Breaking the Caste Barrier: Intergenerational Mobility in India*

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March 2012

Abstract

Amongst the various inequities typically associated with the caste system in India, probably one of the most debilitating is the perception that one is doomed by birth, i.e., social and economic mobility across generations is difficult. We study the extent and evolution of this lack of mobility by contrasting the intergenerational mobility rates of the historically disadvantaged scheduled castes and tribes (SC/ST) in India with the rest of the workforce in terms of their education attainment, occupation choices and wages. Using household survey data from successive rounds of the National Sample Survey between 1983 and 2005, we find that inter-generational education and income mobility rates of SC/STs have converged to non-SC/ST levels during this period. Moreover, SC/STs have been switching occupations relative to their parents at increasing rates, matching the corresponding switch rates of non-SC/STs in the process. Interestingly, we have found that a common feature for both SC/STs and non-SC/STs is that the sharpest changes in intergenerational income mobility has been for middle income households. We conclude that the last twenty years of major structural changes in India have also coincided with a breaking down of caste-based historical barriers to socio-economic mobility.

JEL Classification: J6, R2

Keywords: Intergenerational mobility, wage gaps, castes

*We would like to thank Siwan Anderson, Nicole Fortin, Ashok Kotwal, Thomas Lemieux, Anand Swamy and seminar participants at Delhi School of Economics, Monash University, UBC, the LAEF Conference on "Growth and Development" at UC Santa Barbara and the ISI Growth conference for comments. Special thanks to our referees, Rajeev Dehejia and David Green for extremely helpful and detailed suggestions.

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1 Introduction

One of oldest and most enduring social arrangements in India dating back thousands of years is the caste system. The system is an offshoot of a method of organizing society into ordered classes such as priests, warriors, traders, workers etc.. A key characteristic of this system is that caste status is inherited (by birth). Given the traditional assignment of jobs/tasks by castes, the social restrictions imposed by the hereditary nature of the system have been viewed as probably the biggest impediment to social mobility for the poor and downtrodden. The traditional narrative – which finds resonance amongst politicians, academics and social activists in India to this day – holds that the son of a poor, uneducated cobbler is likely to also end up as a poor, uneducated cobbler because, independent of his relative skill attributes, it is very hard for the son of a cobbler to find employment in other occupations. Hence, the desire to get educated for such a person is also limited since a large part of the attraction of acquiring education is its value in getting jobs.

This concern was the primary motivation behind the founding fathers of the Indian constitution extending affirmative action protection to the lowest castes in the caste hierarchy via the constitution itself. Specifically, the most disadvantaged castes and tribes were provided with reserved seats in higher educational institutions, in public sector jobs and in state legislatures as well as the Indian parliament. The protected groups were identified in a separate schedule of the constitution and hence called Scheduled Castes and Scheduled Tribes or SC/STs. The reservations were intended as a temporary measure to help level the playing field for the disadvantaged SC/STs over a few generations.

It has now been over 60 years since the constitution of India came into effect in 1950. Moreover, over the past 25 years India has also experienced rapid and dramatic macroeconomic changes with a sharp rise in aggregate growth, massive structural transformation of the economy, increasing urbanization, etc.. How have the historically disadvantaged castes and tribes – the SC/STs – performed during this period? Has social mobility increased over time or has it stayed relatively unchanged? How does social mobility in India compare with mobility in modern industrialized economies? In this paper we attempt to answer some of these questions.

We use data from five successive rounds of the National Sample Survey (NSS) of India from 1983 to 2004-05 to analyze patterns of intergenerational persistence in education attainment, occupation choices, and wages of both SC/ST and non-SC/ST households.

Typical studies on intergenerational mobility rates use panel data on parents and children of individual households to ascertain the mobility patterns. However, panel studies on individual households are not widely available in India. We get around this problem by exploiting a specific social characteristic in India, namely, the prevalence of joint or co-resident households wherein multiple generations of earning members of a family live jointly in the same household. Across the sample rounds, over 60 percent of households in the NSS sample comprise of such co-resident generations. The widespread prevalence of co-resident households in India, the large sample size of each survey combined with the availability of multiple survey rounds spanning over 20 years allows us to identify the intergenerational mobility rates as well as their time series evolution using repeated cross-sections of households. We believe that in the absence of panel studies on families, this is a method that may be useful for deducing intergenerational mobility facts in other developing countries as well since co-residency is much more common in developing countries than in developed countries.

We find that intergenerational mobility of SC/STs was lower than that of non-SC/STs at the beginning of our sample in 1983, but has risen faster than that of non-SC/ST households in both education attainment rates and wages. The probability of an SC/ST child changing his level of education attainment relative to the parent was just 42 percent in 1983 but rose sharply to 67 percent by 2004-05. The corresponding probabilities of a change in education attainment for a non-SC/ST child were 57 percent and 67 percent. Hence, there has been a clear convergence of intergenerational *education mobility* rates between SC/STs and non-SC/STs. Moreover, we find that the majority of the switches are improvements in education attainments. Correspondingly, the elasticity of wages of children with respect to the wages of their parent has declined from 0.90 to 0.55 for SC/ST households and from 0.73 to 0.61 for non-SC/ST households, indicating a clear trend towards convergence in intergenerational *income mobility* rates.

Our study also finds that intergenerational *occupational mobility* rates have increased for both groups during this period. However, these changes in occupational mobility rates have been relatively similar across the two groups. As a result, children in non-SC/ST households continue to be more likely to work in a different occupation than their parent relative to children from SC/ST households.

A key issue of interest to us is whether the gains made by SC/STs during this period were restricted to the relatively well-off sections of SC/STs. We study this issue by examining mobility at different points of the education, occupation and wage distributions. In terms of education attainment, we find that the largest changes for SC/STs were in movements out of illiteracy into primary and middle schools. Similarly, there were significant intergenerational movements from agricultural occupations into blue-collar occupations for both SC/STs and non-SC/STs.

In terms of income mobility, we use the recent approaches of Jäntti et al. (2006) and Bhattacharya and Mazumder (2011) to compute non-parametric measures such as income transition matrices and upward mobility measures. We find an increase in intergenerational income mobility in India and convergence of mobility rates between the SC/STs and non-SC/STs for most income groups. Moreover, the probability of a child improving his rank in his generation's income distribution relative to his father's corresponding rank is higher for SC/STs compared to non-SC/ST households.

Our results indicate that the gains during the past two decades have not been restricted to limited sections of SC/STs. Education mobility has occurred for both low and relatively highly educated SC/ST households. Similarly, income mobility has increased for both low and high-income households amongst SC/STs. Moreover, the increase in mobility for SC/STs has, on average, been faster than for non-SC/STs. Indeed, it has now become far more likely that the son of a poor illiterate SC/ST cobbler would become a machine worker with middle or secondary school education having a much higher rank in his generation's income distribution than his father did in his generation.

In summary, our results suggest that neither the lack of occupational mobility nor the lack of education have been a major impediment toward the SC/STs taking advantage of the rapid structural changes in India during this period to better their economic position.

While there has been considerable work on intergenerational mobility in the U.S. and other industrial countries (see Becker and Tomes (1986), Behrman and Taubman (1985), Haider and Solon (2006), amongst others), corresponding work on developing countries has been relatively limited.[1] Furthermore, due to different methodologies and approaches, the estimates for different countries are often difficult to compare. However, a general feature of the results is that intergenerational mobility estimates often are lower in developing countries relative to developed countries like the U.S.. Our study contributes to this literature by providing intergenerational elasticity estimates for one of the largest developing countries in the world. Importantly, our findings are comparable with the intergenerational mobility results in other developing countries. For instance, our intergenerational income elasticity estimate for the last survey round of 2004-05 is around 0.5 which is similar to elasticities estimated for Brazil and South Africa around the same period. We also find that intergenerational mobility has risen over time in India. Studies on *changes* in intergenerational mobility are relatively few and mostly focused on developed countries where the conclusion is mixed. Hence, our study is one of the first to provide a developing country perspective on how mobility has been changing over time. It is worth stressing that the paper goes beyond this literature by also computing elasticity estimates for two different groups in society as well as their changes over

[1] For recent contributions see Dunn (2007), Lillard and Kilburn (1995), Nunez and Miranda (2010), and Hertz (2001) who have estimated intergenerational income elasticities for Brazil, Malaysia, Chile and South Africa, respectively. Excellent overviews of the cross-country evidence on income as well as other indicators of social mobility (including education) can be found in Solon (2002) and Blanden (2009).

time. We believe this to be a significant addition to the existing work on developing countries.

Interestingly, intergenerational mobility has received relatively little attention in work on India. The two notable exceptions are Jalan and Murgai (2009) and Maitra and Sharma (2009) both of which focus on intergenerational mobility in education attainment. The biggest difference between our work and these studies is that we examine intergenerational mobility patterns not just in education attainment but also in occupation choices and income. Our work also differs from Jalan and Murgai (2009) and Maitra and Sharma (2009) in two other respects: (a) we use a much larger sample of households due to our use of the NSS data; and (b) by examining multiple rounds of the NSS data we are also able to study the time-series evolution of intergenerational mobility patterns in India.[2]

In the next section we describe the data and our constructed mobility measures as well as some summary statistics. Section 3 presents and discusses the evidence on intergenerational mobility, while the last section concludes.

2 The Data

Our data comes from the National Sample Survey (NSS) of India Rounds 38 (1983), 43 (1987-88), 50 (1993-94), 55 (1999-2000) and 61 (2004-05). The survey covers the whole country. The number of households surveyed averaged about 121,000 across the rounds. Our working sample consists of all male households heads and their male children/grandchildren between the ages 16 and 65 who provided their 3-digit occupation code information and their education information. Our focus is on full-time working individuals who are defined as those that worked at least 2.5 days per week, and who are not currently enrolled in any education institution.[3] We conduct all our data work using a sample in which the criteria above are satisfied for both household's head and at least one child or grandchild in that household. This selection leaves us with a sample of about 21,000 households comprising around 43,000-51,000 individuals, depending on the survey round. We refer to this sample as "working" sample.[4]

Our dataset does not contain information on individual's years of schooling. Instead, the ed-

[2] In related work Munshi and Rosenzweig (2009) document the lack of labor mobility in India. Also, Munshi and Rosenzweig (2006) show how caste-based network effects affect education choices by gender.

[3] We also consider a broader sample in which we do not restrict the gender of the children and find that our results remain robust (in fact, majority of the children working full-time in our sample are male). We choose the restriction to only males for two reasons. First, female led households are few and usually special in that those households are likely to have undergone some special circumstances. Second, since there are a number of societal issues surrounding the female labor force participation decision which can vary both across states and between rural and urban areas, focusing only on males allows us to avoid having to deal with these complications.

[4] Note that the number of individuals included from each household is typically much smaller than the total members of the household due to the restrictions on age, sex, generations etc.

ucation variable is coded into detailed categories ranging from not-literate to postgraduate and above. We aggregate these categories into 5 broader groups: not-literate; literate but below primary; primary education; middle education; and secondary and above education (which includes higher secondary, diploma/certificate course, graduate and above in different professional fields, postgraduate and above). These categories are coded as education categories 1, 2, 3, 4 and 5 respectively. Our dataset also contains information about the three-digit occupation code (based on the 1968 National Classification of Occupation (NCO)) associated with the work that each individual performed over the last year preceding the survey year.

Data on wages are more limited. The sub-sample with complete wage data for both the head of household and at least one child or grandchild in the same household consists of, on average across rounds, about 7,000-9,000 individuals which is considerably smaller than our working sample but large enough to facilitate formal analysis. Our wage series is the daily wage/salaried income received for the work done during the week previous to the survey week. We evaluate in-kind wages using current retail prices. Wages are converted into real terms using state-level poverty lines differentiated by rural and urban sectors. All wages are expressed in terms of the 1983 rural Maharashtra poverty line. Details regarding the dataset are contained in the Appendix A.

In order to conduct the intergenerational comparisons, we collect all household heads into a group called "parents" and the children/grandchildren into the group "children". This sorting is done for each survey round and the statistics are computed for each generation for that round. Table 1 gives some summary statistics of the data. Panel (a) reports average age, education level, share of males and married individuals among children; while panel (b) reports the corresponding statistics for household heads (parents). Panel (b) also reports the percentage of rural households in our sample, as well as the average household size. Note that "All" refers to the full working sample, while the "Non-SC/ST" and "SC/ST" panels refer to the corresponding caste sub-samples.[5]

Household-heads are around 52 years of age while their male working children are typically around 23 years old. Around 81 percent of surveyed households are rural and engaged in farming/pastoral activities. This number is slightly higher for SC/ST households, 88-89 percent of whom live in rural areas on average. Finally, the average education level of children is greater than that of parents, and has increased over time. Non-SC/STs are also consistently more educated than SC/ST. The proportion of SC/ST households in the sample across the different rounds is around

[5] To account for the survey design of our data we use sampling weights provided by the NSS. This allows us to obtain consistent estimates of the population parameters (see Bhattacharya (2005)). Our data, however, does not allow us to correct standard errors for survey design in a straightforward way. This is because the design of multistage stratification is not uniform across rounds and because there are multiple singleton strata in our sample. We checked for the robustness of our results by making the necessary adjustments to the sample to obtain standard errors that are robust to sample-design effects. We find that they are very similar to the uncorrected ones, which are reported in the paper. These results are available upon request.

24 percent.

Table 1: Sample summary statistics

	(a) children			(b) parents				
All	age	edu	married	age	edu	married	rural	hh size
1983	22.83	2.58	0.53	51.67	1.79	0.92	0.81	7.18
	(0.04)	(0.01)	(0.00)	(0.07)	(0.01)	(0.00)	(0.00)	(0.02)
1987-88	23.13	2.69	0.53	51.65	1.88	0.92	0.83	6.98
	(0.04)	(0.01)	(0.00)	(0.06)	(0.01)	(0.00)	(0.00)	(0.02)
1993-94	23.17	2.97	0.48	51.78	2.01	0.94	0.82	6.51
	(0.04)	(0.01)	(0.00)	(0.06)	(0.01)	(0.00)	(0.00)	(0.02)
1999-00	23.43	3.21	0.46	51.60	2.20	0.94	0.81	6.56
	(0.05)	(0.01)	(0.00)	(0.07)	(0.01)	(0.00)	(0.00)	(0.02)
2004-05	23.38	3.40	0.46	51.57	2.34	0.94	0.80	6.39
	(0.05)	(0.01)	(0.00)	(0.07)	(0.01)	(0.00)	(0.00)	(0.02)
Non-SC/ST								
1983	23.00	2.78	0.52	52.04	1.93	0.92	0.79	7.29
	(0.05)	(0.01)	(0.00)	(0.08)	(0.01)	(0.00)	(0.00)	(0.03)
1987-88	23.30	2.89	0.51	51.98	2.03	0.93	0.80	7.06
	(0.05)	(0.01)	(0.00)	(0.08)	(0.01)	(0.00)	(0.00)	(0.02)
1993-94	23.36	3.17	0.47	52.10	2.19	0.94	0.79	6.6
	(0.05)	(0.01)	(0.00)	(0.07)	(0.01)	(0.00)	(0.00)	(0.02)
1999-00	23.76	3.42	0.47	52.01	2.41	0.95	0.78	6.62
	(0.05)	(0.01)	(0.00)	(0.08)	(0.02)	(0.00)	(0.00)	(0.03)
2004-05	24.04	3.56	0.46	52.01	2.52	0.95	0.77	6.42
	(0.06)	(0.01)	(0.01)	(0.08)	(0.02)	(0.00)	(0.00)	(0.03)
SC/ST								
1983	22.30	1.95	0.56	50.59	1.38	0.92	0.89	6.86
	(0.08)	(0.02)	(0.01)	(0.13)	(0.01)	(0.01)	(0.01)	(0.04)
1987-88	22.63	2.06	0.56	50.72	1.45	0.91	0.90	6.76
	(0.08)	(0.02)	(0.01)	(0.12)	(0.01)	(0.00)	(0.00)	(0.04)
1993-94	22.61	2.40	0.49	50.92	1.54	0.92	0.90	6.25
	(0.08)	(0.02)	(0.01)	(0.13)	(0.02)	(0.00)	(0.00)	(0.04)
1999-00	22.85	2.67	0.46	50.61	1.71	0.94	0.88	6.41
	(0.09)	(0.02)	(0.01)	(0.13)	(0.02)	(0.00)	(0.01)	(0.04)
2004-05	23.05	2.99	0.45	50.66	1.87	0.94	0.87	6.3
	(0.09)	(0.03)	(0.01)	(0.14)	(0.02)	(0.00)	(0.01)	(0.05)

Notes: This table reports summary statistics for our sample. Panel (a) gives the statistics for the generational subsample of children, while panel (b) gives the statistics for the household heads (parents). Standard errors are reported in parenthesis.

2.1 Sample Issues

Before proceeding it is important to discuss some key issues regarding our sample. The ideal sample for addressing intergenerational mobility issues is one that has information on education, occupation and wages for parents as well as their adult children. Another desirable feature of such a sample is that it has wage information for parents and adult children at comparable ages rather than at different phases of their lifecycles. The NSS data unfortunately has some limitations in this regard. First, it provides information on parents and their adult children only if the two generations are co-resident in the same household. This immediately raises selection issues as co-resident households may be special and differ systematically from other households. Second, the NSS does not track the same household over time. Hence, for every parent-child pair, we have observations at a point in time which makes wage comparisons between the generations potentially problematic.

How special is our sample? We begin by documenting the incidence of co-resident households in the NSS data. We define co-residence as having multiple adult (16 years of age and above) generations living in the same household: i.e., parents/parents-in-law living with their adult children and/or grandchildren. We find that in contrast to more industrial and western economies, a majority of households in India tend to co-reside. Thus, in the NSS sample across the rounds, on average, about 62 percent of all sampled households were characterized by multiple adult generations co-residing. The fraction of co-resident households for non-SC/STs is slightly above that for SC/STs (at 62 percent for non-SC/STs and 56 percent for SC/STs on average across rounds).[6] Importantly, the shares of co-residency overall and for the two caste groups have remained quite stable across the rounds. Moreover, the marginal movements that have occurred have been symmetric for SC/STs and non-SC/STs. This gives us confidence in our time-series results for intergenerational mobility. Joint households are even more prevalent in rural areas where the majority of India still resides. Hence, in the Indian context, drawing inferences from samples reflecting predominantly nuclear households is arguably more problematic due to their unrepresentative nature.

Unfortunately, we cannot directly use the co-resident sample described above because the NSS identification code lumps parents and parents-in-laws together in one category making it problematic for computation of direct intergenerational trends. We choose to focus instead on households with an adult head of household co-residing with at least one adult of lower generation (identified as child and/or grandchild of household head), both being in the age-group 16-65. This sub-sample of households comprises about 75 percent of co-resident households. Imposing the additional restrictions on sex, education, occupation information and full-time employment status gives us our working sample which covers about 24 percent of the full dataset with the same restrictions. Crucially, this ratio is stable across the rounds. We contrast the characteristics of the co-resident households with the households from the unrestricted sample, where the latter is obtained by imposing the same restrictions on age, sex, education, occupation information and full-time employment status of individuals, but no co-residence requirement. Table 2 reports the results.

Panel (a) of Table 2 reports the household characteristics in our working sample of co-resident households, while panel (b) does the same for the households in the unrestricted sample (no co-residence requirement). The household age column (hh age) reports the average age of all household members. Columns # adults, # kids, # earning mem refer to the number of adult household members (defined as those aged 16 and above), number of kids (below 16 years in age), and the number of earning members in the household (defined as those who reported their employment status as employed during the survey). Column labelled “rural” refers to the share of rural households, and

[6] Round-by-round co-residence shares are provided in Table S1 in the online appendix available at http://faculty.arts.ubc.ca/vhnatkovska/research.htm

Table 2: Sample comparisons

(a) working sample						
round	hh age	# adults	# kids	# earning mem	rural	# households
1983	25.00	4.99	3.15	3.46	0.81	19225
	(0.05)	(0.02)	(0.02)	(0.02)	(0.00)	
1987-88	25.48	5.00	2.96	3.32	0.83	21977
	(0.05)	(0.02)	(0.02)	(0.01)	(0.00)	
1993-94	26.68	4.91	2.48	3.44	0.82	19870
	(0.05)	(0.02)	(0.02)	(0.01)	(0.00)	
1999-00	26.97	5.06	2.52	3.46	0.81	19997
	(0.06)	(0.02)	(0.02)	(0.02)	(0.00)	
2004-05	27.39	5.03	2.35	3.48	0.81	21560
	(0.06)	(0.02)	(0.03)	(0.02)	(0.00)	

(b) unrestricted sample						
round	hh age	# adults	# kids	# earning mem	rural	# households
1983	23.12	3.56	2.98	2.29	0.76	87873
	(0.03)	(0.01)	(0.01)	(0.01)	(0.00)	
1987-88	23.39	3.53	2.81	2.18	0.77	94676
	(0.03)	(0.01)	(0.01)	(0.01)	(0.00)	
1993-94	24.16	3.45	2.53	2.24	0.75	87099
	(0.03)	(0.01)	(0.01)	(0.01)	(0.00)	
1999-00	24.46	3.55	2.55	2.22	0.74	87768
	(0.04)	(0.01)	(0.01)	(0.01)	(0.00)	
2004-05	25.38	3.57	2.38	2.29	0.75	87102
	(0.04)	(0.01)	(0.01)	(0.01)	(0.00)	

Note: The unrestricted sample is derived by imposing the same restrictions on sex, age, education, occupation and full-time employment status that were imposed in deriving the working sample. The key difference between the working and unrestricted samples is that the latter does not impose the co-residence requirement. Standard errors are in parenthesis.

column "# households" reports the number of household in the sample.

As is to be expected, our households are, on average, slightly older, have more adults and earning members, and are more likely to be from rural areas than those in the unrestricted sample. Importantly, however, these differences are small and stable over time. Furthermore, the greater representation of rural households in our sample indicates the importance of incorporating controls for rural effects in our empirical analysis below.[7] In summary, we view Table 2 as being indicative of the fact that our sub-sample is a stable representation of the households sampled by the NSS. More generally, the facts above suggest to us that co-residence patterns have not changed significantly during the period under study. Hence the representativeness of the sample under this identification have remained comparable across rounds.

We conduct a further check of the representativeness of our sample by comparing the characteristics of the parents and children generations in our working sample with the counterparts of these generations in the unrestricted sample. This comparison necessarily involves making some assumptions in order to construct the generational counterparts in the unrestricted sample. For

[7] We also examined the daily average real per capita consumption expenditures of the two sets of household and found that those differences too were small, stable and insignificant across the rounds. These results are available from the authors upon request.

the counterpart to the parents generation, we consider the household heads of all households in the unrestricted sample subject to them meeting the age, sex, education, occupation, and full time employment status requirement that we imposed on our working sample. Hence, we are essentially comparing the characteristics of household heads in the unrestricted sample with the characteristics of household heads in co-resident households. We construct the children's generation in the unrestricted sample by including all non-household head adults whose ages are in a band of plus or minus one standard deviation of the mean age of the children in our working sample.

We report the characteristics of the constructed parents and children generations in the unrestricted sample in Table 3. To contrast their characteristics with those of parents and children generations in the co-resident households we refer the reader to panels (a) and (b) in Table 1. The children in our working sample are quite similar to the children in the unrestricted sample on most characteristics in all the rounds. The parents in our working sample are older, less educated and more rural than those in the unrestricted sample. However, crucially for our goal of determining time trends in mobility patterns, the differences between the two samples are stable over time. Hence, our conclusions regarding the time trends in intergenerational mobility patterns remain valid despite the limitations of the dataset.

Table 3: Characteristics of children and parents in the unrestricted sample

	(a) children (unrestricted sample)				(b) parents (unrestricted sample)			
	age	edu	married	rural	age	edu	married	rural
1983	22.38	2.62	0.50	0.77	35.55	2.37	0.79	0.75
	(0.02)	(0.01)	(0.00)	(0.00)	(0.05)	(0.01)	(0.00)	(0.00)
1987-88	22.43	2.71	0.49	0.79	35.81	2.44	0.80	0.77
	(0.02)	(0.01)	(0.00)	(0.00)	(0.04)	(0.00)	(0.00)	(0.00)
1993-94	22.40	3.02	0.43	0.77	36.11	2.66	0.80	0.75
	(0.02)	(0.01)	(0.00)	(0.00)	(0.04)	(0.01)	(0.00)	(0.00)
1999-00	22.59	3.28	0.42	0.76	36.36	2.87	0.80	0.73
	(0.03)	(0.01)	(0.00)	(0.00)	(0.05)	(0.01)	(0.00)	(0.00)
2004-05	22.64	3.44	0.39	0.75	36.99	3.02	0.79	0.73
	(0.03)	(0.01)	(0.00)	(0.00)	(0.05)	(0.01)	(0.00)	(0.00)

Note: This table presents summary statistics for children (panel (a)) and parents (panel (b)) generations in the unrestricted sample. The unrestricted generation of parents is obtained as all co-resident and not co-resident household heads that are males within 16-65 age range, and provided their education, occupation information, are employed full-time and are not enrolled in any education institution. The unrestricted generation of children is obtained as all those individuals whose age lies within 1 std dev band around the mean age of the children in our working (co-resident) sample. Standard errors are in parenthesis.

Our focus on co-resident households potentially misses important intergenerational mobility information that is contained in the decision to move out of the parents' household by younger generations. However, this missing information could bias our mobility measures in either direction. On the one hand, more able and educated children may be more likely to move out of their parents' home. In this case, our sample would underestimate the true intergenerational mobility as it does not include these children. On the other hand, the less educated and wealthy are the parents, the more likely it is that their children may continue to live in the same household in order to take care of them (the intra-household insurance and risk sharing motive). Since these households are included in our sample, we would tend to overestimate the degree of intergenerational mobility. On balance, the net bias could go either way. Importantly, the stability of the share of co-resident households implies that there would not be any time-series trends in the bias. Hence, our estimates of the *changes* in intergenerational mobility should remain unaffected by this.

The second issue is about when one observes the wage information for parents and their children. NSS reports the data for both generations at the same point in time rather than at the same point in their lifecycle. This is a perennial problem in intergenerational mobility studies. We address this by using the same approaches and instruments that were developed and implemented in the intergenerational mobility literature by Haider and Solon (2006) and Lee and Solon (2009). We discuss them in greater detail in Section 3.3 below.

3 Intergenerational Mobility

We now turn to the key question that we started with: how have the patterns of intergenerational mobility in India changed between 1983 and 2004-05? Our primary interest is in studying how the occupation choices, education attainment levels and wages of children compare with the corresponding levels for their parents. We shall look at each of these in turn.

In the foregoing analysis we shall define the intergenerational education/ occupation switch as a binary variable that takes a value of one if the child's or grandchild's education level/ occupation is different from his parent's (who is the head of the household) education achievements/ occupation; and zero otherwise. We label the education switch variable as **switch-edu;** and the occupation switch variable as **switch-occ.** We also distinguish education and occupation *improvements* and *deteriorations.*

3.1 Education Mobility

We begin by analyzing intergenerational education switches. To obtain average probabilities of education switches we posit the following probit model:

$$P_i \equiv \Pr(y_i = 1|x_i) = E\left(y_i|x_i\right) = \psi(x_i\beta),$$

where $\psi(x_i\beta) = \Phi(x_i\beta)$, with $\Phi(.)$ representing the cumulative standard normal distribution function, y_i is a binary variable for education switch as defined above (*switch-edu*), and x_i is a vector of controls. We allow the education switch for individual i to depend on his individual characteristics, such as age, age squared, belonging to an SC/ST group (SC/ST), and religion (*muslim*); household-level characteristics, such as household size (*hh_size*), his rural location (*rural*); and the reservation quota for SC/STs in the state s that he lives in, and fixed effects of the region that he lives in. Thus,

$$\begin{aligned} x_i\beta &= \beta_0 + \beta_1 age_i + \beta_2 age_i^2 + \beta_3 SC/ST_i + \beta_4 muslim_i \\ &\quad + \beta_5 rural_i + \beta_6 hh\_size_i + \beta_7 quota_s + \alpha' R. \end{aligned} \tag{1}$$

where R denotes the vector of region dummies, where regions are defined as North, South, East, West, Central and North-East.[8] We include a Muslim dummy in our regression specification to control for the fact that Muslims, on average, have done poorly in modern India. If included in the non-SC/ST group, the poor outcomes of Muslims may bias our results towards finding more convergence between non-SC/STs and SC/STs.

The introduction of reservations for SC/STs in public sector employment and in higher education institutions was a key policy initiative in India.[9] Due to their potentially important effects on the historical inequities against SCs and STs, reservations in India have been studied in several papers. Thus, Pande (2003) examines the effects of reservations on government policies, while Prakash (2009) studies the effects of reservations on the labor market outcomes of SC/STs. Both authors find evidence of positive effects of reservations on the targeted groups. Hence, it is important to control for state level reservation quotas in the analysis.[10]

We estimate the model for each survey round separately and use it to obtain fitted values for each individual. These fitted values are used to compute the average probability of intergenerational education switch. We compute these probabilities for the overall sample as well as for SC/STs and non-SC/STs separately.[11]

[8] This grouping reflects similarities across states along their geographic characteristics, and characteristics that are shared based on proximity.

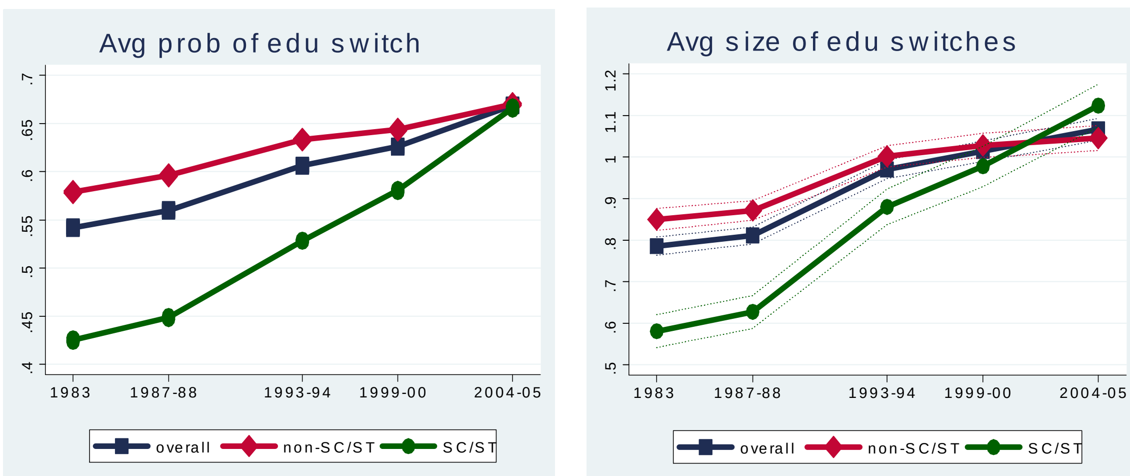
[9] The reservations were provided in proportion to the population shares of SCs and STs. State-level reservations can change over time due to changes in SC/ST population shares. In 1991 the Indian government extended the reservation policy to include other backward castes (OBCs). In our analysis we focus only on the group of SC/STs while OBCs are included in the non-SC/ST reference group. If reservations benefited OBCs then our results potentially understate the true degree of convergence between SC/STs and non-SC/STs (excluding OBCs), especially since the extension of reservations to OBCs in 1991.

[10] In the regression analysis we include reservation quotas that were in effect when information on household-head and his children and grandchildren was collected.

[11] It is worth noting that rather than estimating the probability of education switches using a regression specification we could have instead just computed the frequency distribution of education switches between generations. The two

Panel (a) of Figure 1 depicts the computed probabilities of intergenerational switches in education attainment together with the ± 2 standard error confidence bands (dashed lines).[12] There are two features of the Figure worth pointing out. First, intergenerational mobility as reflected by the switch probabilities have increased for both SC/STs and non-SC/STs over the sample period. Second, and possibly more remarkably, the switch probabilities of the two groups have converged at 67 percent by the end of our sample period in 2004-05. This is particularly impressive once one notes that in 1983, the probability of an intergenerational education switch for SC/ST households was a meagre 42 percent relative to the 57 percent corresponding probability of non-SC/ST households.

Figure 1: Average probability of intergenerational education switches



(a) (b)

Notes: Panel (a) of this figure presents the average predicted probability of intergenerational education switch, while panel (b) reports the average size of the intergenerational education switches for our overall sample, for SC/STs and non-SC/STs. The numbers are reported for the five NSS survey rounds. Dotted lines are ± 2 std error bands.

A related question is about the degree or size of the change in education levels. In particular, amongst the children who switch education levels relative to their parent, how large is the change? How has this evolved over our sample period? Panel (b) of Figure 1 reveals that the average size of the switch has been increasing over time for both groups. Crucially, by the end of our sample, the switch sizes for the two groups not only converged but SC/STs were in fact switching education levels by more than non-SC/STs. This again is noteworthy since the average size of a switch for SC/STs was significantly lower at 0.6 in 1983 relative to 0.84 for the non-SC/ST households. Note

approaches yield very similar computed probabilities. We choose to proceed with the regression approach as we are also interested in the effect of caste on the probability of switching education categories across generations *conditional* on other controls. As we show below, the marginal effects of caste on the estimated probabilities are almost always significant.

[12] Confidence bands around the probability of education switch are very narrow and do not appear on the graph for that reason.

that positive numbers for the size of the switch indicate improvements in education categories.

We also find that most of the increase in the probability of education mobility over our sample period was due to a fall in the negative effect of caste, conditional on other attributes. Thus, Table 4 reports the marginal effects associated with the SC/ST dummy (1-SC/ST, 0-non SC/ST) from the probit regression for education switches defined in equation (1).[13] The Table shows that the caste marginal effect was negative and significant for all but the last round. Crucially, the absolute value of that marginal effect has declined secularly over time culminating in it becoming insignificant in 2004-05. Thus, while being an SC/ST used to have a significant negative effect on the probability of a child switching his education category relative to his parent, by the end of our sample period caste had seemingly lost any independent explanatory power for the switch probability. The panel of Table 4 labeled "Changes" reports the changes in the SC/ST marginal effect during the entire period 1983-2004/05 as well as the two decadal sub-periods 1983-1993/94 and 1993/94-2004/05. All the changes were highly significant.

Table 4: Marginal effect of SC/ST dummy in probit regressions for intergenerational education switches

							Changes	
	1983	1987-88	1993-94	1999-00	2004-05	83 to 94	94 to 05	83 to 05
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
all switches	-0.1412***	-0.1394***	-0.1047***	-0.0665***	-0.0155	0.0365***	0.0892***	0.1257***
	(0.0097)	(0.0088)	(0.0089)	(0.0095)	(0.0105)	(0.0132)	(0.0138)	(0.0143)
improvements	-0.1283***	-0.1305***	-0.0827***	-0.0477***	0.0022	0.0456***	0.0849***	0.1305***
	(0.0099)	(0.0089)	(0.0093)	(0.0098)	(0.0109)	(0.0135)	(0.0143)	(0.0147)
deteriorations	-0.0165***	-0.0120**	-0.0246***	-0.0207***	-0.0180***	-0.0081	0.0066	-0.0015
	(0.0056)	(0.0057)	(0.0054)	(0.0060)	(0.0064)	(0.0077)	(0.0084)	(0.0085)

Notes: This table reports the marginal effects of the SC/ST dummy (1-SC/ST, 0-non-SC/ST) from the probit regression (1) in which the dependent variable is (a) whether or not there was an intergenerational education switch – panel named "all switches"; (b) whether or not there was an improvement in education attainment – panel named "improvements"; and (c) whether or not there was a deterioration in education attainments – panel named "deteriorations". Columns (i)-(v) refer to the survey round. Panel "Changes" with columns (vi)-(viii) report change in SC/ST marginal effect over the successive decades and the entire sample period. Standard errors are in parentheses. * p-value$\leq$0.10, ** p-value$\leq$0.05, *** p-value$\leq$0.01.

We also investigate whether education switches were associated with improvements or deteriorations in education attainments of children relative to their fathers. We find that most of the intergenerational education switches are in fact increases in educational attainment levels of kids relative to their parents. The estimated probability of an SC/ST child increasing his level of education attainment relative to the parent was just 36 percent in 1983 but rose sharply to 59 percent by 2004-05. The corresponding probabilities of an increase in education attainment for a non-SC/ST

[13] Complete estimation results are included in Table S2 of online appendix.

child were 49 percent and 58 percent. The probability of an education reduction is around 9 percent for non-SC/STs and 7 percent for SC/STs. Both these probabilities have remained stable over the sample period. Table 4 also confirms that most of the increase in the probability of education improvements could be attributed to a fall in the negative effect of the caste, conditional on other attributes (see panel labeled "improvements"). At the same time, the effect of the caste on the probability of education reductions (see panel labeled "deteriorations"), while negative, has not changed significantly over time.[14]

3.1.1 Education Transition Matrix

While the overall mobility trends in education are informative, they do not reveal the underlying changes at the disaggregated level. A key question of interest to us is whether there are underlying distributional patterns in the intergenerational education mobility trends of the two groups. In particular, is most of the increase in intergenerational education mobility due to children of the least educated parents moving up the education ladder or is it the upward mobility of the children of the relatively highly educated parents that accounts for the aggregate pattern? Are there differences in the patterns between SC/STs and non-SC/STs?

We explore these issues by computing the education transition matrix for our sample of households separately for non-SC/STs and SC/STs for the sample years 1983 and 2004-05. For each NSS round we compute p_{ij} – the probability of a household head with education category i having a child with education category j. A high p_{ij} where $i = j$ reflects low intergenerational education mobility, while a high p_{ij} where $i \neq j$, would indicate high mobility.

Table 5 shows the results. Panel (a) shows the mobility matrix for 1983 while panel (b) reports the results for the 2004-05 round. Each row of the table shows the education of the parent while columns indicate the education category of the child. Column "size" reports the average share of parents with a given education attainment level in a given round. Thus, the row labelled "Edu1" in the top-left panel of the Table says that in 1983, 85 percent of the adult male children of illiterate non-SC/ST parents remained illiterate, 9 percent acquired some education, 5 percent finished primary school, 1 percent had middle school education, and almost none had secondary school education. The last entry in that row says that 32 percent of non-SC/ST parents were illiterate in 1983.[15]

Table 5 reveals some interesting features. For both groups, the intergenerational persistence of illiteracy has declined across the rounds. For non-SC/STs, 85 percent of the children of illiterate

[14] The estimation results for the education improvement and deterioration probabilities are reported in Tables S4 and S5, respectively, of the online appendix.

[15] Standard errors are shown in parenthesis below the estimates.

Table 5: Intergenerational education transition probabilities

(a). Average mobility in the 1983 round

Non-SC/ST							**SC/ST**						
	Edu**1**	Edu**2**	Edu**3**	Edu**4**	Edu**5**	size		Edu**1**	Edu**2**	Edu**3**	Edu**4**	Edu**5**	size
Edu**1**	0.85	0.09	0.05	0.01	0.00	0.32	Edu**1**	0.91	0.06	0.02	0.01	0.00	0.56
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)
Edu**2**	0.49	0.37	0.11	0.02	0.01	0.12	Edu**2**	0.63	0.28	0.07	0.01	0.01	0.13
	(0.02)	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)		(0.02)	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)
Edu**3**	0.46	0.24	0.22	0.06	0.02	0.20	Edu**3**	0.62	0.22	0.12	0.03	0.02	0.15
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)		(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Edu**4**	0.35	0.24	0.21	0.14	0.05	0.20	Edu**4**	0.55	0.18	0.18	0.07	0.03	0.11
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)		(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Edu**5**	0.24	0.17	0.20	0.17	0.22	0.17	Edu**5**	0.44	0.20	0.17	0.12	0.08	0.05
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)		(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.00)

(b). Average mobility in the 2004-05 round

Non-SC/ST							**SC/ST**						
	Edu**1**	Edu**2**	Edu**3**	Edu**4**	Edu**5**	size		Edu**1**	Edu**2**	Edu**3**	Edu**4**	Edu**5**	size
Edu**1**	0.79	0.09	0.06	0.04	0.02	0.13	Edu**1**	0.87	0.06	0.05	0.02	0.01	0.23
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)		(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
Edu**2**	0.61	0.26	0.07	0.04	0.02	0.10	Edu**2**	0.67	0.22	0.07	0.02	0.01	0.14
	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)		(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Edu**3**	0.45	0.21	0.19	0.10	0.05	0.17	Edu**3**	0.58	0.18	0.16	0.05	0.03	0.21
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)		(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Edu**4**	0.32	0.19	0.21	0.18	0.10	0.28	Edu**4**	0.47	0.17	0.17	0.13	0.06	0.26
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)		(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Edu**5**	0.19	0.11	0.16	0.19	0.36	0.32	Edu**5**	0.34	0.14	0.15	0.16	0.21	0.17
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)		(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)

Notes: Each cell ij represents the average probability (for a given NSS survey round) of a household head with education i having a child with education attainment level j. Column titled 'size' reports the fraction of parents in education category 1, 2, 3, 4, or 5 in a given survey round. Standard errors are in parenthesis.

parents remained illiterate in the 1983 round. In 2004-05, the persistence of illiteracy had declined to 79 percent. For SC/STs, the corresponding numbers were 91 percent and 87 percent. Moreover, a large part of this upward intergenerational education mobility was children of illiterate parents beginning to acquire middle school or higher education levels. Hearteningly, the shares of illiterate parents also declined sharply across the rounds. For non-SC/STs, the share of illiterate parents declined from 32 to 13 percent while for SC/STs it fell from 56 to 23 percent.

Another positive feature of the time trends in education mobility for both groups was that amongst parents with primary school education and above (categories 3, 4 and 5), there was a significant decline in the share of children with lesser education attainment than their parents. Concurrently, both groups saw an increase in the persistence or improvement of the education status of children of parents with the relatively higher education levels of 4 and 5 (middle school or secondary school and above). Only in households in which the head of the household had below primary level of education (category 2) was there an increase in regress of education attainments of children. Even for these households though, the children that improved over their parents tended to do so by a large margin – they often acquired middle school or secondary and above education levels.

Overall, there was a clear trend of convergence of household education attainment levels of the two groups with sharper movements into categories 4 and 5 for SC/STs. Most importantly, the upward education mobility was not restricted to the more educated households. Rather, this appears to have been a more wide-spread phenomenon during this period.

3.2 Occupation Mobility

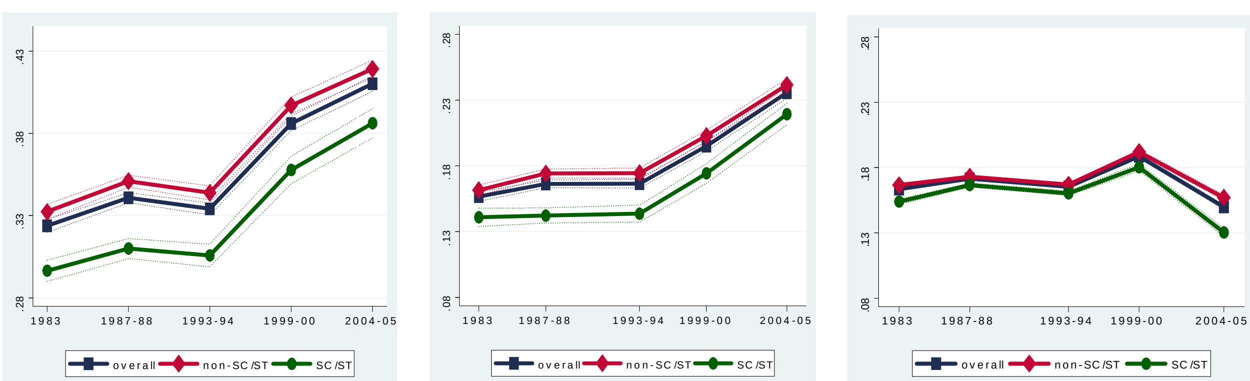
We now turn to intergenerational occupation mobility. The conditional probability of an occupation switch is obtained in a similar manner to the education switch probabilities. Now, y_i is a binary variable for occupation switch as defined above (*switch-occ*) while x_i is a vector of controls:

$$\begin{aligned} x_i\beta &= \beta_0 + \beta_1 age_i + \beta_2 age_i^2 + \beta_3 SC/ST_i + \beta_4 muslim_i + \beta_5 rural_i \\ &\quad + \beta_6 hh\_size_i + \beta_7 quota_s + \theta' E + \alpha' R + \gamma' O. \end{aligned} \tag{2}$$

where E, R and O are complete sets of education category dummies, region dummies and occupation dummies, respectively.[16]

The model is estimated for each sample round separately and then used to obtain fitted values for each individual. These fitted values provide us with estimates of the probability of occupation switches in each round.

Figure 2: Average probability of intergenerational occupation switches



(a) occ switches (b) occ improvements (c) occ deteriorations

Notes: This figure presents the average predicted probability of intergenerational occupation switch for our overall sample, for SC/STs and non-SC/STs. The numbers are reported for the five NSS survey rounds. Dotted lines are ± 2 std error bands.

Panel (a) of Figure 2 depicts the computed probabilities of occupation switches at the three-digit level (dotted lines plot the $\pm$ 2 standard error confidence bands). As the Figure shows,

[16] Occupation fixed effects are defined for one-digit occupation categories.

the overall probability of an occupation switch by the next generation relative to the household-head has steadily increased from 32 percent in 1983 to 41 percent in 2004-05. This increase has been mirrored in the two sub-groups. For non-SC/STs the switch probability has risen from 33 to 42 percent while for SC/STs it has gone from 30 to 39 percent. Crucially, there is no trend towards convergence of these probabilities across the two groups which indicates that differences in intergenerational mobility between them has not changed over this period. We also estimated the occupation switch probabilities at the one-digit and two-digit levels and found that the patterns are similar to the three-digit probabilities. The main difference is that the probability of an occupation switch is universally lower at the two-digit and more so at the one-digit level.[17]

The noteworthy feature about the estimation results of equation (2) is that the SC/ST dummy is consistently positive across the rounds even though it is at times insignificant.[18] Hence, after controlling for the covariates of occupation choice, SC/ST effect on the probability of switching occupations was actually non-negative. This indicates that the overall lack of convergence of occupation switch rates between the groups was due to a lack of complete convergence in the other covariates rather than due to caste related factors.

The preceding results leave unanswered the question of whether the switches in occupations by the next generation reflected switches into better occupations or worse ones. We use median wages to construct a ranking of occupations in our dataset, and split all occupation switches into occupation improvements and deteriorations based on this ranking. We then estimate the probit regression equation (2) separately for occupation improvements and deteriorations. Panels (b) and (c) of Figure 2 show the results. The key features to note are that movements in the probability of occupation improvements are similar to the patterns in the overall occupation switch probabilities. Indeed, most of the occupation switches for both groups are occupation improvements. Interestingly, in as much as there are occupation deteriorations, the SC/STs have become increasingly less likely to regress across generations relative to non-SC/STs. This would suggest that quality adjusted, the gaps in occupation choices between the groups may be shrinking faster than what the overall numbers suggest.[19]

3.2.1 Occupation Transition Matrix

While the overall probability of switches indicates the degree of mobility across occupations, we are also interested in determining the pattern of movements within occupations: children who

[17] The results for the one- and two-digit occupation categories are available upon request.

[18] The detailed regression results for the probability of occupation switches are provided in Table S7 of the online appendix.

[19] The estimation results for the occupation improvement and deterioration probabilities are reported in Tables S8 and S9, respectively, of the online appendix.

Table 6: Intergenerational occupation transition probabilities

(a). Average mobility in the 1983 round

Non-SC/ST	To				**SC/ST**	To			
From	Occ **1**	Occ **2**	Occ **3**	size	From	Occ **1**	Occ **2**	Occ **3**	size
Occ **1**	0.49	0.33	0.18	0.06	Occ **1**	0.29	0.40	0.31	0.03
	(0.02)	(0.01)	(0.01)	(0.00)		(0.05)	(0.06)	(0.05)	(0.00)
Occ **2**	0.06	0.82	0.12	0.26	Occ **2**	0.04	0.77	0.19	0.20
	(0.00)	(0.01)	(0.01)	(0.00)		(0.01)	(0.01)	(0.01)	(0.01)
Occ **3**	0.03	0.10	0.86	0.67	Occ **3**	0.02	0.09	0.90	0.78
	(0.00)	(0.00)	(0.01)	(0.00)		(0.00)	(0.01)	(0.01)	(0.01)

(b). Average mobility in the 2004-05 round

Non-SC/ST	To				**SC/ST**	To			
From	Occ **1**	Occ **2**	Occ **3**	size	From	Occ **1**	Occ **2**	Occ **3**	size
Occ **1**	0.48	0.38	0.14	0.10	Occ **1**	0.35	0.45	0.20	0.05
	(0.01)	(0.01)	(0.01)	(0.00)		(0.03)	(0.03)	(0.03)	(0.00)
Occ **2**	0.07	0.84	0.09	0.30	Occ **2**	0.04	0.85	0.11	0.27
	(0.00)	(0.01)	(0.00)	(0.00)		(0.01)	(0.01)	(0.01)	(0.01)
Occ **3**	0.04	0.19	0.77	0.60	Occ **3**	0.03	0.18	0.79	0.68
	(0.00)	(0.01)	(0.01)	(0.00)		(0.00)	(0.01)	(0.01)	(0.01)

Notes: Each cell ij represents the average probability (for a given NSS survey round) of a household head working in occupation i having a child working in occupation j. Occ 1 collects white collar workers, Occ 2 collects blue collar workers, while Occ 3 refers to farmers and other agricultural workers. Column titled 'size' reports the fraction of parents employed in occupation 1, 2, or 3 in a given survey round. Standard errors are in parenthesis.

are switching are most likely to have parents working in which occupation? Which sectors are absorbing most of the intergenerational switchers? Have these trends varied over time? Are there any differences between SC/STs and non-SC/STs in these patterns?

To address these issues, we compute the transition probabilities across occupations. Thus, for each NSS round we compute p_{ij} – the probability of a household head working in occupation i having a child working in occupation j. We compute transition probabilities for the three broad occupation categories. In particular, we aggregate the 3-digit occupation codes that individuals report into a one-digit code, leaving us with ten categories. We then group these ten categories further into three broad occupation categories: Occ 1 comprises white collar administrators, executives, managers, professionals, technical and clerical workers; Occ 2 collects blue collar workers such as sales workers, service workers and production workers; while Occ 3 collects farmers, fishermen, loggers, hunters etc.. This grouping reflects the similarity of occupations based on skill requirements.[20]

Table 6 presents the results. Each row of the Table denotes the occupation of the parent while columns indicate the occupation of the child. Clearly, off-diagonal elements measure the degree of intergenerational occupational mobility. Column "size" reports the average share of parents employed in each of the occupations in a given round. Panel (a) gives the numbers for 1983 and Panel (b) for 2004-05.[21]

[20] We confirm that our occupation groupings are plausible by examining education attainments and wages of the three groups. Indeed, Occ 1 is characterized by the highest education attainments and wages, followed by Occ 2, and Occ 3. See Appendix A for more details on the definitions of occupation categories.

[21] Standard errors are in parenthesis.

Table 6 reveals a few interesting features. First, the diagonal elements of both Panel (a) and (b) are quite high, indicating relatively little intergenerational occupation mobility over this period. The highest persistence rates (or the least mobility) in 1983 was in occupation 3 (agriculture) for both SC/STs and non-SC/STs with the persistence rate being slightly higher for SC/STs. In 2004-05, the persistence rate in occupation 3 was significantly lower for both caste groups, though the SC/ST rate remained larger. The intergenerational persistence in occupation 2, in contrast, increased, and significantly so for SC/STs. In fact, in the 2004-05 round, occupation 2 shows the most intergenerational persistence among all occupations. Interestingly, SC/STs also experienced a large increase in intergenerational persistence in occupation 1, while non-SC/STs saw a reduction in that persistence. These trends imply a dramatic convergence in the intergenerational persistence of all occupations between the two caste groups.

Second, the probability of the son of a farmer (Occ 3) switching to occupations 1 or 2 has risen for both groups. This probability is of interest as it indicates an improvement in the quality of jobs across generations. In 1983 the probability of an intergenerational switch from occupation 3 to occupations 1 or 2 was 13 percent for non-SC/STs and 11 percent for SC/STs. By 2004-05 these numbers had risen to 23 percent for non-SC/STs and 21 percent for SC/STs. We interpret these findings as evidence of convergence in upward occupation mobility of both caste groups, with SC/STs experiencing larger positive changes.

Third, the probability of a child working in occupation 3 conditional on his father being employed in occupation 1 or 2 has declined from 50 percent to 31 percent for SC/STs and from 30 percent to 23 percent for non-SC/STs over our sample period. We believe that this reflects a significant reduction in regress prospects of SC/ST households during this period.

Lastly, an interesting feature of this period has been a slight increase in the probability of an intergenerational switch from occupation 1 to occupation 2 for both groups, i.e., children switching from the white collar occupations of their father to working in blue-collar jobs. This mostly reflects an increase in the share of the sales and service sectors during the 1990s after the reforms – an outcome of the key changes that the economy was undergoing in its industrial composition during this period.

3.3 Income Mobility

Our third, and probably the most typical, measure of intergenerational mobility is on income. We proxy income with the individual's wage. Before describing our results we should note that the sample size for the wage data is, on average, a third of the sample size for the education and occupation distribution data due to a large number of households with missing wage observations.

The missing wage observations are mostly accounted for by the segment of the rural population who identify themselves as being self-employed and therefore do not report any wage data. Across the rounds, on average, about 65 percent of the sample are self-employed with 76 percent of them residing in rural areas. The missing wage data raises sample selection concerns. In particular, if non-SC/ST rural households are more likely to be land-owning and hence self-employed, then the wage data (particularly for rural households) would be skewed towards landless SC/ST households. The problem would be compounded by the fact that the wage earning non-SC/ST households may also be the most worse off amongst the non-SC/STs who may have the lowest mobility rates. In this event we would be biasing our results toward finding low wage mobility gaps between the two groups.

We examined this issue in two ways. First, we estimate that on average, 21 percent of the self-employed belong to SC/ST households. This is comparable to the 24 percent share of SC/STs in our working sample. Clearly, SC/STs are not disproportionately under-represented amongst the self-employed. Second, to assess the seriousness of the potential sample selection problem, we computed the per capita household consumption expenditure of non-SC/STs relative to SC/STs for self-employed households and wage earning households separately. Stable across rounds, the ratio was 1.24 for both. Hence, self-employed households do not appear to be distinctly different from wage earning households. Based on these two findings, we feel that the sample selection issues raised by the missing wage observations are not too serious and that the patterns of inter-group welfare dynamics indicated by the wage data are likely to generalize to the self-employed as well.[22]

The goal of measuring income mobility is to provide a measure of the degree to which the long run income of a child of a family is correlated with the long run income of his father. One such commonly used measure is the intergenerational elasticity (IGE). IGE of long run income is typically estimated as the slope coefficient in a regression of the log of the long run income (relative to the mean) of the child on the log of the parents' long run income (relative to the mean for the parents' generation). The estimated coefficient indicates the degree to which income status in one generation gets transmitted to the next generation. More precisely, IGE provides a measure of intergenerational persistence in income, while one minus IGE measures intergenerational mobility.

The typical problem surrounding income mobility regression specifications is the absence of measures of long run income. The standard procedure is to use short run measures of income as proxies for long run income. We face the same problem since our income data is the daily

[22] We should also note one important anomaly in the 1987-88 round of the survey. We find that the number of observations for wages in this round falls substantially relative to the other rounds, mainly due to a very large and disproportionate decline in the rural wage observations for this round. We could not find any explanations in the data documentation or in conversation with NSS officials as to the reasons for this sudden decline. Therefore, we eliminated the 43rd round from the income mobility analysis.

wage during the census period. Clearly, the daily wage may be a very noisy measure of long run income with significant associated measurement error. Moreover, as pointed out by Haider and Solon (2006), an additional problem with using short run measures for children's income is the systematic heterogeneity in income growth over the life cycle. In particular, individuals with higher lifetime income also tend to have steeper income trajectories. As a result, early in the lifecycle, current income gaps between those with high lifetime incomes and those with low lifetime incomes tend to understate their lifetime income differences while current income gaps later in the lifecycle overstate the lifetime income gaps.

We follow Lee and Solon (2009) to address these issues by (a) introducing controls for children's age to account for the stage of the life-cycle at which the income is observed; (b) introduce an interaction between parents's income and children's age to account for the systematic heterogeneity in the profiles; and (c) by instrumenting parents's income with household consumption expenditure and household size to mitigate the measurement error associated with using daily wage data.[23] Hence, our regression specification is

$$\begin{aligned} w_{ic} &= \alpha + \beta w_{ip} + \gamma_1 A_{ip} + \gamma_2 A_{ip}^2 + \gamma_3 A_{ip}^3 + \delta_1 \tilde{A}_{ic} + \delta_2 \tilde{A}_{ic}^2 + \delta_3 \tilde{A}_{ic}^3 \\ &\quad + \theta_1 w_{ip} \tilde{A}_{ic} + \theta_2 w_{ip} \tilde{A}_{ic}^2 + \theta_3 w_{ip} \tilde{A}_{ic}^3 + \varepsilon_i \end{aligned} \tag{3}$$

where w_{ic} denotes the log daily wage of the child of household i and w_{ip} is the log daily wage of the male head of the same household. A_{ip} denotes the head of household i's age while $\tilde{A}_{ic}$ is the child's age, which we normalized to equal zero at age 23 which is the mean age of children in our sample.[24]

We run this regression separately for each NSS sample year and for each caste group. The key parameter of interest is β. We compute IGE elasticities using OLS regressions, as well as the Instrumental Variable (IV) regressions where we instrument parent's income with household consumption expenditure and household size.[25] Figure 3 presents our results for OLS (panel (a)) and IV (panel (b)) estimations. We should note that all the point estimates in both figures are significant at the 1 percent level. There are three features of the results worth noting. First, the income persistence across generations has declined sharply over the period 1983 and 2004-05 for

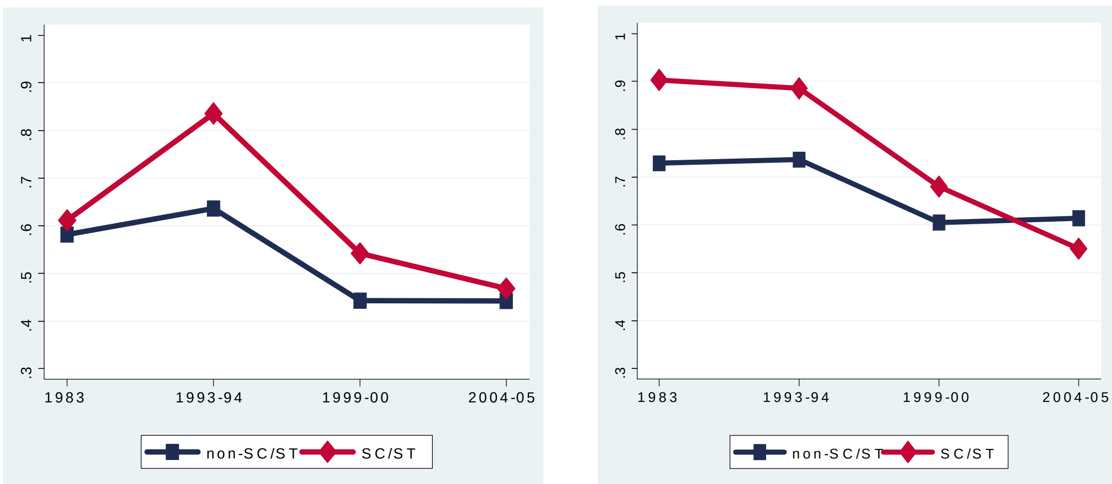
[23] In using household consumption and size as instruments we appeal to the permanent income theory of consumption, so that per capita consumption provides a good proxy for long-term income of the father. Household size has a similar interpretation in that it tends to respond to the permanent income of the parent.

[24] The control for a cubic in parents' age is to account for differences in the ages of parents in the sample at the time of observing their child's income. We also note that the relatively low age of children in our study is due to our focus on working age individuals (16 to 65 y.o.). We conduct robustness checks by restricting the sample to children whose mean age is within one standard deviation band around 30 years and find that our IGE estimates remain practically unchanged. Those results are available from the authors upon request.

[25] The detailed estimation results are reported in Tables S11 and S12 of the online appendix.

both SC/STs and non-SC/STs. In fact by the end of our sample period the estimates are much closer to the typical numbers around 0.45 that are reported for the USA by a number of different studies (see Solon, 2002). Second, there has been a clear convergence in intergenerational income persistence across the two groups.

Figure 3: Intergenerational income mobility



(a) Income mobility: OLS

(b) Income mobility: IV

Notes: Figures (a) and (b) present the results from the OLS and IV regressions, respectively, of child's per day log real wage on parent's per day log real wage and a set of controls. The figure plot the coefficients on the parent's wage from those regressions estimated separately for non-SC/STs and SC/STs. All estimated coefficients are statistically significant. Detailed estimation results are presented in the online Appendix.

Third, the IV estimates are uniformly higher than the OLS estimates. This is similar to the findings of Solon (1992) for the US. More importantly however, they confirm our findings from the OLS estimation. In fact, the IV estimates suggest that SC/STs' intergenerational income persistence has declined from a whopping 0.90 to 0.55 and, by the end of our sample period, was below that for non-SC/STs.

One drawback of IGE when comparing intergenerational mobility of sub-populations is that each group's mobility measure only captures the persistence of that group relative to its mean, not the mean of the entire distribution. For instance, the IGE coefficient for SC/STs tells us the rate at which income of an SC/ST child regresses to the mean of the SC/ST income distribution. To the extent that SC/STs and non-SC/STs mean earnings are different and are changing over time, the IGE coefficients of the two groups will be of limited comparability. Furthermore, if mobility patterns are different at various points in the income distribution, IGE will not be able to capture these differences.

To account for both shortcomings, two alternative approaches to measuring intergenerational mobility have been proposed in the literature (see Black and Devereux (2010) for a review of the literature). The first approach consists of computing mobility matrices which summarize transition probabilities of child's earnings conditional on father's earnings for different quantiles. Transition probabilities for each social group are obtained using distribution for the entire generation comprising both social groups. This facilitates meaningful comparisons of mobility patterns across subpopulations.

Another approach to measuring intergenerational mobility has been developed recently by Bhattacharya and Mazumder (2007, 2011). They criticize the existing transition probability approach as being sensitive to the choice of quantiles since the predicted mobility patterns depend on whether the researcher used quintiles, quartiles, etc. Instead, they propose an upward mobility measure which measures the probability that the son's relative standing in his generational distribution exceeds the relative standing of the father in his generational distribution. A key advantage of this approach is that it accounts for even small upward movements in son's relative position, thus providing a more forgiving measure of mobility. In contrast, mobility matrices require son's income to improve sufficiently to jump the specified quantile. Given that SC/STs are typically poorer than non-SC/STs for every quantile, SC/STs sons would be required to make larger income gains than non-SC/ST sons in order to record an improvement in income mobility.

We conduct both evaluations next. Following Jäntti et al. (2006) we begin by computing mobility matrices for SC/STs and non-SC/STs based on income quintiles. The results are presented in Table 7. Each row i of the table reports the probability of child's income being in quintile $j = 1..5$, of the child's generation conditional on father's income being in quintile i of the father's generation. Note that the quintiles for each generation are constructed from the *joint* income distribution of SC/STs and non-SC/STs of that generation. The computed mobility matrices are reported separately for SC/STs and non-SC/STs. Panel (a) reports the results for 1983, while panel (b) does the same for 2004-05 survey round.[26]

Several feature of the data stand out from the table. First, in 1983 the intergenerational income persistence, as captured by the diagonal entries in the mobility matrices, was substantially larger for SC/STs relative to non-SC/STs located in the bottom quintiles of income distribution; while it was significantly smaller in the top quintiles of income distribution.[27] That is, the son of low income SC/ST was *more* likely to remain in the bottom income quintiles than the son of low income non-SC/ST. At the same time, the son of a high income SC/ST was *less* likely to remain in the high income quintiles relative to non-SC/ST sons. The situation changes a lot by 2004-05. In particular,

[26] Standard errors are computed using bootstrap procedure in which we accounted for the complex survey design of the NSS data. In particular, in our procedure we use adjusted sampling weights. The variance is estimated using the resulting replicated point estimates (see Rao and Wu (1988), and Rao et al. (1992)).

[27] We should note that differences in the diagonal entries between SC/ST and non-SC/ST are highly statistically significant for the top quintile, but they are not significant for the bottom quintiles.

Table 7: Intergenerational income transition probabilities

	(a). Average mobility in the 1983 round											
Non-SC/ST							**SC/ST**					
	q1	q2	q3	q4	q5	size	q1	q2	q3	q4	q5	size
q1	0.51	0.36	0.08	0.04	0.01	0.17	0.57	0.29	0.08	0.03	0.02	0.24
	(0.05)	(0.05)	(0.02)	(0.01)	(0.01)	(0.01)	(0.05)	(0.05)	(0.03)	(0.01)	(0.01)	(0.01)
q2	0.18	0.44	0.30	0.06	0.02	0.18	0.13	0.51	0.30	0.04	0.02	0.23
	(0.02)	(0.05)	(0.04)	(0.02)	(0.01)	(0.01)	(0.02)	(0.05)	(0.04)	(0.02)	(0.01)	(0.01)
q3	0.14	0.17	0.44	0.20	0.05	0.18	0.07	0.14	0.45	0.30	0.04	0.22
	(0.02)	(0.02)	(0.04)	(0.03)	(0.01)	(0.01)	(0.02)	(0.02)	(0.04)	(0.04)	(0.01)	(0.01)
q4	0.09	0.06	0.11	0.49	0.25	0.20	0.06	0.04	0.08	0.45	0.37	0.21
	(0.02)	(0.01)	(0.02)	(0.03)	(0.03)	(0.01)	(0.02)	(0.02)	(0.02)	(0.05)	(0.05)	(0.01)
q5	0.07	0.04	0.08	0.17	0.64	0.27	0.05	0.07	0.16	0.24	0.48	0.10
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)	(0.04)	(0.05)	(0.06)	(0.01)
	(b). Average mobility in the 2004-05 round											
Non-SC/ST							**SC/ST**					
	q1	q2	q3	q4	q5	size	q1	q2	q3	q4	q5	size
q1	0.52	0.33	0.08	0.04	0.03	0.20	0.58	0.33	0.03	0.04	0.02	0.22
	(0.03)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)	(0.01)	(0.01)	(0.02)	(0.01)
q2	0.15	0.40	0.34	0.06	0.05	0.20	0.15	0.32	0.42	0.05	0.06	0.20
	(0.03)	(0.04)	(0.05)	(0.02)	(0.01)	(0.01)	(0.03)	(0.05)	(0.05)	(0.01)	(0.03)	(0.01)
q3	0.07	0.15	0.35	0.35	0.08	0.19	0.07	0.08	0.34	0.45	0.06	0.24
	(0.01)	(0.03)	(0.05)	(0.05)	(0.02)	(0.01)	(0.02)	(0.02)	(0.05)	(0.05)	(0.02)	(0.02)
q4	0.09	0.12	0.11	0.35	0.32	0.19	0.09	0.05	0.11	0.34	0.41	0.20
	(0.02)	(0.02)	(0.02)	(0.04)	(0.03)	(0.01)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.01)
q5	0.11	0.08	0.09	0.18	0.54	0.22	0.11	0.11	0.10	0.16	0.52	0.14
	(0.02)	(0.02)	(0.01)	(0.03)	(0.03)	(0.01)	(0.03)	(0.03)	(0.02)	(0.03)	(0.04)	(0.01)

Note: Each cell i j reports the probability (for a given NSS survey round) of a household head with income in quintile i having his child earning income in quintile j. q1-q5 refer to the quintile of the generational income distribution (fathers' in the columns; kids' in the rows). Column "size" refers to the fraction of parents falling in a given income quintile in that round. Bootstrapped standard errors are in parenthesis.

the intergenerational income persistence has declined for both social groups for all quintiles.[28]

Second, the decline in persistence was accompanied by an increase in upward intergenerational income mobility of both social groups, with SC/STs often experiencing more dramatic improvements. In fact, by 2004-05 SC/STs have surpassed the non-SC/STs in terms of upward income mobility for all quintiles except the very bottom quintile (q1 in the table). Interestingly, Table 7 also shows that for non-SC/STs, the highest income quintile households (q5 in the table) actually experienced an increase in the probability of intergenerational regress for quintiles 4 and 5 whereas the corresponding SC/ST households had the opposite or more muted trends.

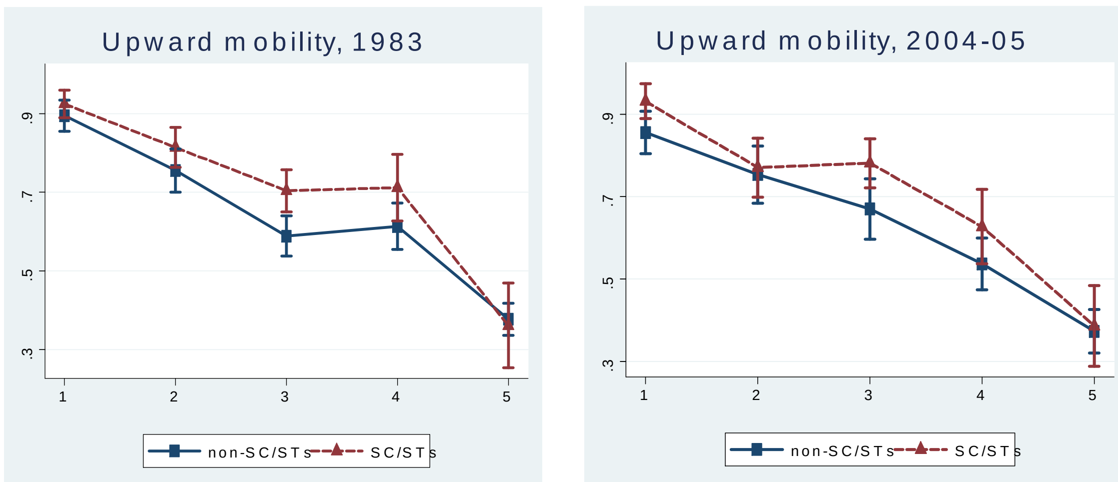
A third noteworthy feature is that the biggest movements in the intergenerational income transitions for both groups have occurred in the middle of the distribution – quintiles 2 and 3 for SC/STs and quintile 3 for non-SC/STs. Thus, the probability of a SC/ST father in the 2nd income quintile having a son in the third and higher quintiles was 0.36 in 1983 and increased to 0.52 in 2004-05. The same probability for non-SC/ST sons was 0.38 in 1983 and 0.44 in 2004-05. For the SC/ST fathers in the third income quintile, the upward transitions probabilities for their sons were 0.35 in 1983 and 0.52 in 2004-05; for non-SC/ST the corresponding probabilities were 0.26 in 1983

[28] The only exception was the 5th quintile of SC/STs, in which the persistence has increased over time.

and 0.42 in 2004-05.[29]

Next we compute a more direct measure of upward mobility, as proposed by Bhattacharya and Mazumder (2011). It is computed as the probability that a son's income rank in his generational income distribution exceeds the income rank of his father in the income distribution of father's generation. Figure 4 reports the estimated probabilities for SC/STs and non-SC/STs conditional on father's quintile. Panel (a) is for 1983, while panel (b) is for 2004-05 survey round.

Figure 4: Intergenerational upward mobility in income



(a) (b)

Note: Figures present upward income mobility conditional on parent's quintile (see text for details). Panel (a) is for 1983, while panel (b) is for 2004-05 survey round. Bootstrapped 95% pointwise confidence intervals are shown as bands.

Interestingly, according to this measure, SC/ST kids show higher upward mobility than non-SC/ST kids for all quintiles of fathers' distribution, and this is so in both 1983 and 2004-05 survey rounds.[30] This result is further confirmed by examining a measure of upward mobility obtained by conditioning on father's income being below some threshold, rather than falling within a particular quintile. As noted in Bhattacharya and Mazumder (2011), this approach avoids the aggregation bias that may arise because of income heterogeneity within a given quintile. We report the results in Table 8, where we use quintiles of father's distribution as the threshold for computing upward

[29] One reason for why the changes in intergenerational mobility occur in the middle of the income distribution rather than at the very top or bottom may be the evolution of credit constraints during this period (see, for example Becker and Tomes (1986), Grawe and Mulligan (2002), Corak and Heisz (1999)). For instance, Corak and Heisz (1999) argue that the wealthiest households can self-finance education while the constraint is unlikely to bind for the lowest income groups as long as ability and earnings are correlated on average. Hence, credit constraints are most likely to bind for the middle income groups. They find support for this view in the Canadian data. One of the key characteristics of the reforms in India during our sample period of 1983 to 2005 was the progressive liberalization of the financial sector. This has made credit access in India both wider and deeper. In as much as a relaxation of binding credit constraints may have facilitated greater investments in children's education, this may be an explanation for the large increases in intergenerational mobility in the middle of the income distribution in India.

[30] The differences however are mostly insignificant.

Table 8: Intergenerational upward mobility in income

	(a) 1983		(b) 2004-05	
	non-SC/ST	SC/ST	non-SC/ST	SC/ST
q1	0.90	0.93	0.86	0.93
	(0.0193)	(0.0162)	(0.0276)	(0.0214)
q2	0.83	0.87	0.81	0.86
	(0.0163)	(0.0150)	(0.0240)	(0.0196)
q3	0.75	0.82	0.76	0.83
	(0.0187)	(0.0151)	(0.0186)	(0.0185)
q4	0.71	0.79	0.71	0.78
	(0.0172)	(0.0122)	(0.0152)	(0.0177)
q5	0.62	0.75	0.63	0.73
	(0.0165)	(0.0142)	(0.0138)	(0.0159)

Note: Table upward income mobility conditional on parent income being below a threshold. Quintiles are used as thresholds (see text for details). Panel (a) is for 1983, while panel (b) is for 2004-05 survey round. Bootstrapped standard errors are in parenthesis.

mobility. These results indicate that upward mobility for SC/STs is higher than for non-SC/STs in both periods. In combination with the transition probabilities obtained in Table 7, we deduce that SC/ST children were more likely to improve their relative standing in income distribution as compared to non-SC/STs even though the size of the improvements tended to be smaller than for non-SC/STs. The magnitude of these improvements, however, increased over time, especially for SC/STs.

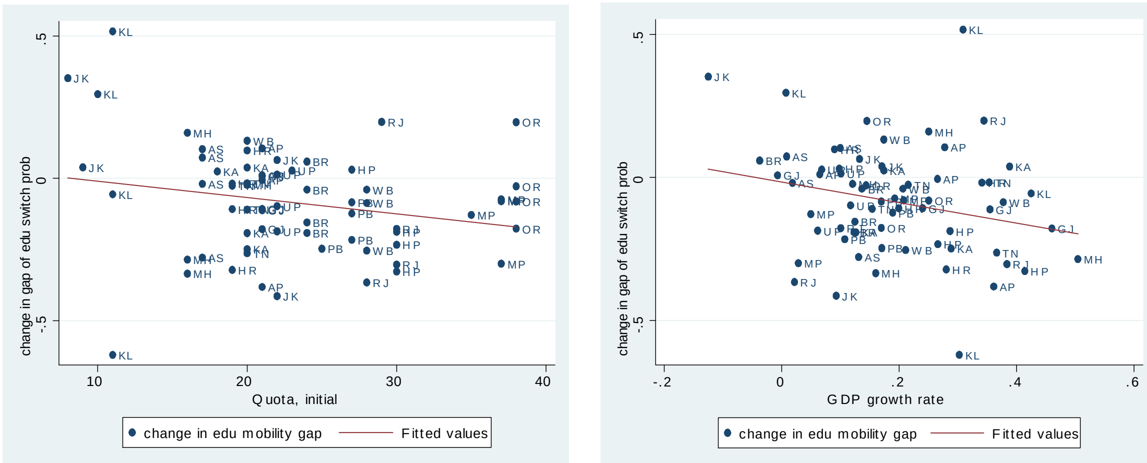
Overall, our results suggest that there has indeed been an upward trend in the degree of intergenerational mobility in education, occupation, and income of SC/STs with a significant convergence in the intergenerational educational and wage mobility to non-SC/ST levels.

3.4 Potential Explanations

The results obtained above illustrate quite unequivocally that the past two decades have seen a sharp and significant increase in intergenerational mobility rates of SC/STs towards non-SC/ST levels. These results naturally raise the issue of what factors may have been influential in inducing these convergent trends between the castes. Amongst the list of potential causal factors, we examine two specifically: (a) the role of reservations for SC/STs; and (b) the effects of increases in the aggregate growth rate.

Given the variation in quotas and growth outcomes across the states in India, we now exploit that cross-section variation to identify the effects of these two margins. Accordingly, we examine the co-movements of state-specific mobility gaps with (a) quotas and (b) output growth rates in the seventeen major states in India. In our analysis we only focus on education mobility gaps. We have already seen that occupation mobility gaps remained relatively unchanged during this period, hence there is no convergence to attribute to different factors. Income mobility at the level of the

Figure 5: Intergenerational Education Mobility by State



(a) Education mobility and quotas

(b) Education mobility and growth

Note: The figures present the relationship between changes in the SC/ST intergenerational education mobility gap between round t and $t-1$ and reservation quotas for SC/STs in round $t-1$ for the 17 major states in India for all survey rounds (Panel (a)); and per capita output growth between round t and $t-1$ for the 17 major states in India for all survey rounds (Panel (b)). The SC/ST gap in intergenerational education mobility rate is computed as the gap in the probability of education switch of a child relative to his father between non-SC/STs and SC/STs from regression (1). The solid lines are the fitted lines for the relationships.

state is difficult to compute accurately due to small numbers of observations for each social group at the state level. Education mobility, on the other hand, has exhibited the strongest convergence across the two social groups, and rich data is available to facilitate the state-level analysis.

Since our interest is in explaining convergence over time, we focus on the change in the education mobility across successive rounds. Specifically, we compute the change in the caste gap in intergenerational education switch probability between rounds $t-1$ and t in state x and correlate it with our two potential causal factors: (a) the SC/ST quota in period $t-1$ for that state; (b) per capita output growth in state x between rounds $t-1$ and t. We do this for all the 17 major states in India. Panel (a) of Figure 5 shows the results for the quota, while panel (b) presents the results for output growth. Since there are five survey rounds in the sample, there are four changes in gaps per state, giving us 68 data points in total in each figure. Clearly, higher quotas were associated with larger declines in the caste gaps in intergenerational education mobility.[31] Similarly, states with higher output growth rates tended to also have larger declines in the caste gaps in the

[31] Notice that this is not inconsistent with the negative coefficient on the interaction term between the caste dummy and quotas described above because that indicates a negative effect on the degree of education mobility of SC/STs at a specific time. The results for the states, on the other hand, indicates the effect of caste on the *change* in mobility between periods, not the *level* of mobility.

intergenerational education mobility rates. Both results are statistically significant.[32]

Overall, these results suggest that aggregate factors, such as reservations and macroeconomic growth may have contributed to the dramatic catch-up of lower castes to upper castes in terms of intergenerational mobility. However, this evidence is only suggestive. A much more comprehensive analysis of factors behind the intergenerational convergence across castes is clearly needed, which we hope to address in future work.

4 Conclusion

In this paper we have contrasted the evolution of intergenerational mobility rates in education attainment rates, occupation choices and wages of SC/STs between 1983 and 2005 with the corresponding mobility rates of non-SC/STs. Using successive rounds of the NSS, we have shown that this period has been marked by a remarkable convergence in the intergenerational mobility rates of SC/STs to non-SC/ST levels in both education attainment and wages. SC/STs have also been switching occupations relative to their parents at increasing rates during this period and have matched non-SC/STs in this regard. Interestingly, we have found that a common feature for both SC/STs and non-SC/STs is that the sharpest changes in intergenerational income mobility has been for middle income households.

While we have focused here on disparities in inter-generational social mobility, in related work in Hnatkovska et al. (2011) we have also studied *intra*-generational disparities between SC/STs and non-SC/STs. In findings mirroring those in this paper, we found intra-generational gaps in education attainment levels, occupation choices, wages and consumption also declined between 1983 and 2004-05. The two sets of results combined suggest to us that the past three decades of major macroeconomic changes in India have also coincided with a rapid and significant reduction in caste-based restrictions to socioeconomic mobility.

In terms of explaining these trends, we have examined two potential channels: the role of aggregate growth and the role of reservations for SC/STs in higher education and public sector

[32] To check whether the effect of caste on intergenerational education and occupation mobility depends on quotas, we also expanded the benchmark specifications in equations (1) and (2) to include an interactive term between SC/ST dummy and quotas. The coefficient on the interactive term was negative and almost always significant for education mobility, but insignificant for occupation mobility. Moreover, introducing the interactive term into the education mobility regression makes both the quota and the SC/ST dummy variables individually insignificant. This suggests that (a) the effect of quotas was mostly insignificant for non-SC/STs but significantly negative for SC/STs; and (b) the caste effect appears to have operated differentially across states depending on the quotas: the negative effect of SC/ST status on education mobility was small in states with small quotas but large in states with high quotas (recall that the quotas were state specific). The detailed estimation results with the interactive term between SC/ST dummy and quota are contained in Table S6 of the online appendix for education mobility, and in Table S10 of the online appendix for occupation mobility.

employment. We have found some evidence in support of the role of both channels for education mobility convergence. We believe that there are three other candidate explanations for the observed pick-up in the socioeconomic mobility rates of SC/STs in India. First, economic reform in India over the past 25 years have unleashed strong competitive pressures on vast segments of a previously protected economy. As has been argued by Becker (1957), increasing competition could reduce discrimination by making it more expensive for businesses to pursue discriminatory labor market practises. This could reduce caste-based discrimination in both hiring and wages and thereby induce a faster rise in the intergenerational mobility rates of SC/STs. Second, a strengthening of caste-based networks of SC/STs could also have been at play during this period. As has been recently shown in Munshi (2010), caste-based networks can often form quickly amongst the more disadvantaged groups in order to help them escape low-skill occupation traps. Third, the increasing political empowerment of the lower castes over the past 30 years may have been a contributing factor as well in accelerating this process. We intend to examine these different possibilities in greater detail in future work.

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Appendix

A Data Appendix

A.1 National Sample Survey (NSS)

The National Sample Survey Organization (NSSO), set up by the Government of India, conducts rounds of sample surveys to collect socioeconomic data. Each round is earmarked for particular subject coverage. We use the latest five large quinquennial rounds – 38(Jan-Dec 1983), 43(July 1987-June 1988), 50(July 1993-June 1994), 55(July 1999-June 2000) and 61(July 2004-June 2005) on Employment and Unemployment (Schedule 10). The survey covers the whole country except for a few remote and inaccessible pockets. The NSS follows multi-stage stratified sampling with villages or urban blocks as first stage units (FSU) and households as ultimate stage units. The field work in each round is conducted in several sub-rounds throughout the year so that seasonality is minimized. The sampling frame for the first stage unit is the list of villages (rural sector) or the NSS Urban Frame Survey blocks (urban sector) from the latest available census. We describe the broad outline of sample design – stratification, allocation and selection of sample units - with a caveat that the details have changed from round to round.

The whole country is divided politically into states and union territories, and each state is further divided into districts for administrative purpose. The NSSO also constructs regions by grouping contiguous districts within a state which are similar in population density and crop pattern for the sampling purpose. Two different stratification methods are used for rural and urban sector in each state. In the rural sector, each district is generally counted as a separate stratum (populous districts are split into two or more strata) whereas in the urban sector, strata are formed within the NSS region based on population size of cities. For example, all towns with population less than 50,000 in a region will form stratum 1 and so on. In the 61st round, the stratification method was changed substantially. For this round, each district is divided into two basic strata – rural and urban. Then the rural and urban strata are further divided into sub-strata.

The total sample size of first stage unit (villages/urban blocks) is allocated to the states and union territories in proportion to population. The subsequent allocations to rural and urban sector and at stratum level within a state are based on population size as well. In rural sectors, sample FSUs are selected with probability proportional to population from each stratum (sub-stratum for 61st round). In urban sectors, they are selected by simple random sampling without replacement in 38th and 61st round and circular systematic sampling with equal probability in the 43rd, 50th and

55th round. Within each stratum (sub-stratum for 61st round), samples are drawn in the form of two independent sub-samples for both rural and urban sectors. Once the FSUs are randomly drawn, the large FSUs are subdivided into certain number of parts (hamlet-group/sub-block) with approximately equal population and one of them selected randomly for listing of households. Complex second stage stratification based on "means of livelihood class" is implemented to select households randomly from the sample frame of households in each FSU (or hamlet-group/sub-block).

As the sample design changes over the rounds, estimation without considering the complex design may be misleading. The NSSO supplies household level multipliers with the unit record data for each round to help minimize estimation errors on the part of researchers. The questionnaire collects demographic details like age, sex, marital status, education, etc. and information about occupation, industry, activity, time disposition in reference week, wage, etc. of household members. It also collects monthly total household expenditure along with other household level characteristics.

The data are given in fixed format text files with a list of variable names and byte positions. We have checked the validity of our data extraction process by comparing the statistics on a number of the variables with numbers reported in published works by other authors. However, there is some miscoding which is typical for any survey data and we tried our best to clean it. Other notable changes over the rounds are formation of new states, deletion of the social group called "Neo-Buddhist" and formation of new social group called "Other Backward Class" or "OBC" (see below), and changes in coding for education, enrolment in educational institution, activity status and industry. We recoded all these changes to make it uniform and consistent over time.

A.2 Sample Selection

We drop all households for which we have no information on social group or whose social group is miscoded (3/ 120706 households in 38th round, 43/ 129060 households in 43rd round, none for 50th and 55th rounds (115409 and 120386 households, respectively), and 86/124680 households for 61st round are dropped). The classification of Scheduled Castes (SC) and Scheduled Tribes (ST) groups remain unchanged over the rounds. However, there is a new classification of "Other Backward Classes" (OBC) from the 55th round while the "Neo-Buddhist" classification was discontinued from the 50th round. We club these groups with non-SC/ST so that the scheduled caste and scheduled tribe groups (SC/ST) remain uniform throughout the period.

In our data work, we only consider individuals that report their 3-digit occupation code and education attainment level. Occupation codes are drawn from the National Classification of Occupation (NCO) – 1968. We use the "usual" occupation code reported by an individual for the usual principal activity over the previous year (relative to the survey year). The dataset does not contain information on the years of schooling for the individuals. Instead it includes information on general education categories given as (i) not literate -01, literate without formal schooling: EGS/ NFEC/ AEC -02, TLC -03, others -04; (ii) literate: below primary -05, primary -06, middle -07, secondary -08, higher secondary -10, diploma/certificate course -11, graduate -12, postgraduate and above -13. We aggregate those into five similarly sized groups as discussed in the main text.

In our analysis we dedicate a lot of attention to studying wage dynamics. NSS only reports wages from activities undertaken by an individual over the previous week (relative to the survey week). Household members can undertake more than one activity in the reference week. For each activity we know the "weekly" occupation code, number of days spent working in that activity, and wage received from it. We identify the main activity for the individual as the one in which he spent maximum number of days in a week. If there are more than one activities with equal days worked, we consider the one with paid employment (wage is not zero or missing). Workers sometimes change the occupation due to seasonality or for other reasons. To minimize the effect of transitory occupations, we only consider wages for which the weekly occupation code coincides with usual occupation (one year reference). We calculate the daily wage by dividing total wage paid in that activity over the past week by days spent in that activity.

Lastly, we identify full time workers in our dataset. We assume that an individual is a full time worker if he is employed (based on daily status code) for at least two and half days combined in all activities during the reference week.[33] We drop observations if total number of days worked in the reference week is more than seven.

A.3 Occupation Categories

Table A1 summarizes the one-digit occupation categories in our dataset and presents our grouping of these categories into the Occ 1 - "white collar", Occ 2 - "blue collar" and Occ 3 - "agriculture" groups that we used in the text.

Table A1: Occupation categories

Occupation code	Occupation description	Group
0-1	Professional, technical and related workers	Occ 1
2	Administrative, executive and managerial workers	Occ 1
3	Clerical and related workers	Occ 1
4	Sales workers	Occ 2
5	Service workers	Occ 2
6	Farmers, fishermen, hunters, loggers and related workers	Occ 3
7-8-9	Production and related workers, transport equipment operators and labourers	Occ 2

[33] Based on daily status code we can classify all individuals into employed, unemployed and not in labor force.