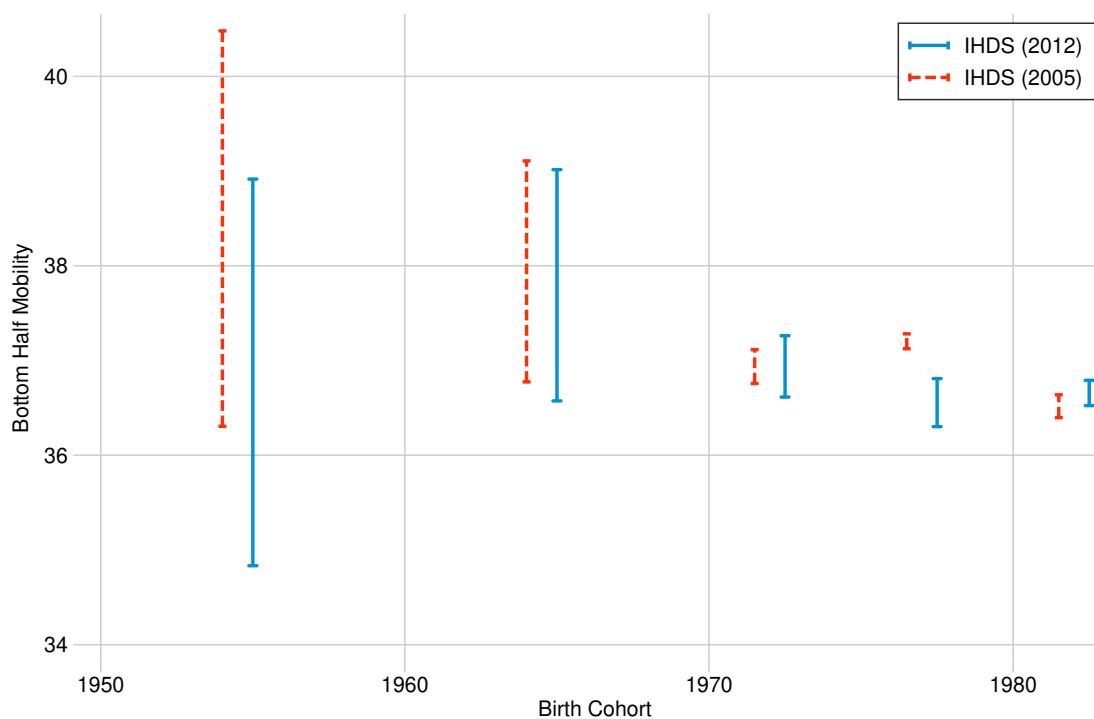


Figure A3 shows a test of survivorship bias in estimates of bottom half mobility. The figure shows estimates of bottom half mobility calculated for the same birth cohorts in the 2005 and 2012 rounds of the IHDS. If there was substantial survivorship bias in the mobility measures, we would expect the estimates to differ across the two surveys because of the deaths of some of the respondents.

Figure A4
 Bottom Half Mobility (μ_0^{50}) for Mother-Son and Mother-Daughter Pairs

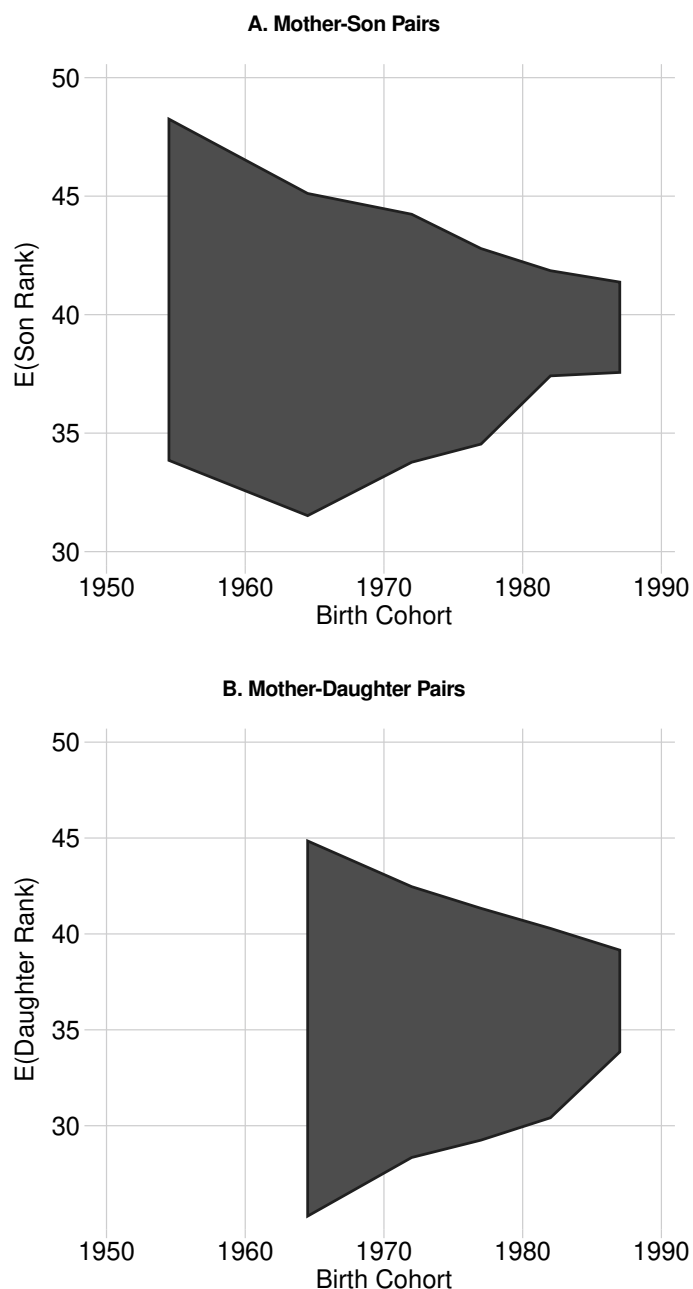


Figure A4 shows bounds on aggregate trends in intergenerational mobility, using cohorts born from 1950–59 through 1985–89, focusing on mother-son and mother-daughter links. The measure used is bottom half mobility (μ_0^{50}), which is the average rank attained by children born to parents who are in the bottom half of the education distribution. The bounds are very wide because of the large share of mothers who report bottom-coded education levels. Source: IHDS (2012).

Figure A5
Trends in Mobility by Subgroup, 1950–1989 Birth Cohorts
Education Level Outcomes

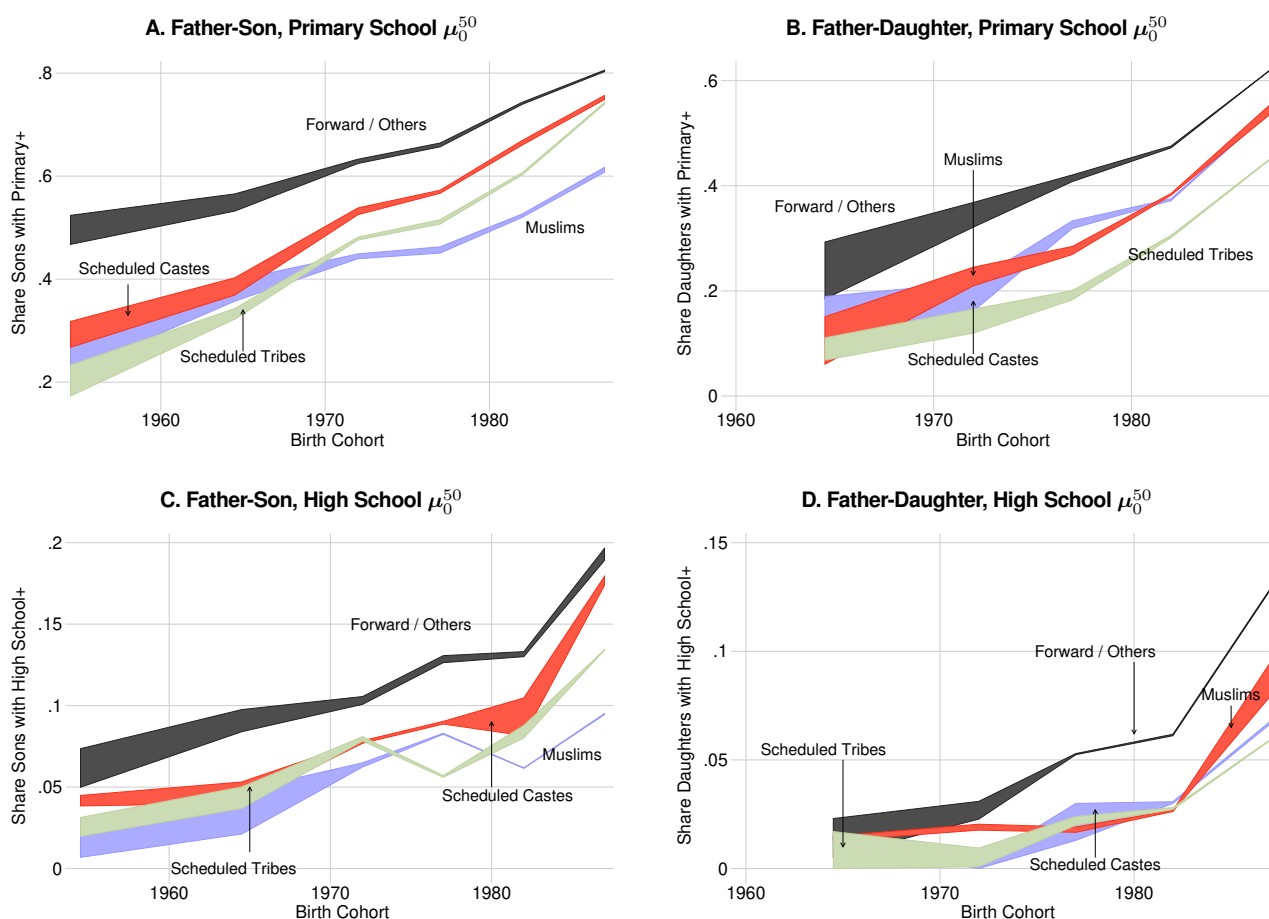


Figure A5 presents bounds on intergenerational mobility, stratified by four prominent social groups in India: Scheduled Castes, Scheduled Tribes, Muslims, and Forward Castes/Others. The figure is analogous to Figure 6, but shows the expected probability that a child attains a given education level (primary in Panels A and B, and secondary in Panels C and D), conditional on having a father in the bottom half of the father education distribution. Linked father-daughter education data are not available for the 1950–59 birth cohort. Source: IHDS (2012).

Figure A6
Bottom Half Mobility, Separated by Urban/Rural Population

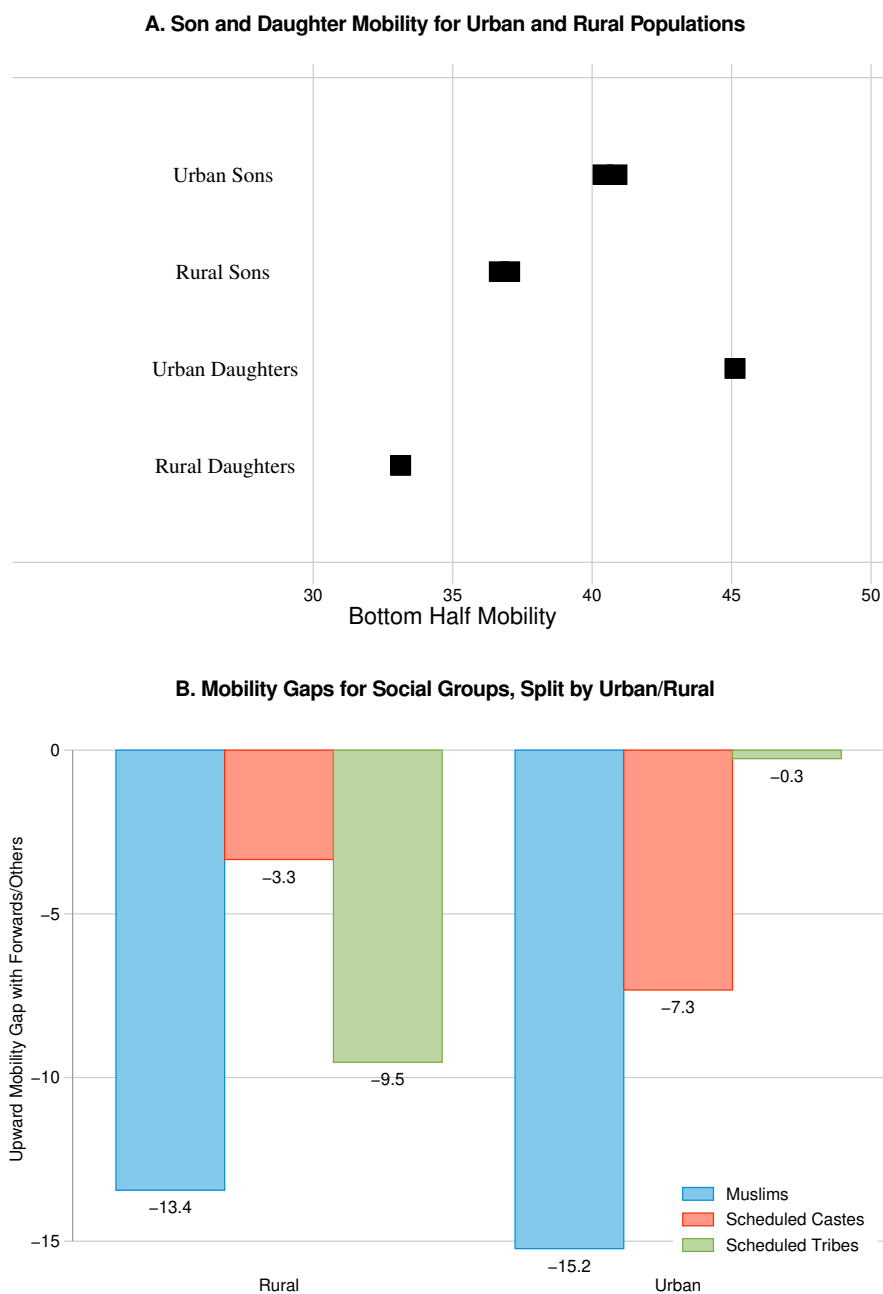


Figure A6A shows estimates of bottom half mobility (μ_0^{50}) for the 1985–89 birth cohort, disaggregated by gender and by urban/rural residence at the time of the survey. Panel B of the figure shows the gap in upward mobility between each population subgroup and the Forward/Other group, disaggregated by urban and rural residence. For example, the first bar shows that Muslim upward mobility is 12.2 rank points lower than Forward/Other upward mobility. Source: IHDS (2012).

Table A1
Transition Matrices for Father and Son Education in India

A. Sons Born 1950-59

Father ed attained	Son highest education attained						
	< 2 yrs. (31%)	2-4 yrs. (11%)	Primary (17%)	Middle (13%)	Sec. (13%)	Sr. sec. (6%)	Any higher (8%)
<2 yrs. (60%)	0.47	0.12	0.17	0.11	0.09	0.03	0.03
2-4 yrs. (12%)	0.10	0.18	0.22	0.19	0.16	0.09	0.06
Primary (13%)	0.07	0.08	0.31	0.16	0.19	0.08	0.10
Middle (6%)	0.06	0.05	0.09	0.30	0.17	0.14	0.18
Secondary (5%)	0.03	0.02	0.04	0.12	0.37	0.11	0.30
Sr. secondary (2%)	0.02	0.00	0.03	0.11	0.11	0.35	0.38
Any higher ed (2%)	0.01	0.01	0.01	0.03	0.08	0.13	0.72

B. Sons Born 1960-69

Father ed attained	Son highest education attained						
	< 2 yrs. (27%)	2-4 yrs. (10%)	Primary (16%)	Middle (16%)	Sec. (14%)	Sr. sec. (7%)	Any higher (10%)
<2 yrs. (57%)	0.41	0.12	0.16	0.14	0.09	0.04	0.04
2-4 yrs. (13%)	0.12	0.17	0.18	0.22	0.15	0.08	0.08
Primary (14%)	0.09	0.05	0.26	0.18	0.20	0.09	0.13
Middle (6%)	0.06	0.04	0.09	0.29	0.21	0.13	0.19
Secondary (6%)	0.03	0.02	0.08	0.12	0.35	0.16	0.25
Sr. secondary (2%)	0.02	0.02	0.03	0.07	0.19	0.25	0.41
Any higher ed (2%)	0.01	0.01	0.02	0.03	0.09	0.11	0.73

C. Sons Born 1970-79

Father ed attained	Son highest education attained						
	< 2 yrs. (20%)	2-4 yrs. (8%)	Primary (17%)	Middle (18%)	Sec. (16%)	Sr. sec. (10%)	Any higher (12%)
<2 yrs. (50%)	0.33	0.10	0.19	0.17	0.12	0.05	0.04
2-4 yrs. (11%)	0.11	0.16	0.20	0.22	0.15	0.08	0.08
Primary (15%)	0.08	0.06	0.24	0.23	0.18	0.11	0.11
Middle (8%)	0.05	0.03	0.09	0.29	0.21	0.17	0.16
Secondary (9%)	0.03	0.02	0.06	0.12	0.31	0.19	0.27
Sr. secondary (3%)	0.01	0.01	0.02	0.08	0.17	0.29	0.42
Any higher ed (4%)	0.00	0.00	0.02	0.05	0.10	0.17	0.66

D. Sons Born 1980-89

Father ed attained	Son highest education attained						
	< 2 yrs. (12%)	2-4 yrs. (7%)	Primary (16%)	Middle (20%)	Sec. (16%)	Sr. sec. (12%)	Any higher (17%)
<2 yrs. (38%)	0.26	0.10	0.21	0.20	0.12	0.06	0.05
2-4 yrs. (11%)	0.08	0.17	0.19	0.24	0.15	0.09	0.08
Primary (17%)	0.05	0.04	0.22	0.23	0.20	0.13	0.13
Middle (12%)	0.03	0.02	0.10	0.28	0.20	0.17	0.20
Secondary (11%)	0.02	0.01	0.05	0.13	0.23	0.24	0.32
Sr. secondary (5%)	0.02	0.01	0.04	0.09	0.15	0.24	0.46
Any higher ed (5%)	0.01	0.01	0.02	0.05	0.10	0.16	0.65

Table A1 shows transition matrices by decadal birth cohort for Indian fathers and sons in the study. Source: IHDS (2012).

Table A2
Internal Consistency of Reports of Parents' Education

	Father-Son		Father-Daughter		Mother-Daughter	
	(1)	(2)	(3)	(4)	(5)	(6)
Age		-0.000 (0.008)		-0.018 (0.016)		-0.008 (0.007)
Child years of education		0.008 (0.013)		0.037* (0.021)		0.003 (0.011)
Log household income		-0.005 (0.029)		-0.051 (0.058)		-0.026 (0.036)
Constant	0.053 (0.056)	0.054 (0.431)	-0.002 (0.103)	0.912 (0.841)	0.006 (0.052)	0.545 (0.466)
N	1258	1255	440	440	726	725
r ²	0.00	0.00	0.00	0.01	0.00	0.00

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2 shows measures of internal consistency when there are multiple reports of an individual's father in the IHDS. Each column is a regression of the level difference between two different measures of a parent's education. The constant term in Columns 1, 3, and 5 thus shows the average differences, and Columns 2, 4, and 6 effectively regress that difference on individual characteristics to measure the extent to which they predict the discrepancy. Source: IHDS (2012).

B Appendix B: Details on Methodology

This section provides details about the analytical and numerical procedures to bound the CEF and functions of the CEF. These methods are straightforward applications of Novosad et al. (2020). In Appendix B.1 and Appendix B.2, we reproduce the text of several propositions contained in Novosad et al. (2020) for ease of reference, but relegate the proofs to Novosad et al. (2020). In Appendix B.3, we explain the simple procedure to adapt the numerical techniques in Novosad et al. (2020) to this setting.

Relationship to Novosad et al. (2020). Novosad et al. (2020) is concerned with estimating bounds on $E(y|x=i)$ and various functions of that CEF, where x is an interval-censored adult education rank and y is that same adult's mortality rate. This paper is concerned with the same mathematical problem, where x is an interval-censored parent education rank and y is a measure of child socioeconomic status. Note that the monotonicity condition here is reversed from that in Novosad et al. (2020). Here, we assume child status is *increasing* in parent education rank; Novosad et al. (2020) assumes adult mortality is *decreasing* in adult education rank. The propositions and problem setups are otherwise the same.

B.1 Formal Statement of Proposition 1

Let the function $Y(x) = E(y|x)$ be defined on $[0,100]$. Form the set of non-overlapping intervals $[x_k, x_{k+1}]$ that cover $[0,100]$ for $k \in \{1, \dots, K\}$. We seek to bound $E(y|x)$ when x is known to lie in the interval $[x_k, x_{k+1}]$; there are K such intervals. Suppose that

$$x \sim U(0,100), \quad (\text{Assumption U})$$

and define

$$r_k := \frac{1}{x_{k+1} - x_k} \int_{x_k}^{x_{k+1}} Y(x) dx.$$

Adopt the following assumptions from Manski and Tamer (2002):

$$\text{Prob}(x \in [x_k, x_{k+1}]) = 1. \quad (\text{Assumption I})$$

$$E(y|x) \text{ must be weakly increasing in } x. \quad (\text{Assumption M})$$

$$E(y|x, x \text{ is interval censored}) = E(y|x). \quad (\text{Assumption MI})$$

Proposition 1. *Let x be in bin k . Under assumptions M, I, MI (Manski and Tamer, 2002) and U, and without additional information, the following bounds on $E(y|x)$ are sharp:*

$$\begin{cases} r_{k-1} \leq E(y|x) \leq \frac{1}{x_{k+1} - x} ((x_{k+1} - x_k)r_k - (x - x_k)r_{k-1}), & x < x_k^* \\ \frac{1}{x - x_k} ((x_{k+1} - x_k)r_k - (x_{k+1} - x)r_{k+1}) \leq E(y|x) \leq r_{k+1}, & x \geq x_k^* \end{cases}$$

where

$$x_k^* = \frac{x_{k+1}r_{k+1} - (x_{k+1} - x_k)r_k - x_k r_{k-1}}{r_{k+1} - r_{k-1}}.$$

B.2 Formal Statement of Analytical Bounds on μ_a^b

We now state a proposition, also contained in Novosad et al. (2020), that permits us to bound μ_a^b .

Define

$$\mu_a^b = \frac{1}{b-a} \int_a^b E(y|x) di.$$

Let Y_x^{min} and Y_x^{max} be the lower and upper bounds respectively on $E(y|x)$ given by Proposition 1. We seek to bound μ_a^b when x is only known to lie in some interval $[x_k, x_{k+1}]$.

Proposition 2. *Let $b \in [x_k, x_{k+1}]$ and $a \in [x_h, x_{h+1}]$ with $a < b$. Let assumptions M , I , MI (Manski and Tamer, 2002) and U hold. Then, if there is no additional information available, the following bounds are sharp:*

$$\begin{cases} Y_b^{min} \leq \mu_a^b \leq Y_a^{max}, & h = k \\ \frac{r_h(x_k - a) + Y_b^{min}(b - x_k)}{b - a} \leq \mu_a^b \leq \frac{Y_a^{max}(x_k - a) + r_k(b - x_k)}{b - a}, & h + 1 = k \\ \frac{r_h(x_{h+1} - a) + \sum_{\lambda=h+1}^{k-1} r_\lambda(x_{\lambda+1} - x_\lambda) + Y_b^{min}(b - x_k)}{b - a} \leq \mu_a^b \leq \frac{Y_a^{max}(x_{h+1} - a) + \sum_{\lambda=h+1}^{k-1} r_\lambda(x_{\lambda+1} - x_\lambda) + r_k(b - x_k)}{b - a}, & h + 1 < k. \end{cases}$$

B.3 Bounding Functions of the CEF

We now describe our procedure for bounding arbitrary functions of the CEF. We conduct the following process.

1. Consider the set of CEFs that can: (a) match the observed mean levels of child rank within each parent rank bin, and (b) are consistent with any additional assumptions (e.g., monotonicity and/or smoothness assumptions).
2. For every CEF in this set, generate a function of the CEF. Report the maximum and minimum value of this function, collecting values over all CEFs in this set.

Formally, index interval-censored bins by k : define the non-overlapping intervals $[x_k, x_{k+1}]$ that cover $[0, 100]$ for $k \in \{1, \dots, K\}$. Then define $\{r_k\}_{k=1}^K$ as the set of observed mean values of y over each bin $k \in \{1, \dots, K\}$. Further define $S(\{r_k\}_{k=1}^K)$ to be the collection of CEFs that is consistent with these bin means and any desired auxiliary assumptions. For example, noting that x is uniformly distributed, we can put:

$$\begin{aligned} S(\{r_k\}_{k=1}^K) &= \left\{ Y(x) \mid Y(x) \text{ is weakly increasing} \right\} \\ &\cap \left\{ Y(x) \mid \frac{1}{x_{k+1} - x_k} \int_{x_k}^{x_{k+1}} (Y(x) - r_k(x)) dx = 0, \text{ for all } k \right\}. \end{aligned} \quad (\text{B.1})$$

Our objective is to bound $\gamma = \gamma(Y)$, some function of the CEF. In particular, we face the following constrained optimization problem to obtain the maximum and minimum values of γ :

$$\gamma^{\min} = \min_{Y \in S(\{r_k\}_{k=1}^K)} \tilde{\gamma}(Y) \quad (\text{B.2})$$

$$\gamma^{\max} = \max_{Y \in S(\{r_k\}_{k=1}^K)} \tilde{\gamma}(Y). \quad (\text{B.3})$$

Novosad et al. (2020) provide details on the numerical techniques used to solve this problem. The bounds we report are the set $[\gamma^{\min}, \gamma^{\max}]$. We now describe how we apply this process in the case of the rank-rank gradient and with curvature constraints.

Rank-rank gradient. In the case of the rank-rank gradient, we let γ represent the slope of the linear approximation to the CEF. That is, fixing a CEF $Y(x)$, define

$$(\gamma, b) := \operatorname{argmin}_{\gamma', b' \in \mathbb{R}} \int_0^{100} (Y(x) - \gamma'x + b')^2 dx.$$

Curvature constraints. In the case of reporting the CEF with curvature constraints (e.g., Figure 2B), we simply define $p_x(Y)$ to be the value of the CEF at a given x . We define S to be the set of CEFs that are consistent with monotonicity and a second derivative that lies below a given magnitude in absolute value. In the case where there are no CEFs that precisely match the bin means (e.g., for a small enough curvature constraint), we solve a modified problem described formally in Novosad et al. (2020). Define $T(\{r_k\}_{k=1}^K)$ to be the set of CEFs that (a) minimize some distance metric between the bin means and the CEF, and (b) are consistent with the observed bin means and extra assumptions (monotonicity and curvature). In particular, for distance metric $\|\cdot\|$, define

$$M(Y) := \int_0^{100} \|Y(x) - r_k(x)\| dx,$$

where $r_k(x) := r_k$ if $x \in [x_k, x_{k+1}]$. $M(Y)$ is the weighted distance between a given CEF Y and the bin means $\{r_k\}$. Then define

$$T(\{r_k\}_{k=1}^K) = P \cap \left\{ Y(x) \mid \left(\int_0^{100} \|Y(x) - r_k(x)\| dx \right) \leq \underline{M(P)} \right\}, \quad (\text{B.4})$$

for

$$\underline{M(P)} := \min_{Y \in P} M(Y)$$

and

$$P := \left\{ Y(x) \mid Y(x) \text{ is weakly increasing and has second derivative less than } \underline{C} \right\}.$$

Put otherwise, we find the minimum distance between the CEFs and observed bin means, as long as these CEFs obey certain properties. Then, we find the set of CEFs that obey these properties and satisfy this minimum distance. If there are CEFs that precisely meet the bin means, then $T = S$.

Finally, we report:

$$p_x^{\min} = \min_{Y \in T(\{r_k\}_{k=1}^K)} \tilde{p}_x(Y) \quad (\text{B.5})$$

$$p_x^{\max} = \max_{Y \in T(\{r_k\}_{k=1}^K)} \tilde{p}_x(Y). \quad (\text{B.6})$$

In practice, we choose the mean-squared error as the distance metric.

C Appendix C: Robustness to Alternate Assumptions

C.1 Robustness to Non-Uniform Within-Bin Subgroup Distributions

Our bounds on the full sample CEF $E(y|x)$ (explained in Section 3.3) use the uniformity of the rank distribution, which is given when working with the national sample. However, when working with population subsamples (e.g. Muslims), uniformity is not guaranteed. Take the example of the 1960s, where 57% of fathers are in the lowest education bin. Conditional on being in the bottom bin, the distribution of latent ranks of Muslim fathers is *not* necessarily uniform.

This lack of uniformity creates a potential bias. For example, approximately 10% of the fathers in the bottom education bin are Muslims. If the latent ranks of these fathers were all concentrated at the bottom of the bin, and the latent ranks of Hindus were concentrated at the top of the bin, then the mobility gap between Hindus and Muslims would be biased upward. In other words, the gap in son outcomes between Hindus and Muslims could not be driven by a difference in outcomes conditional on father education rank, but could be driven by unobserved differences in the latent father ranks.

The extent of bias is determined by the extent to which the within-bin latent education rank distribution for each subgroup differs from the uniform distribution. In this section, we demonstrate that these departures appear to be too small to bias our primary results. We do this by estimating a series of continuous parametric functions to the coarse education distribution and then predict latent ranks of population subgroups using those continuous functions. We can then examine the size of the bias that would be generated by ignoring the distribution of latent ranks within education bins. We find that the maximal bias would be very small and unlikely to affect our conclusions.

The issues addressed in this appendix are not unique to our analysis, but are present in any comparison of groups that conditions on education levels. However, our discussion of latent education ranks makes this concern particularly noticeable.

C.1.1 Inferring Latent Education Rank from Parametric Assumptions

We impute the within-bin latent education rank distribution for each population subgroup by fitting a parametric function to the entire subgroup education distribution, using the binned data. From

these parameterized distributions, we then predict a continuous latent rank distribution for each subgroup. We can compare that predicted continuous latent distribution to the uniform distribution to determine the extent of bias arising from the assumption of uniformity.

For each population subgroup, we fit a normal and a lognormal distribution to the sample distribution of years of education. We then create a simulated population that has the same proportion of each subgroup as the true population, and for each individual, we draw their years of education from the fitted parametric distribution. This gives us a continuous education distribution that matches the moments from the discrete sample distribution. Finally, we transform the years of education variable into ranks with respect to the entire population. This gives us a simulated population with continuous ranks.

We focus on the 1960–69 and 1985–89 cohorts, as we aim to check the validity of our conclusion that Muslim and SC mobility have diverged over this period.

Table C1 compares the moments from the IHDS sample with the moments from the simulated distributions. For both the 1960–69 and the 1985–89 birth cohorts, the simulated moments are close matches to the raw data. The group ordering and approximate gaps between groups is preserved; the standard deviation of the simulated data is slightly higher than that of the true binned data, which is to be expected, given the truncation of the binned data.

Table C1
Actual and Simulated Moments from the Education Rank Distribution

A. 1960-1969 Birth Cohort

	<u>Binned Data</u>		<u>Simulated Distributions</u>			
			Normal		Lognormal	
	Mean	SD	Mean	SD	Mean	SD
Forward / Other	55.2	26.8	55.6	30.1	56.1	29.3
Muslim	46.7	24.5	47.0	27.3	46.6	27.7
Scheduled Castes	40.8	21.0	39.9	23.0	39.3	24.6
Scheduled Tribes	39.1	20.2	38.6	23.4	37.3	23.9

B. 1985-1989 Birth Cohort

	<u>Binned Data</u>		<u>Simulated Distributions</u>			
			Normal		Lognormal	
	Mean	SD	Mean	SD	Mean	SD
Forward / Other	56.5	27.6	56.4	28.6	56.6	27.8
Muslim	45.1	26.7	45.0	27.5	45.7	28.5
Scheduled Castes	42.9	26.7	42.9	27.4	42.7	28.2
Scheduled Tribes	35.6	25.0	36.0	25.2	34.6	26.1

In Table C2, we use the simulated data to examine the distribution of the latent variable *within* the bins where our method assumes uniformity. In particular, we examine the mean parent education rank conditional on being in the bottom 50%. As expected, parents from less educated social groups have lower latent ranks even after conditioning on being in the bottom 50%.⁶³ However, the differences are very small, and they do not change much from the 1960–69 to the 1985–89 birth

⁶³If the subgroup distributions were all uniform within this bin, then all groups would have a mean rank of 25.

cohorts, under any of the distributional assumptions. Even in the worst case scenario (the lognormal distribution with constant variance), the gap between Muslim and SC parents in the bottom 50% shrinks from 2.5 to 1, a 1.5 percentage point change.

Table C2
Simulated Average Parent Rank Conditional on Rank ≤ 50

A. 1960-1969 Birth Cohort

	<u>Group-level Variance</u>		<u>Constant Variance</u>	
	Normal	Lognormal	Normal	Lognormal
Forward / Other	24.4	25.4	27.0	27.1
Muslim	24.9	24.9	24.1	24.8
Scheduled Castes	26.1	24.7	22.8	22.4
Scheduled Tribes	25.2	24.1	22.1	22.1

B. 1985-1989 Birth Cohort

	<u>Group-level Variance</u>		<u>Constant Variance</u>	
	Normal	Lognormal	Normal	Lognormal
Forward / Other	26.6	27.7	27.2	27.4
Muslim	24.5	24.0	24.0	24.3
Scheduled Castes	23.8	23.0	23.6	23.4
Scheduled Tribes	22.4	20.8	21.2	20.7

Given the average CEF slope of 0.5, this suggests that changing latent parental status within the coarse education bins can explain at most 0.75 rank points of the growing difference between Muslims and SC/STs. Under other distributional assumptions the potential bias is even smaller. In comparison, our midpoint estimate of this change from 1960–69 to 1985–89 in the body of the paper is 7.4 rank points.

We therefore consider it unlikely that changing parental position within observed rank bins can explain the growing mobility gap between SCs and Muslims. The relative positions of other groups within their bins has similarly not changed enough to substantially bias our group-level estimates.

C.2 Robustness to Adjusting for Censored Child Ranks

In the main part of the paper, we focus on bounding a function $Y(x) = E(y|x)$ when y is observed without error, but x is observed with interval censoring. In this section, we modify the setup to consider simultaneous interval censoring in the conditioning variable x and in observed outcomes y . In the mobility context, this double-censoring setup arises when the y variable is a child rank (as in Figure 5A and 5B), but not when the y variable is a child level of education (as in Figure 5C and 5D). As noted in the paper, all of our results are consistent whether we use levels or ranks as outcomes. We nevertheless proceed here to examine the potential bias from ignoring the censoring of child ranks.

One approach to this problem would be to use a problem setup similar to that presented in Section 3, that takes into account the information on child ranks that is lost by binning. We developed a numerical optimization that could bound the CEF by searching over all possible joint distributions of latent x and y variables, but with n^2 the number of parameters compared with the single-censoring model, it proved computationally infeasible.

We therefore present two alternate approaches to the problem here. First, we define the latent distributions of y variables that would generate the maximal and minimal mobility statistic in theory. We can then bound the mobility statistic following our standard method under these best- and worst-case assumptions. This union of these bounds is a very conservative bound on the mobility statistic given censoring in both the y and x variables.

Second, we can shed light on the distribution of the true average value of y in each x bin if other data is available. This approach is feasible whenever more information is available about children than about their parents, as is the case in our context (and in many others). Specifically, we use data on child wages to predict whether the true latent child rank distribution (y) is better represented by the best- or worst-case mobility scenario. The joint wage distribution suggests that the true latent distribution of y in each bin is very close to the best case distribution, which we used in Section 5.

C.2.1 Best and Worst Case Mobility Distributions

In this section, we take a sequential approach to the double-censoring problem. We first calculate the set of child CDFs for each level of parent education that would correspond to the highest and lowest possible intergenerational mobility. From these CDFs, we can calculate the average latent rank of children in each parent bin. These may be different from the latent rank implied by assigning each child the midpoint of their bin. With these latent ranks, we can then follow the estimation procedure outlined in Section 3. This gets us a wider set of bounds that takes the censoring of child ranks into account.

To make the example concrete, consider two children who have less than 2 years of education; one is from a rich family and one is from a poor family. Assume that 20% of children in the population have less than 2 years of education. In the body of the paper, we would assume that each of these children has a rank of 10 (i.e. the midpoint of the bottom bin). But it is possible that the child from a poor family has a latent rank of 7 and the child from a rich family has a latent rank of 13. In this case, mobility would be lower than what we have measured in the paper.

Given that child rank is known only to lie in one of h bins, there are two hypothetical scenarios that describe the best and worst cases of intergenerational mobility. Mobility will be lowest if child outcomes are sorted perfectly according to parent outcomes *within* each child bin, and highest if there is no additional sorting within bins.⁶⁴

Note that the case of perfect sorting within bins fits very poorly with the standard human capital model. In this model, the binned education data reflects a continuous demand for education with a lumpy number of years available for purchase. It is difficult to theorize a distribution where there is a large mass of rich children bunched just below a bin boundary, and no rich children just above that boundary. Given that children of rich and poor parents appear in every bin in the child distribution, the true distribution is likely to be closer to the uniform case than the perfectly ordered case. Note also that we do not consider the case of perfectly reversed sorting, where the children of the least educated parents occupy the highest ranks within each child rank bin, as it would violate

⁶⁴Specifically, these scenarios respectively minimize and maximize both the rank-rank gradient and μ_0^x for any value of x . To minimize and maximize p_x , a different within-bin arrangement is required for every x . We leave this out for the sake of brevity, and because bounds on p_x are minimally informative even with uncensored y .

the stochastic dominance condition (and is implausible).

Appendix Figure C1 shows two set of CDFs that correspond to these two scenarios for the 1960–69 birth cohort. In Panel A, children’s ranks are perfectly sorted according to parent education within bins. Each line shows the CDF of child rank, given some father education. The points on the graph correspond to the observations in the data—the value of each CDF is known at each of these points and thus the CDFs must pass through them. Children below the 27th percentile are in the lowest observed education bin. Within this bin, the CDF for children with the least educated parents is concave, and the CDF for children with the most educated parents is convex—indicating that children from the best off families have the highest ranks within this bin. This pattern is repeated within each child bin. The implausibility of this scenario is reflected by the kinked nature of these CDFs, which are unlikely to appear in the real world. Panel B presents the high mobility scenario, where children’s outcomes are uniformly distributed within child education bins, and are independent of parent education within child bin.

Each of these CDFs can be collapsed to a single mean child rank for each parent bin. From these expected child ranks, we can then use the method from Section 3 to calculate bounds on any mobility statistic. The top two rows of Table C3 shows bounds on μ_0^{50} and on the rank-rank gradient for the high and low mobility scenarios. Taking censoring in the child distribution into account widens the bounds on all parameters. The effect is proportionally larger for bottom half mobility, because it was so precisely estimated before—the bounds on μ_0^{50} approximately double in width when censoring of son data is taken into account.

These bounds are very conservative, as the worst case scenario is implausible, as noted above. In the next subsection, we draw on additional data on children, which suggests that the best case mobility scenario is close to the true joint latent distribution.

C.2.2 Estimating the Child Distribution Within Censored Bins

Because we have additional data on children, we can estimate the shape of the child CDF within parent-child education bins using rank data from other outcome variables that are not censored. Under the assumption that latent education rank is correlated with other measures of socioeconomic rank, this exercise sheds light on whether Panel A or Panel B in Figure C1 better describes the true latent distribution.

Figure C2 shows the result of this exercise using wage data from men in the 1960s birth cohort. To generate this figure, we calculate children's ranks first according to education, and then according to wage ranks within each education bin.⁶⁵ The solid lines depict this uncensored rank distribution for each father education; the dashed gray lines overlay the estimates from the high mobility scenario in Panel B of Figure C1.

If parent education strongly predicted child wages *within* each child education bin, we would see a graph like Panel A of Figure C1. The data clearly reject this hypothesis. There is some additional curvature in the expected direction in some bins, particularly among the small set of college-educated children, but the distribution of child cumulative distribution functions is strikingly close to the high mobility scenario, where father education has only a small effect on child wage ranks after child education is taken into account. The last row of Table C3 shows mobility estimates using the within-bin parent-child distributions that are predicted by child wages; the mobility estimates are nearly identical to the high mobility scenario. This result suggests that our assumption in Section 5 that the latent child rank is the midpoint of the rank bin for all parent groups is not affecting our estimates very much.

Note that there is no comparable exercise that we can conduct to improve upon the situation when parent ranks are interval censored, because we have no information on parents other than their education, as is common in mobility studies. If we had additional information on parents, we could conduct a similar exercise. The closest we can come to this is by observing the parent-child rank distribution in countries with more granular parent ranks, as we did in Section 3. The results in that section suggest that interval censoring of parent ranks does indeed mask important features of the mobility distribution.

Note finally that the potential bias from assuming uniformity within child rank bins is increasing in the size of the rank bins. Because children are more educated than parents in every cohort, this bias is smaller for children than it would be for parents. It is also smaller for the younger cohorts of children born in the 1980s than it is for the example we used here.

⁶⁵We limit the sample to the 50% of men who report wages. Results are similar if we use household income, which is available for all men. Household income has few missing observations, but in the many households where fathers are coresident with their sons, it is impossible to isolate the son's contribution to household income from the father's, which biases mobility estimates downward.

Figure C1
Best- and Worst-Case Son CDFs
by Father Education (1960-69 Birth Cohort)

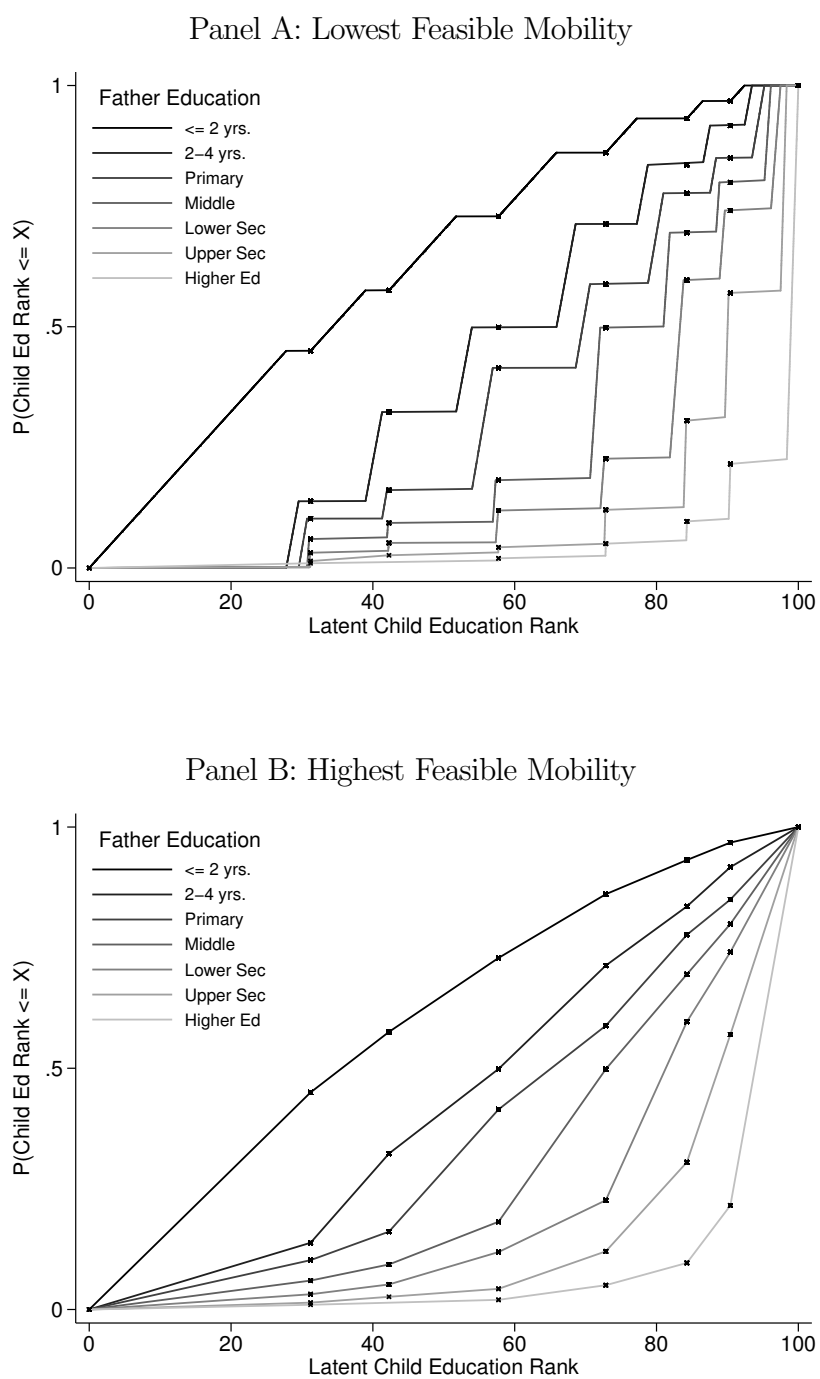


Figure C1 shows a set child CDFs conditional on each level of father education that correspond to the best and worst case scenarios for intergenerational mobility. The lines index father types. Each point on a line shows the probability that a child of a given father type obtains an education rank less than or equal to the value on the X axis in the national education distribution. The large markers show the points observed in the data.

Figure C2
Son Outcome Rank CDF
by Father Education (1960-69 Birth Cohort)
 Joint Education/Wage Estimates

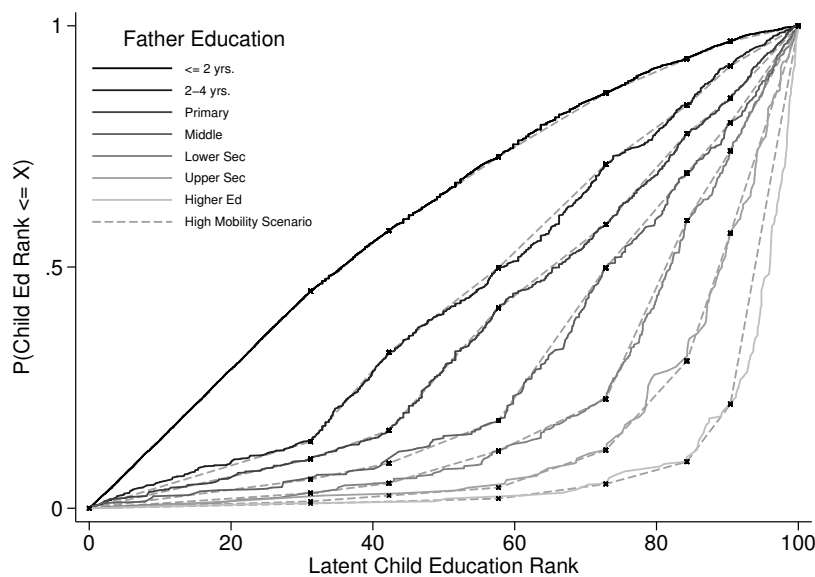


Figure C2 plots a son rank CDF separately for each father education level, for sons born in the 1960s in India. Sons are ranked first in terms of education, and then in terms of wages. Sons not reporting wages are dropped. For each father type, the graph shows a child's probability of attaining less than or equal to the rank given on the X axis.

Table C3
Mobility Estimates under Double-Censored CEF

	Upward Interval Mobility (μ_0^{50})	Rank-Rank Gradient (β)
Low mobility scenario	[32.33, 35.90]	[0.55, 0.80]
High mobility scenario	[35.86, 38.80]	[0.45, 0.67]
Wage imputation scenario	[35.79, 38.70]	[0.46, 0.67]

Table C3 presents bounds on μ_0^{50} and the rank-rank gradient β under three different sets of assumptions about child rank distribution within child bins. The low mobility scenario assumes children are ranked by parent education within child bins. The high mobility scenario assumes parent rank does not affect child rank after conditioning on child education bin. The wage imputation predicts the within-bin child rank distribution using child wage ranks and parent education.

D Appendix D: Data Construction

This section describes the data sources and data construction in detail.

D.1 IHDS

The India Human Development Survey (IHDS) is a nationally representative survey of 41,554 households, with rounds in 2004–05 and 2011–12. Definitions of social groups are described in the body of the paper. This section focuses on linking parents to children.

The primary module of IHDS records the education of the father of the household head. A secondary module, the women’s survey, records the education of the father and mother of the female respondent, as well as the father and mother of her husband if she is married. The women’s survey is given to one or two women aged 15–49 in each household. Because of the upper age restriction on the women’s survey, the oldest daughter in our sample is born in 1962; we therefore do not have any links from mothers or links to daughters for the 1950–59 birth cohort.

Finally, we created additional parent-child links using information from the relationship field in the household roster. Specifically, we linked the household head to their children and parents. We linked the spouse of the household head to their children. We linked grandchildren of the household head to the child of the household only in cases where there was no possible ambiguity about the parents of the grandchildren. In cases with no possible ambiguity, we linked nieces/nephews of the household head to brothers of the household head. We did not link individuals on the basis of in-law relationships, because of the ambiguity in the definition of the sibling-in-law (i.e. sibling of spouse vs. spouse of sibling).

In many cases, a parent’s education is recorded in multiple ways, allowing us to cross-check the validity of the responses. For example, the household head’s father’s education may be obtained from (i) the household roster (if he is coresident); (ii) from the household head’s response to the father education question; and (iii) from his wife’s responses to the husband’s father’s education question. The average correlation between parent education measured across different sources is 0.9. Appendix Table A2 shows that the discrepancies between measures are not correlated with household characteristics.

D.2 SECC

The 2011–12 Socioeconomic and Caste Census (SECC), an administrative socioeconomic database covering all individuals in the country that was collected to determine eligibility for various government programs.

The data underlying SECC were posted to the internet by the government, with each village and urban neighborhood represented by hundreds of pages in PDF format. Each town/village was posted for only ninety days. Over a period of two years, we scraped over two million files, parsed the embedded data into text, and translated the text from twelve different Indian languages into English. This process is described in more detail in Asher and Novosad (2019).

At the end of this process, we have individual data from approximately 450,000 villages and 2000 towns. This

covers 90% of villages and 25% of towns in India; the town data are less complete because many towns had only partial data posted on the SECC web site, or were not posted at all. The set of towns in the data cover all major states of the country and have a very similar population distribution to the full distribution of towns.

We use SECC to create linked data on father and son education. As noted in the body of the paper, we focus on ages 20–23, and do not look at girls, who are much less likely to be coresident with their parents at that age. We also do not create mother-child links, because of the substantial censoring of mothers' education ranks, described in Section 5.1.

When SECC records the relationship between individuals in a household, we create parent-child links following the same algorithm as used in the IHDS, as described above. For records where SECC did not provide family relationships, we impute the identity of the father based on the household structure. As noted, our child sample consists of men aged 20–23. We assume that a coresident man aged between 15 and 50 years older is the father. In most cases, there is only one such individual, and the father identity is directly assigned. We exclude observations where there is more than one potential father by this definition; results are virtually identical if we assume the father's education is the mean of the candidate fathers.

To validate this algorithm, we replicated the algorithm in the IHDS, where we observe the identity of the individual's father. In 5% of cases, the algorithm identified a father where there was none. In an additional 5% of cases, the algorithm did not identify a father (due to ambiguity) when there was one. In the 90% of cases where the algorithm identified a father and there was a father present, the correlation between the education measures was 99.7%. It is therefore unlikely that significant bias arises from the subset of SECC observations where we do not observe the relationship field.

D.3 Other data sources

This section describes several other data sources which we drew upon to calculate the correlates of upward mobility in Section 5.3.

The 2001 and 2011 Population Censuses provides basic demographic information for villages and towns, include the Scheduled Caste share. The village and town directories in the same census describe local public goods, including number of primary and high schools, and access to paved roads and electricity. Consumption and consumption inequality were calculated from the SECC using small area estimates following Elbers et al. (2003); the specific process we used is described in more detail in Asher and Novosad (2019). Average years of education in a location were calculated from the education variable in the SECC. Manufacturing jobs per capita were calculated by dividing the number of non-farm jobs recorded in the 2013 Economic Census by the 2011 census population. SC/ST segregation is the dissimilarity measure of segregation. We calculated this at the subdistrict level for rural areas, describing dissimilarity across villages. At the town level, it describes dissimilarity across enumeration blocks, which are units of about 200 households.

D.4 Data from other countries

We refer in the paper to mobility data from several other countries. Data from Denmark, Sweden, and Norway were generously shared with us by Boserup et al. (2014) and Bratberg et al. (2015). Income mobility estimates for the U.S. were drawn from Chetty et al. (2014b) and Chetty et al. (2018). Educational mobility estimates from the U.S. were calculated from a parent-child education transition matrix describing children in the 2005–2015 ACS and parents in the 2000 Census, from the data package of Chetty et al. (2018).