Castes and Labor Mobility*

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December 2010

Abstract

Can large macroeconomic changes also alter the historical economic mobility patterns of various social groups? We examine this question by contrasting the fortunes 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. We study the period 1983-2005 using household survey data from successive rounds of the National Sample Survey. Our key findings are that wages have been converging across the two groups with rising education attainments accounting for the majority of this convergence. SC/STs have also been switching occupations at increasing rates during this period. Moreover, inter-generational education and income mobility rates of SC/STs have converged to non-SC/ST levels. Clearly, the last twenty years of major structural changes in India have seen a sharp improvement in the relative economic fortunes of these historically disadvantaged social groups. In fact, the median wages of SC/STs relative to non-SC/STs in India have surpassed the median wages of blacks relative to whites in the USA.

JEL Classification: J6, R2

Keywords: Intergenerational mobility, wage gaps, castes

*We would like to thank Siwan Anderson, Nicole Fortin, Ashok Kotwal, Thomas Lemieux and seminar participants at UBC, Monash University, and LAEF Conference on "Growth and Development" at UC Santa Barbara for comments. Special thanks to David Green for extremely helpful and detailed suggestions.

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"If there is no enthusiasm, life becomes drudgery - a mere burden to be dragged. Nothing can be achieved if there is no enthusiasm. The main reason for this lack of enthusiasm on the part of a man is that an individual loses the hope of getting an opportunity to elevate himself. Hopelessness leads to lack of enthusiasm. The mind in such cases becomes deceased…When is enthusiasm created? When one breathes an atmosphere where one is sure of getting the legitimate reward for one's labor, only then one feels enriched by enthusiasm and inspiration"

"This condition obtains even where there is no slavery in the legal sense. It is found where as in caste system, some persons are forced to carry on the prescribed callings which are not their choice..."

B. R. Ambedkar (Chief architect of the Indian Constitution.)

1 Introduction

Large macroeconomic changes and major structural changes of the economy often go hand-in-hand. These phases are often associated with winners and losers at the level of individuals, sectors or social groups. Hence, managing the microeconomic distributional consequences of macroeconomic changes is often a key challenge for policymakers. But do large-scale macroeconomic changes tend to accentuate or dampen historical inequities? Do these economic redistributions necessarily benefit the economically stronger sections of society or can they also lead to a reduction in economic inequality? What are the key margins which account for these distributional changes?

The Indian economy provides a natural environment to investigate these questions due to a dramatic process of structural changes, implementation of a series of comprehensive reforms and rapid economic growth since the 1980s. At the same time, India has had a long history of social division due to a traditional institution of caste that created a social stratification along education, occupation and income lines. These factors motivate our focus on contemporary India in addressing the questions above. We study the evolution of the economic well-being of individuals belonging to historically disadvantaged castes between 1983 and 2005. We show that there has been a significant narrowing of economic backwardness of this group relative to the rest. We find that a large part of this economic catch-up has occurred through a catch-up in the relative education attainment level of this group.

The past 25-30 years have been a period of massive changes in the Indian economy. Average annual GDP growth rates have climbed rapidly from the anaemic 3-3.5 percent that characterized the first 35 years since 1947 to between 8 and 10 percent. Accompanying this growth takeoff has been a hastening process of structural transformation of the economy. The agricultural sector, which historically had the largest employment and output share, has rapidly lost ground in both during this period. Such rapid structural changes often deeply affect the lives of people in these economies by redistributing income and economic opportunities from some groups to others. As an example, a particularly emotive issue that has been debated energetically with regard to the Indian experience is the effect of this economic take-off on the fortunes of the poor.

In this paper we study the impact of the recent rapid transformation of the Indian economy on one such historically disadvantaged group: the Scheduled Castes and Scheduled Tribes (SC/STs). SC/STs were historically economically backward, mostly very poor, concentrated in low-skill (mostly agricultural) occupations and primarily rural. Moreover, they were also subject to centuries of systematic caste-based discrimination both economically and socially. This was so endemic that the constitution of India aggregated these castes into a Schedule of the constitution and provided them with affirmative action cover in both education and public sector employment. Indeed, this was viewed as a key component of attaining the ultimate policy goal of raising the social and economic mobility of the SC/STs to the levels of the non-SC/STs.

The existence of caste-based frictions in labor market allocations and social matching processes have been documented by a number of micro-level studies. Indeed, a key goal of the reservations policy was to make it easier for, say, the child of an illiterate SC or ST farm worker living below the poverty line to get educated and find productive employment in a better paying occupation. How have the tectonic changes in India since the early 1980s affected this goal? What has been the net effect on the fortunes of SC/STs of the interplay between these micro-level frictions and the massive aggregate macroeconomic changes in India over the past two decades? Has the rapid growth percolated down to the SC/STs in terms of tangible changes in their economic and social conditions? Is the primary reason for the economic deprivation of these underprivileged castes the types of occupations they tend to work in, i.e., do successive generations of SC/STs tend to get stuck in low wage jobs? Alternatively, is the key impediment the lack of education, i.e., do they get stuck in low wage jobs due to the lack of education? Or, is ongoing discrimination in occupations and wages the primary problem facing these groups? This paper attempts to answer some of these questions.

We use data from five successive rounds of the National Sample Survey (NSS) from 1983 to

2004-05 to analyze patterns of occupation choices, education attainment and wages of both SC/ST and non-SC/ST households. We conduct our analysis along two dimensions. First, we contrast the time-series evolution of education, occupation and industry choices and wages of SC/STs with their non-SC/ST counterparts from the same age cohort. We conduct this cohort-level analysis both at an aggregated generation level of parents and children as well as at a more disaggregated level of five different age cohorts.[1] Second, we contrast the time series behavior of the intergenerational persistence of education, occupation, industry of employment and wage levels of SC/ST and non-SC/ST households.

Our analysis yields four main results. First, while SC/ST households are, on average, less educated than their non-SC/ST counterparts throughout the sample period and across cohorts, the education attainment levels of SC/STs have been converging toward the level of their non-SC/ST cohort. This trend is particularly pronounced for SC/ST children. Moreover, the trend towards education convergence of the two groups emerges both in rural and urban sectors but is sharper in urban areas. The trend also shows up clearly across occupations.

Second, there have been similar compositional changes in the occupational distributions of SC/STs and non-SC/STs between 1983 and 2004-05. Children and parents of both SC/ST and non-SC/ST households have been moving out of low skill agrarian occupations into relatively higher skill occupations. However, these changes have occurred slightly faster for SC/STs. As a result, the occupation distribution of the two groups appear to be converging during this period. We also study trends in industry mobility of the two groups and find that the results for industry mobility are broadly similar to those for occupation mobility.

Third, we find a clear trend of convergence of the relative wage of the two groups towards one, i.e., the median wage premium of non-SC/STs relative to SC/STs has declined systematically from 17 percent in 1983 to 3 percent 2004-05. The trend is particularly strong for children where the wage premium of non-SC/STs has declined from 14 percent to approximately zero. For the parent cohort, the non-SC/ST wage premium has declined from 25 percent to 10 percent during this period. This pattern of relative wage convergence also emerges in mean wages and across more disaggregated age cohorts. Overall, our conditional wage regressions suggest that less than 5 percent of the observed wage gap is attributable to SC/ST factors alone (independent of the other correlates of wages like education and occupation). To put these wage gaps in perspective, the median white male to black male wage premium in the US has hovered stubbornly between 25 and

[1] We look at aggregated cohorts of parents and children to set the stage for the intergenerational mobility analysis.

40 percent over the past 35 years, which makes the SC/ST relative wage behavior in India even more striking.

Fourth, we find that *intergenerational mobility* of SC/STs 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. Correspondingly, the elasticity of wages of children with respect to the wages of their parent has declined from 88 percent to 45 percent for SC/ST households and from 76 to 58 percent for non-SC/ST households. Clearly, the intergenerational *income mobility* rates have also converged. Lastly, intergenerational *occupational and industry mobility* rates have increased for both groups during this period. However, these changes in occupational and industry 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 and/or different industry than their parent relative to children from SC/ST households.

In summary, these results suggest some uplifting answers to the questions we set out to answer. Over the last 20 years SC/STs have sharply narrowed both their education and wage gaps relative to non-SC/STs. The fact that these trends are sharpest amongst younger age-cohorts and amongst urban households suggests that the overall statistics are likely to improve even more sharply in their favor in the coming years as these cohorts become older and as the country becomes more urbanized. Moreover, children from the historically disadvantaged SC/ST households are increasingly raising their education attainments levels, switching occupations and improving their income positions relative to their parents. Crucially, intergenerational income and educational mobility of SC/ST households has been rising faster than for non-SC/STs. Overall, we conclude 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. This period of rapid structural changes appears to have been very beneficial for SC/STs who have used this period to rapidly narrow their huge historical economic disparities with non-SC/STs.

To the best of our knowledge, our's is the first study to jointly analyze caste differences in education, occupation, industry and wage outcomes in a single study, track the time series evolution of these outcomes, and do so using data that covers the entire country. It is worth reiterating that we do this using the NSS data which has the broadest coverage for India both spatially and over time.

There exists a large literature which has investigated the existence and extent of labor market discrimination in India. Amongst others, Banerjee and Knight (1985) and Madheswaran and Attewell (2007) have studied the extent of wage discrimination faced by SC/STs in the urban Indian labor market. Borooah (2005) has studied the extent of discrimination in employment in the urban labor market. Ito (2009) studies both wage and employment discrimination simultaneously by examining data from two Indian states – Bihar and Uttar Pradesh. Our study differs from these in that we examine the data for all states and for both rural and urban areas. Moreover, as opposed to most of these studies, our study controls for the presence of occupation and industry effects on wage outcomes. Lastly, by using data for five rounds of the National Sample Survey of households we are also able to provide a time series perspective on the evolution of SC/ST fortunes in India, a feature that other studies have typically not examined.

While there has been considerable work on intergenerational mobility in the US and other western countries (see Becker and Tomes (1986), Behrman and Taubman (1985), Haider and Solon (2006) amongst others), this issue has received remarkably little attention in the 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 other studies is that we examine intergenerational mobility patterns not just in education attainment but also in occupation choices, industry of employment, and income. We are not aware of any other study that documents intergenerational mobility patterns in occupation, industry, 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 measures as well as some summary statistics. Section 3 contrasts SC/STs with their non-SC/ST cohorts in terms of the evolution of the distributions of education attainment rates, occupations, industry of employment and wages. Section 4 presents and discusses the evidence on intergenerational mobility, while the last section

[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.

concludes.

2 The Data

Our data comes from the National Sample Survey (NSS) of India and its various rounds. In particular, we use the NSS Rounds 38 (1983), 43 (1987-88), 50 (1993-94), 55 (1999-2000) and 61 (2004-05). The survey covers the whole country except for a few remote and inaccessible pockets. The rounds that we use include detailed information on over 120,000 households and 600,000 individuals. Our working sample consists of all households heads and their children/grandchildren who provided their 3-digit occupation code information and their education information. We restrict our sample to males whose age is between 16 and 65.[3] 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. 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 restriction is necessitated by our interest in examining inter-generational mobility trends. We choose to work with this sample for our intra-generational exercises as well in order to retain comparability of the samples and the results. This selection leaves us with a sample of around 43,000-51,000 individuals, depending on the survey round and we refer to this sample as "working" sample. If we do not restrict the sample to households with working heads and at least one working child or grandchild, the sample size grows to between 136,000-152,000 individuals, depending on the round. We refer to this sample as "extended sample" and in the later sections verify the robustness of our key results to these alternative sample restrictions.[4]

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. In the extended sample, we have wage data for about

[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] Both the number of households with co-residing generations as well as the total number of individuals living in such households are not too different acoss rounds. This suggests to us that co-residence patterns have not changed too dramatically during the period under study. Hence the representativeness of the sample under this identification should have remained comparable across rounds.

55,000 individuals across rounds. Wages are obtained as the daily wage/salaried income received for the work done by respondents during the previous week (relative to the survey week). Wages can be paid in cash or kind, where the latter are evaluated by the current retail prices. We convert wages into real terms using state-level poverty lines that differ for rural and urban sectors. We express all wages in 1983 Maharashtra prices. Details regarding the dataset are contained in the Appendix.

Our education variable contains 5 categories: 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 occupation choices of individuals. In particular, we know the three-digit occupation code associated with the work that each individual performed over the last year (relative to the survey year). We use only those individuals for whom the occupation code reported for the last year coincided with the occupation code for which wages over the last week were collected (relative to the survey week). Our dataset also contains information on the four-digit industry of employment for each individual.

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 sub-samples.

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. Of the working children living with the Household-head, 49 percent are married on average. While the percent of married children has declined over time, this change was characteristic of both non-SC/ST and SC/ST children. Finally, the average education level of children is greater than that of parents for both SC/STs and non-SC/STs, 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 24 percent.

Table 1: Sample summary statistics

All	(a) children age	edu	%married	(b) parents 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	23.51	3.21	0.46	51.6	2.2	0.94	0.81	6.56
	(0.05)	(0.01)	(0.00)	(0.07)	(0.01)	(0.00)	(0.00)	(0.02)
2004-05	23.77	3.41	0.46	51.63	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.

3 Intragenerational Cohort Comparison: How Have the Scheduled Castes Fared?

We start our analysis by comparing SC/STs with non-SC/STs across age and generational cohorts. We construct cohorts in two ways. First, for every round of the census we split our sample into five broad age cohorts: 16-25, 26-35, 36-45, 46-55 and 56-65. Second, in each round we split the sample into household heads and children in co-residence with a household head. We call these generational cohorts "Parents" and "Children", respectively. For each age and generational cohort we compute the occupation distribution, the industry distribution, the average education attainment level and the average daily wage earned for the entire group as well as for SC/STs and non-SC/STs separately. Issues of particular interest to us are: (a) whether the education attainment levels of SC/ST children and parents are converging to the levels of their non-SC/ST cohorts? (b) whether their occupation and industry choices are converging over time; and (c) whether wages of SC/STs are converging to non-SC/ST levels.

A few notes on our generational cohort classification are in order. First, we refer to household heads as parents. In a literal sense household heads are not always the parents of younger working members in the household since there are a few households with a grandparent as the head of a household that also contains his working children and grandchildren.[5] More generally, our terminology is meant as a stand-in for parent-figures. Second, since we evaluate the performances of parents and children in successive rounds of the census, there will definitely be cases where children in one round become household heads, and therefore "parents", in later rounds. However, across the different census rounds the mean age of parents remains relatively stable at around 52 years while the mean age of children remains around 23 years. Thus, all children under the age of 30 in 1983 would still be less than the mean parent age in the last round of the sample in 2004-05. This suggests that while there definitely is some movement of people from one cohort into another over time, it doesn't appear to be a large share of the sample. Hence, the changes over time in the statistics of parents are not solely attributable to the changing age composition of the cohort, i.e., due to children in earlier rounds becoming parents in later rounds.

Third, we choose to work with age cohorts rather than birth cohorts. This is a deliberate choice which reflects our interest in determining the effects of changing aggregate conditions and how they alter the incentives of agents over time. The age-cohort approach allows us to contrast the behavior of 16-25 year olds in 2004-05 with 16-25 year olds in 1983. If the behavior is different then it would indicate that the incentives underlying the choices being made by this age cohort have changed over this period. While some of the dynamics of the age-cohorts may potentially include the cohort effects related to birth, the constant and historically determined caste identity of the groups combined with the impossibility of changing caste identities makes us less concerned about a big "cohort" effect underlying our results. The alternative of examining birth cohorts and tracking them over time makes it harder to make this deduction since some of the changes over time would also reflect the ageing process.

[5] Due to the 16-65 age restriction, however, the share of such households is small in our sample.

3.1 Education Attainment

We start with the record on education attainment rates. Panel (a) of Table 2 shows the average education attainment level of the overall population as well as those for working children and parents separately. Both generational groups increased their education attainment levels over the sample period. Panel (b) of Table 2 shows the relative education gap between non-SC/STs and SC/STs, computed as the ratio of their corresponding education attainments. In 1983, non-SC/STs had three quarters of a category more education than SC/STs.[6] However, over the sample period, there is a clear trend towards convergence in education levels of SC/STs toward their non-SC/ST counterparts. This trend is particularly pronounced for the cohort of children. While the difference in 1983 was almost one full education category, by 2004-05 this had narrowed to half a category.[7] Both groups increased their education attainment levels over the period with the SC/STs rising faster.

Table 2: Education attainment levels and gaps

	(a). Levels			(b). Gaps		
	all	children	parents	all	children	parents
1983	2.23	2.58	1.79	1.43	1.42	1.40
	(0.01)	(0.01)	(0.01)			
1987-88	2.33	2.69	1.88	1.41	1.40	1.40
	(0.01)	(0.01)	(0.01)			
1993-94	2.55	2.97	2.01	1.36	1.32	1.42
	(0.01)	(0.01)	(0.01)			
1999-00	2.77	3.21	2.20	1.33	1.28	1.41
	(0.01)	(0.01)	(0.01)			
2004-05	2.94	3.41	2.34	1.25	1.19	1.35
	(0.01)	(0.01)	(0.01)			

Notes: This table presents the average education attainment levels for our overall benchmark sample and separately for two generational groups – parents and children. Gaps refer to the ratio of average education attainment levels of non-SC/STs to SC/STs for the same three groups. The reported statistics are obtained for each NSS survey round which is shown in the first column. Standard errors are in parenthesis.

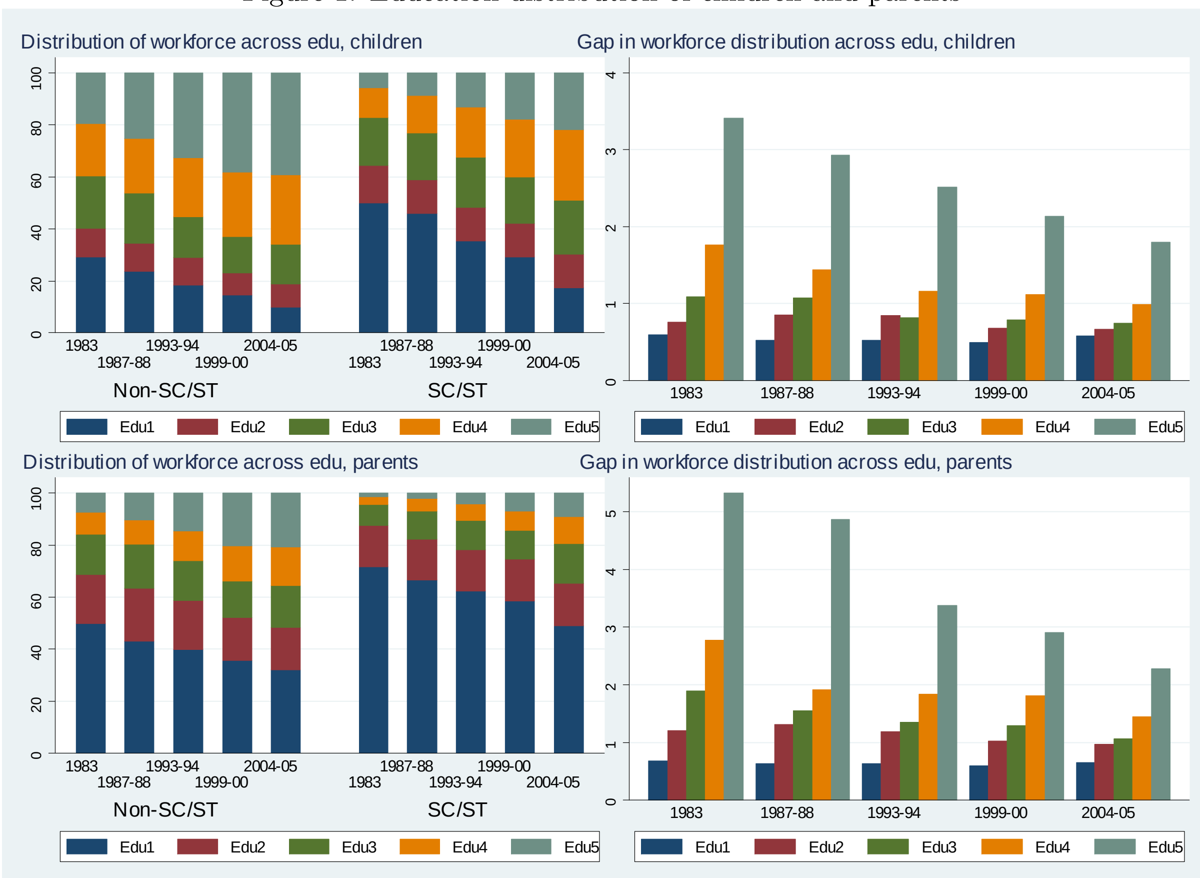
The picture is a bit different for parents. First, the increase in average education levels has been more tepid for parents relative to their children. Second, there is no trend toward convergence in the average levels across the parents: SC/STs parents start and end the sample period with about a half category lower education level than non-SC/STs.

[6] The level of education attainments for SC/STs in 1983 was 1.69, while for non-SC/STs it was 2.41.

[7] In 1983, education attainment levels of SC/ST and non-SC/ST children were 1.95 and 2.78, respectively. By 2004-05 these levels have increased to 2.98 and 3.55, respectively.

A related issue of interest is the distribution of parents and children across the five education categories. In particular, is the change in the average attainment level due to more illiterates beginning to go to primary school or is it primarily due to more people going on to middle school or higher? We answer this question using Figure 1.

Figure 1: Education distribution of children and parents



(a) (b)

Notes: Panel (a) of this figure presents the distribution of workforce of children and parents across five education categories across different NSS rounds. The left set of bars on each figure refers to non-SC/STs, while the right set is for SC/STs. Panel (b) presents relative gaps in the distribution of non-SC/STs relative to SC/STs across five education categories. The gaps are also reported for children and parents. See the text for the description of how education categories are defined (category 1 is the lowest education level - illiterate).

Panels (a) and (b) of Figure 1 show the distribution of the workforce across education categories and the corresponding non-SC/ST–SC/ST ratios for children and parents respectively. The top graph of Panel (a) shows the distribution of non-SC/ST children across the five education categories (left set of bars) and the corresponding distribution of SC/ST children (right set of bars). It is clear that SC/ST children are systematically less educated than their non-SC/ST counterparts.

The difference is most glaring in the lowest and highest categories. In category 1 (the illiterate groups) SC/STs are hugely over-represented while in category 5 (secondary education or above) they are strongly under-represented. The scale of the lack of education in India, both in general and amongst SC/STs, is probably best summarized by the fact that as recently as in 1983, about 64 percent of SC/ST children were either illiterate or had below primary level education while the corresponding number for non-SC/STs was 40 percent. These numbers declined to 30 percent for SC/ST children and 19 percent for non-SC/ST children by 2004-05.

The figure also makes clear that there has been a sustained decrease over time in the share of illiterates amongst both SC/STs and non-SC/STs. Thus, by 2004-05 the proportion of illiterate SC/ST children (category 1) fell from 50 percent to 17 percent. This was by far the sharpest change amongst all education categories. Correspondingly, the sharpest increases occurred in education categories 4 (middle school) and 5 (secondary or above). The pattern for non-SC/STs is broadly similar except for the fact that their sharpest increase occurred in the secondary or above education category 5.

The top graph of Panel (b) of Figure 1 shows the ratio of the percentage of non-SC/ST children and SC/ST children within each education category. Thus, the first bar from the left in the top graph of Panel (b) shows that the percentage of all SC/ST children who belonged to education category 1 in 1983 exceeded the corresponding percentage of non-SC/ST children in category 1 in that year by more than thrice. This panel captures the tendency toward convergence of patterns across the two groups. With one exception, the ratios in the proportion of children in the different education categories have come closer together and to one, thus exhibiting a definite trend towards convergence for the two groups. The exception was in category 3 (primary). In 1983 about 19 percent of non-SC/ST children had secondary school or higher levels of education while the number was just around 6 percent for SC/STs. By 2004-05, 39 percent of non-SC/ST children had secondary or higher levels of education while the number for SC/STs had risen to 22 percent. Clearly, for both groups there has been a significant increase in the share of children with secondary or higher education but the difference between the two groups has continued to remain high.

The bottom panel of Figure 1 shows the same information for parents. There are a few key differences between the education distribution patterns for parents and their children. First, the share of illiterates and those with less than primary education (education categories 1 and 2) is higher for both SC/ST and non-SC/ST parents throughout and declined at a slower rate than that of their children. Thus, in 1983 the combined share of categories 1 and 2 was 69 percent for non-

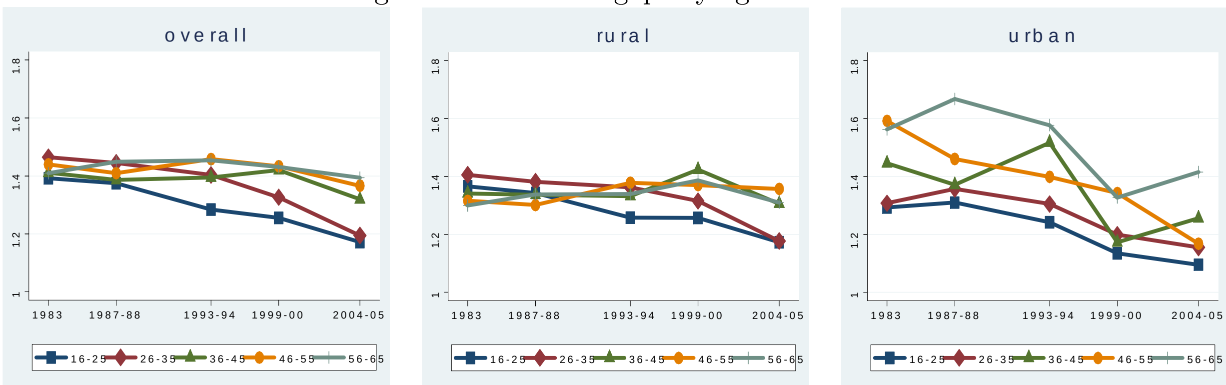
SC/ST parents and 88 percent for SC/ST parents. These numbers fell over time but still remained at a very high 48 percent and 66 percent, respectively, in 2004-05. Second, at the high end of the education distribution the changes have been more tepid for parents of both groups relative to that of their children. The share of secondary or higher educated parents amongst non-SC/STs rose from 7 percent in 1983 to 21 percent in 2004-05. Correspondingly, the share for SC/ST parents rose from 2 percent to 9 percent. Third, similar to the pattern amongst children, there is a clear trend towards homogenization of the two groups in their educational composition. This feature is clearly brought out in Panel (b) of Figure 1, in particular, by the heights of the bars depicting the shares for education categories 1 and 5. This convergence, however, is a bit more muted for parents than for children.[8]

Do these trends in aggregated generational cohorts mask key differences in the relative movements within more disaggregated age cohorts? To investigate this we compute the education attainment levels of non-SC/STs relative to SC/STs within five age-cohorts for each census round. Figure 2 plots the result. Panel (a) reveals a clear pattern of education convergence across the different age-cohorts over time. Importantly, the convergence appears to be the sharpest amongst the younger cohorts. Given the large concentration of households in rural areas, a related question is whether the trends in education attainment rates are different between rural and urban households. To address this, we split the different age-cohorts into rural and urban households and then plot the education attainment gaps for the two sectors separately in panels (b) and (c) of Figure 2. Three features of the figure are noteworthy. First, the variation in education levels across cohorts is much smaller in rural areas than in urban areas. Second, except for the oldest rural cohorts, education attainment levels have been converging in both rural and urban areas. Third, the convergence rates are, on average, faster in urban areas and for younger cohorts.

Overall, the data suggests that there has been a universal trend toward convergence in education levels of SC/STs toward the levels of non-SC/STs. While this trend is common across generations, ages and rural-urban locations, it is sharpest amongst the younger cohorts and in the urban areas. These trend patterns are likely to get sharper in the future as more uneducated parents drop out and more educated children become parents.

[8] The education attainment gaps of the "parents" cohort can change over successive rounds for two reasons. First, as some children become parents in subsequent rounds, the education composition of the parents cohort will clearly change. Second, since 1951 India has introduced a series of literacy initiatives (such the National Literacy Mission) with a special focus on adult literacy. In as much as these programs had a positive effect on adult literacy, the education composition of the parents cohort would change over time due to them as well.

Figure 2: Education gaps by age cohorts



(a) (b) (c)

Notes: The figures show the evolution of the relative education gap between non-SC/STs and SC/STs over time for different age groups. Panel (a) presents the results for the overall sample, while panels (b) and (c) report the results for rural and urban households separately.

3.2 Occupation Choices

We now turn to the occupation choices of the two groups. In order to facilitate ease of presentation, we aggregate the 3-digit occupation codes that individuals report into a one-digit code. This leaves us with ten categories which are then grouped further into three broad occupation categories.[9] Our groupings, while subjective, are based on combining occupations with similar skill requirements. Thus, 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.. The groupings also reflect differences in the returns to skills in the Indian economy: Occ 1 is characterized by the highest mean wage in our sample, followed by Occ 2, and Occ 3.

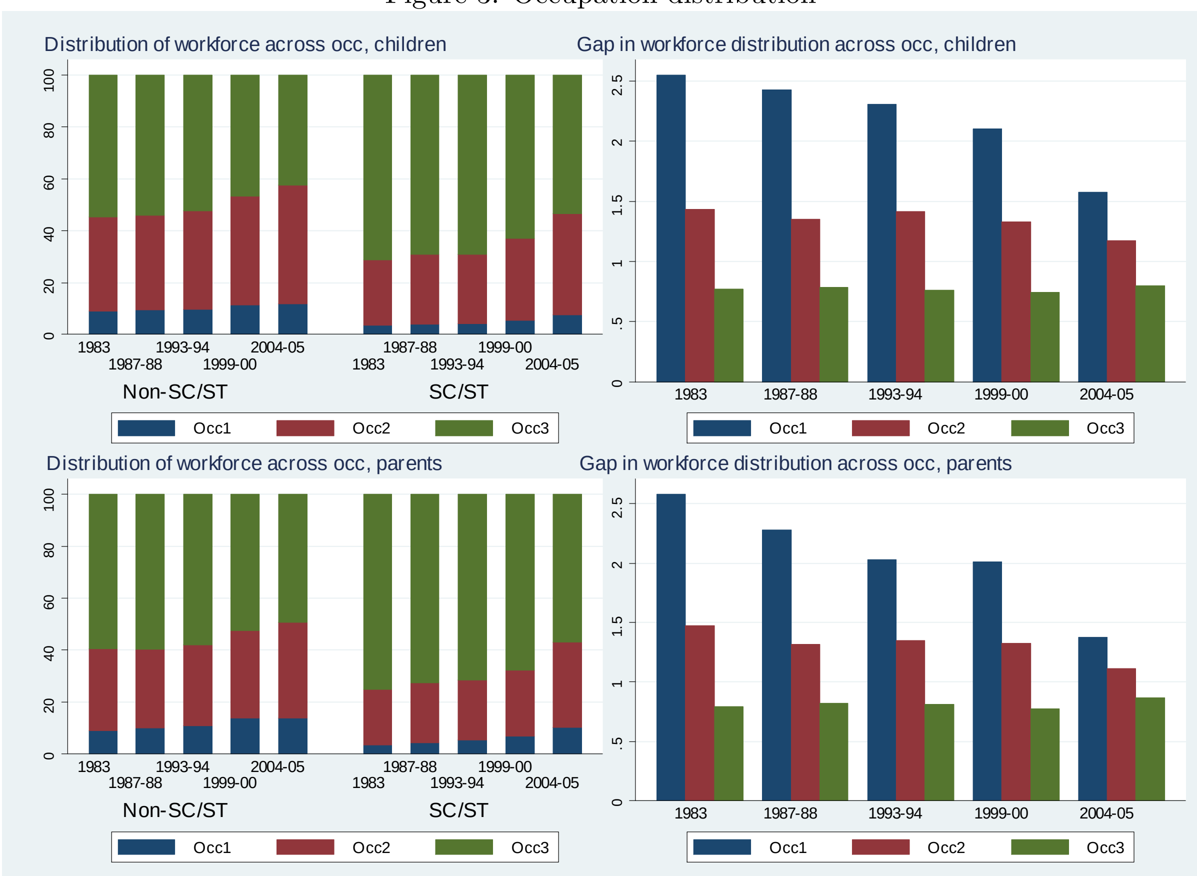
Figure 3 shows the occupation distribution for the working population in our sample, and the ratio of non-SC/STs to SC/STs in this distribution. The top panel of Figure 1 refers to children, while the bottom panel refers to parents. There are three features to note. First, there has been a systematic decline in Occ 3 (farming/pastoral activities) between 1983 and 2004-05 across all groups. The decline has been somewhat sharper for SC/STs – both children and parents, allowing the relative distribution between the two social groups to begin converging. This reflects the structural transformation at the aggregate level for India wherein there has been a gradual decline in the output and employment share of the agricultural sector. Second, the largest expansion in the employment share has been in Occ 2 which comprises mostly low skill blue collar and service

[9] See Appendix A.1 for more details on the occupation categories.

sector jobs. This phenomenon too has been common to both groups. Third, the share of Occ 1 (white collar/high skill) has risen slightly faster for SC/STs than non-SC/STs. This is possibly a sign of increasing mobility for SC/STs and an indicator of possibly faster future improvements.

Since SC/STs were over-represented in Occ 3 and under-represented in Occ 1 and 2 in 1983, the trends in occupation shares of the two groups imply that the overall occupation distribution has become more similar over the sample period for both parents and children, i.e., the distributions have been converging. We should point out though that the occupation distribution appears to be converging marginally faster for parents than for children.

Figure 3: Occupation distribution



(a) (b)

Notes: Panel (a) of this figure presents the distribution of workforce of children and parents across three occupation categories for different NSS rounds. The left set of bars on each figure refers to non-SC/STs, while the right set is for SC/STs. Panel (b) presents relative gaps in the distribution of non-SC/STs relative to SC/STs across three occupation categories. The gaps are also reported for children and parents. Occ 1 collects white collar workers, Occ 2 collects blue collar workers, while Occ 3 refers to farmers and other agricultural workers.

Having documented the large changes in the sectoral distribution of occupations as well as differences in educational attainment levels of SC/STs and non-SC/STs, we now look at two additional aspects of the occupation distribution. First, how different are these occupation categories in terms of their educational requirements? Second, are there systematic differences in the educational levels of SC/STs and non-SC/STs even within occupations?

Panel (a) of Table 3 shows the average educational attainment level of children and parents working in each of the occupations. Clearly, children working in occupation 1 have the highest education level while occupations 2 and 3 employ children with progressively lesser education, on average. Moreover, the average level of education in all occupations has risen throughout the period with the sharpest increase in education levels being in blue collar low-skill jobs (Occ 2) and farming/agricultural jobs (Occ 3). The pattern of average education attainment levels of parents across occupations is similar to that for their children – occupation 1 employs parents with the highest education, with occupations 2 and 3 following in that order. Similar to the pattern for children, the average education levels have been rising in all occupations. However, the rise in education levels of parents in occupations 2 and 3 have been much more muted than the corresponding increase for children.

Panel (b) of Table 3 shows the relative gap in the average education levels of non-SC/STs and SC/STs within the same occupation. Two features are noteworthy here. First, SC/ST children are less educated than non-SC/STs of the same cohort even within the same occupation. Second, gaps in education attainment levels are lowest in the high-skill white collar occupations. Third, education gaps amongst children within the same occupations have declined over time in all occupations. The trends in gaps for parents are broadly similar to those we uncovered for children with one key difference. The education gaps between non-SC/ST and SC/ST parents are much larger in white collar, high-skill occupations (occupation 1). This is in sharp contrast to the pattern for children where the difference are the smallest in these occupations.

Finally, we study the more disaggregated age cohorts and document the evolution of education attainments within each occupation. Panel (a) of Figure 4 shows the relative education gap between non-SC/STs and SC/STs working in occupation 1 for different age cohorts. Similarly, panel (b) summarizes the corresponding gap for those employed in occupation 2; and panel (c) for those working in occupation 3.

These results confirm our earlier findings: education attainment levels are converging between non-SC/STs and SC/STs. They are converging faster for younger age cohorts and for higher-skill occupations 1 and 2. Education gaps in occupation 3 have declined for the youngest age cohorts

Table 3: Education attainment levels and gaps by occupations

Panel (a). Education attainment levels

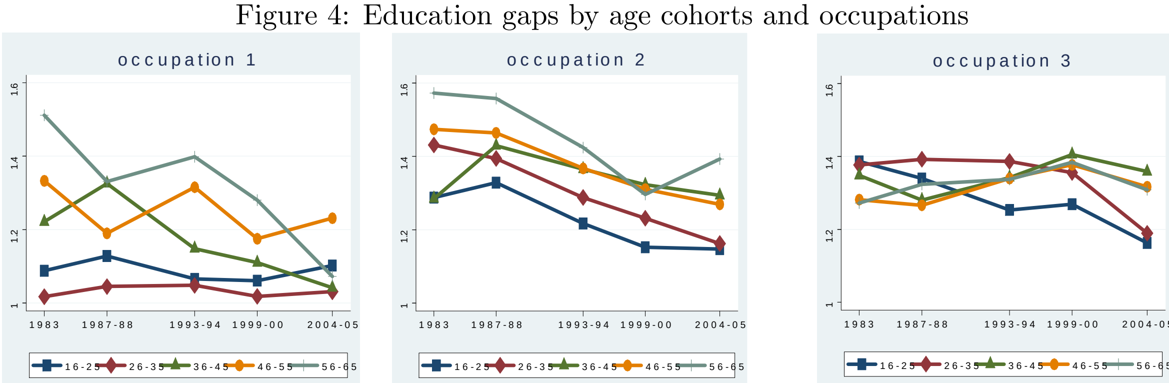
	children			parents		
	Occ 1	Occ 2	Occ 3	Occ 1	Occ 2	Occ 3
1983	4.41	2.93	2.26	3.58	2.11	1.53
	(0.05)	(0.02)	(0.01)	(0.05)	(0.02)	(0.01)
1987-88	4.41	2.97	2.39	3.71	2.11	1.63
	(0.03)	(0.02)	(0.01)	(0.04)	(0.02)	(0.01)
1993-94	4.51	3.28	2.67	3.92	2.28	1.72
	(0.03)	(0.02)	(0.01)	(0.04)	(0.02)	(0.01)
1999-00	4.48	3.44	2.93	3.88	2.44	1.89
	(0.03)	(0.02)	(0.02)	(0.04)	(0.03)	(0.01)
2004-05	4.52	3.53	3.14	3.90	2.56	2.02
	(0.02)	(0.02)	(0.02)	(0.05)	(0.03)	(0.02)

Panel (b). Education attainment gaps

	children			parents		
	Occ 1	Occ 2	Occ 3	Occ 1	Occ 2	Occ 3
1983	1.07	1.33	1.39	1.35	1.41	1.28
1987-88	1.09	1.35	1.36	1.26	1.46	1.27
1993-94	1.06	1.24	1.29	1.28	1.36	1.32
1999-00	1.03	1.18	1.29	1.19	1.29	1.36
2004-05	1.07	1.17	1.18	1.17	1.29	1.31

Notes: Panel (a) of this Table presents the average education attainment levels for the two generational groups – parents and children – by occupations. Panel (b) summarizes the relative education gaps for parents and children computed as a ratio of education attainments levels of non-SC/STs to SC/STs. The reported statistics are obtained for each NSS survey round which is shown in the first column. Occ 1 collects white collar workers, Occ 2 collects blue collar workers, while Occ 3 refers to farmers and other agricultural workers. Standard errors are in parenthesis.

Figure 4: Education gaps by age cohorts and occupations



(a) (b) (c)

Notes: The figures show the evolution of the relative education gap between non-SC/STs and SC/STs over time for different age and occupation groups. Occ 1 collects white collar workers, Occ 2 collects blue collar workers, while Occ 3 refers to farmers and other agricultural workers.

while remaining relatively unchanged or even increasing slightly for the older age cohorts.[10]

[10] One other interesting feature of our data is that the dispersion in education gaps across age cohorts is the highest in occupation 1 with lower dispersions in occupations 2 and 3. This probably reflects the heterogeneity of skills underlying the occupation groups we constructed. Occ 1 combines a variety of high-skill occupations that can lead to more heterogeneity in education gaps. Such skill heterogeneity is lower in occupations 2 and 3.

3.3 Industry choices

Next, we look at the industry of employment choices of households. In order to facilitate the presentation, we aggregate the 4-digit industry code that individuals report into a one-digit code. This gives us seventeen categories. We then group these seventeen categories into three broad industry categories: Ind 1, Ind 2 and Ind 3. Ind 1 comprises the Agricultural sector, Ind 2 collects Manufacturing and Mining and Quarrying, while Ind 3 comprises all Service industries. Our grouping reflects the traditional industrial classification according to United Nations classification system. See Appendix A.1 for more details on the industry grouping.

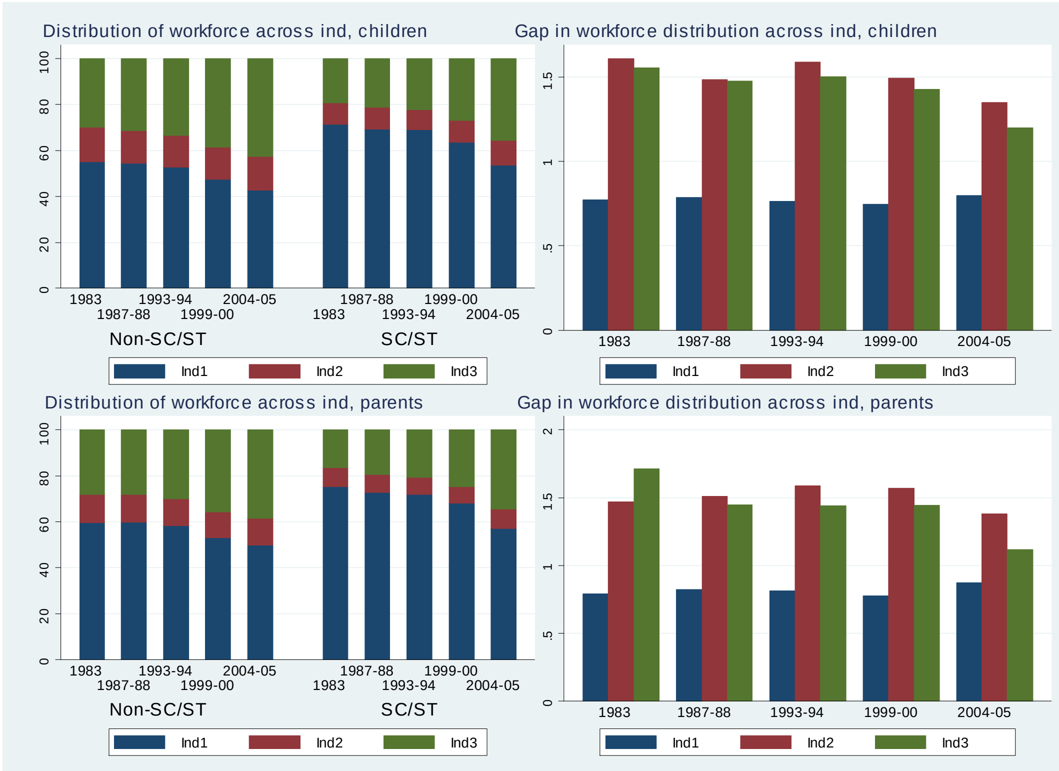
Figure 5 reports the industry distribution of parents and children, and the relative gaps in this distribution. Consistent with the results for occupation choice, SC/STs were and remain more likely to be employed in agriculture and other farming activities (Ind 1) than non-SC/STs. However the gap has somewhat narrowed in the last ten years of our sample. The second largest industry of employment for both social group is services, whose share has also been rising steadily over time. Interestingly, services also exhibit the sharpest convergence pattern between non-SC/STs and SC/STs followed by manufacturing and then agriculture. In particular, the relative gap between non-SC/STs and SC/STs in employment shares in services has shrunk from more than 50 percent in 1983 to below 25 percent in 2004-05.

3.4 Wages

The third issue of interest is the evolution of wages of SC/STs and their non-SC/ST cohorts. We are particularly interested in determining whether the rising educational attainment rates and changing occupation distribution of SC/STs towards relatively higher skilled occupations have also resulted in a change in the wage gap relative to non-SC/STs.

Before describing our results on wages it is important to reiterate 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 primarily due to the large segment of the rural population who identify themselves as being self-employed and correspondingly 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 a natural concern about sample selection. In particular, if non-SC/ST rural households are more likely to be land-owning and hence self-employed, then the

Figure 5: Industry distribution



(a) (b)

Notes: Panel (a) of this Figure presents the distribution of workforce of children and parents across three industry categories for different NSS rounds. The left set of bars on each Figure refers to non-SC/STs, while the right set is for SC/STs. Panel (b) presents relative gaps in the distribution of non-SC/STs relative to SC/STs across three industry categories. The gaps are also reported for children and parents. Ind 1 refers to Agriculture and other farming activities, Ind 2 aggregates Manufacturing and Mining and Quarrying; while Ind 3 refers to Services.

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. In this event we would be biasing our results toward finding low wage gaps between the two groups.

We examined this issue in two ways. First, 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. Averaged 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.

It is also important to note one important oddity in the 1987-88 data generated by the 43th round. In particular, the number of observations for wages in this round falls precipitously to about half the level of the other rounds. This occurs due to a very large and disproportionate decline in the rural wage observations for this round. We are not sure as to the reasons for this sudden increase in the number of missing observations in the 43th round. For the sake of completeness though, we report the results for all rounds. However, the results for the 43th round should be treated with caution on account of the missing rural wage observations.

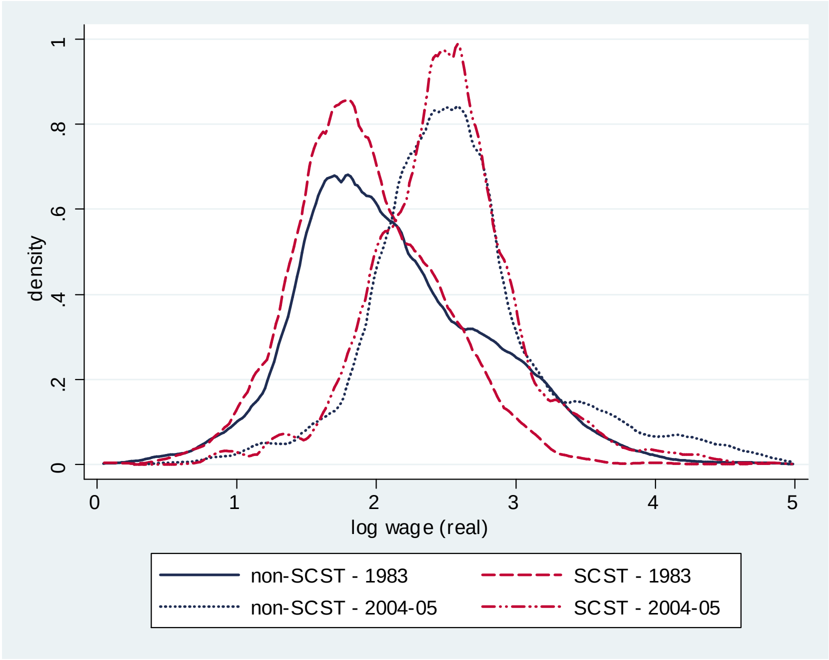
It is instructive to start our analysis of the wage data by presenting the distribution of wages for the first and last rounds of our sample, i.e., for 1983 and for 2004-05. Figure 6 plots the kernel densities of the wage distribution for SC/STs and non-SC/STs separately for both these rounds. Two features emerge clearly from the figure. First, for both groups the wage distribution has shifted sharply to the right. This is to be expected as the period 1983-2005 coincides with the rapid takeoff of the Indian economy. Second, the density functions for the two groups have come much closer together in 2004-05 relative to 1983.[11]

We can examine the changes in wage inequality more closely by looking at the differences in log wages between non-SC/STs and SC/STs for different percentiles of their wage distributions. Panel (a) of Figure 7 shows this for two survey rounds: 1983 and 2004-05.

Several features are worth pointing out from the panel (a) of Figure 7. First, the Figure shows first-order stochastic dominance of the non-SC/ST wage distribution relative to the SC/ST wage distribution since wages are almost uniformly higher for non-SC/STs than for SC/STs for every percentile. However, the degree of the stochastic dominance has declined over time as the line for 2005-05 is much closer to zero for almost all percentiles relative to the earlier round. Second, both lines slope up and to the right, indicating that the wage distribution of non-SC/STs is more unequal that the wage distribution of SC/STs. An upward sloping line indicates that the difference in wages of the two groups is smaller for lower percentiles than for higher percentiles. But this implies that higher percentile non-SC/STs must earn not only more than higher percentile SC/STs,

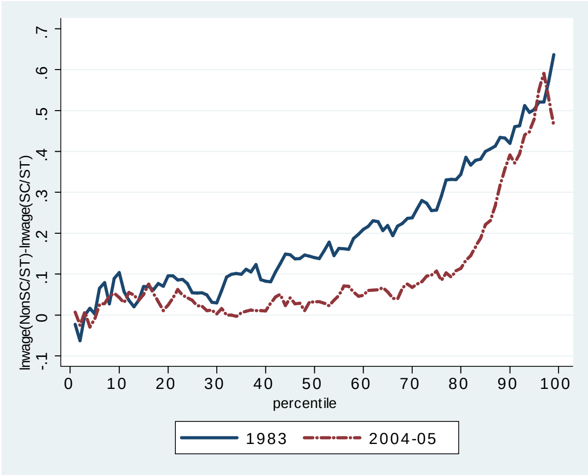
[11] We should note though that a formal Kolmogorov-Smirnov test of the equality of SC/ST and non-SC/ST wage distributions rejects the null hypothesis of equality both for 1983 and 2004-05. Moreover, the test also rejects the null hypothesis of the SC/ST distribution in 1983 being the same as the SC/ST distribution in 2004-05. This conclusion carries over to a comparison of the non-SC/ST wage distributions in these two rounds as well.

Figure 6: Wage density for non-SC/STs and SC/STs

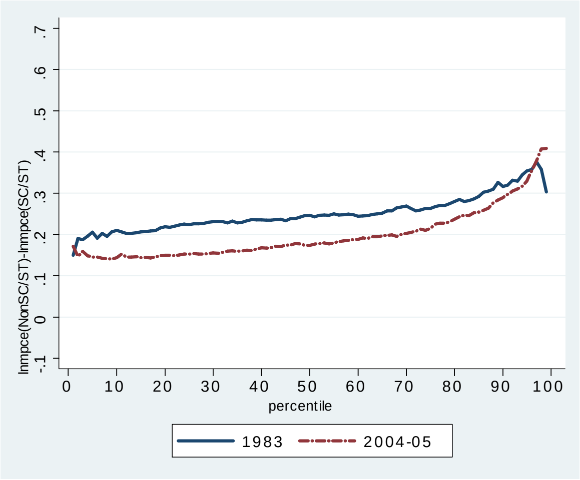


Notes: This figure shows the estimated kernel density of log real wages for non-SC/STs and SC/STs over 1983 and 2004-05 NSS rounds.

Figure 7: Differences in percentiles for non-SC/STs and SC/STs for log wages and log consumption



(a)



(b)

Notes: Figure (a) shows the difference in percentiles of log-wages between non-SC/STs and SC/STs plotted against the percentile, while Figure (b) does the same for real consumption expenditures. The plots are for 1983 and 2004-05 NSS rounds. The line that slopes upward and to the right indicates more unequal distribution for non-SC/STs compared to SC/STs. The lines that are above the horizontal axis indicate stochastic dominance in non-SC/STs wage distribution.

but their wage mark-up relative to lower percentile non-SC/STs must also be greater than the wage mark-up of higher percentile SC/STs relative to their lower percentile counterparts. Hence, an upward sloping line indicates a more unequal wage distribution for non-SC/STs than SC/STs. The flattening out of the lines over time indicates a decrease in the wage inequality of the two distributions even though the sharp positive slope towards the right tail indicates continued wage inequality at the top-end of the income distribution. Overall, the plot confirms our earlier finding of convergence in the two distributions over time as the line for 2004-05 round is well below the line for 1983 round.

As we mentioned earlier, the sample of individuals for whom wages are available is significantly smaller than our working sample. We therefore, verify the robustness of the wage inequality results uncovered above using the data on consumption expenditures which are available for a larger sample than the wage sample. We convert consumption expenditures into real terms using the same deflators that we used for wages and compute the differences in percentiles of consumption distributions between non-SC/STs and SC/STs in the same way as we did for wages. Panel (b) of Figure 7 shows the results for 1983 and 2004-05 survey rounds. The consumption results confirm our findings for wages. The plots indicate stochastic dominance of the non-SC/ST consumption distribution relative to the SC/ST consumption distribution, but show a significant decline in consumption gap between non-SC/STs and SC/STs over time for the most part of the distribution, except at the very highest end.

The wage distributions plotted in Figures 6 and 7 appear to indicate a decline in wage inequality between SC/STs and non-SC/STs between 1983 and 2004-05. We now examine this impression more closely by contrasting the wage evolution of SC/STs with non-SC/STs over finer sub-groups of age and generation cohorts as well as for all the census rounds under study.

We start with the wage evolution of the generational cohorts of parents and children across the census rounds. Table 4 shows the daily wage earned by working children and parents of non-SC/ST households relative to their SC/ST cohorts over the period 1983 to 2004-05. Overall, the wage premium of non-SC/STs has declined from 42 percent to 23 percent during this period. The Table reveals a contrast between the children and parents in terms of the evolution of the wage gap between SC/STs and non-SC/STs during this period. There has been a clear convergence of wages between children of these two groups. The wage premium of non-SC/ST children has secularly declined from around 34 percent in 1983 to 14 percent by 2004-05. For parents too the non-SC/ST wage premium has fallen from 51 percent in 1983 to 31 percent in 2004-05.

The trends we uncover are even more dramatic if we look at wage gaps computed using median wages. In particular, we find that the median wage premium of non-SC/STs relative to SC/STs has declined from 17 percent in 1983 to 3 percent in 2004-05. This decrease is especially pronounced for children for whom the relative wage premium of non-SC/STs relative to SC/STs essentially disappears during this period – falling from 14 percent in 1983 to approximately zero in 2004-05. For parents too the premium fell from 25 percent in 1983 to 10 percent in 2004-05. Clearly, both mean and median wages have been converging across the two groups during this period.

Table 4: Wage gaps

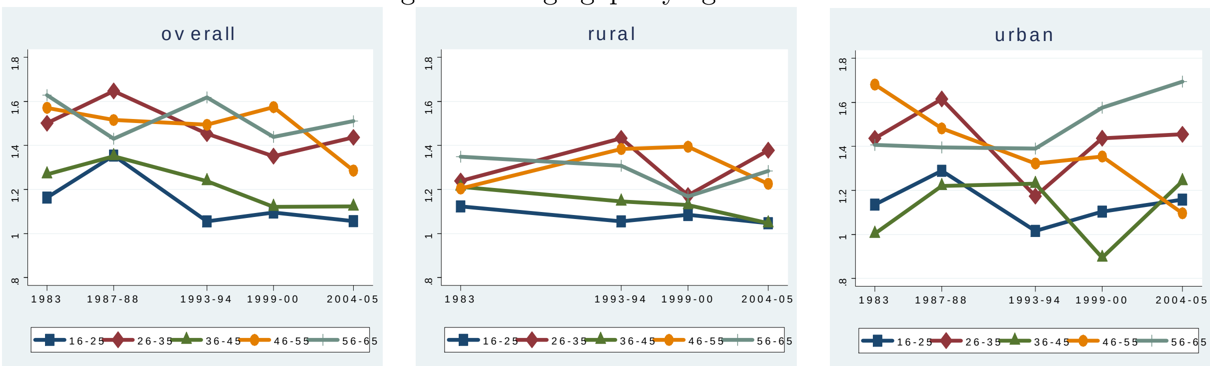
	overall		children		parents	
	mean	median	mean	median	mean	median
1983	1.38	1.15	1.28	1.13	1.48	1.25
1987-88	1.48	1.24	1.48	1.10	1.49	1.40
1993-94	1.30	1.07	1.16	1.04	1.45	1.18
1999-00	1.30	1.07	1.18	1.02	1.42	1.15
2004-05	1.23	1.03	1.14	0.99	1.31	1.10

Notes: This Table presents the relative mean and median wage gaps for our overall benchmark sample (columns "overall") and separately for the two generational groups – children (columns "children") and parents (columns "parents"). The mean gaps are obtained as the ratios of average real wages of non-SC/STs to SC/STs; while median wage gaps are computed as the ratios of median real wages of the two groups. The reported statistics are obtained for each NSS survey round which is shown in the first column.

Next, we switch from the aggregated generational cohorts to the more disaggregated age-cohorts. Our principal interest here is to determine whether the relative wage gap behavior at the aggregate generational level is masking significant variation across different age cohorts. Figure 8 plots the wage gaps for our five age cohorts for the different census rounds. Panel (a) reveals a general pattern of wage convergence across the cohorts with the younger cohorts, on average, closer to parity than the older ones. Do these overall wage gaps between non-SC/STs and SC/STs reflect significant differences between rural and urban areas? Panels (b) and (c) of Figure 8 shows that the evidence is mixed on this. Relative wages have tended to converge for younger cohorts in both sectors but have often widened for the older ones. Thus, the wage gaps have widened for the 46-55 age group in rural areas and for the 56-65 age group in urban areas. Overall, we view this evidence to be along the same lines as the evidence on education, albeit more volatile due to the smaller sample size.

We also examine the behavior of relative wages of non-SC/STs relative to SC/STs by age cohorts across different occupations. Figure 9 presents the results. Panel (a) is for occupation 1, panel (b)

Figure 8: Wage gaps by age cohorts

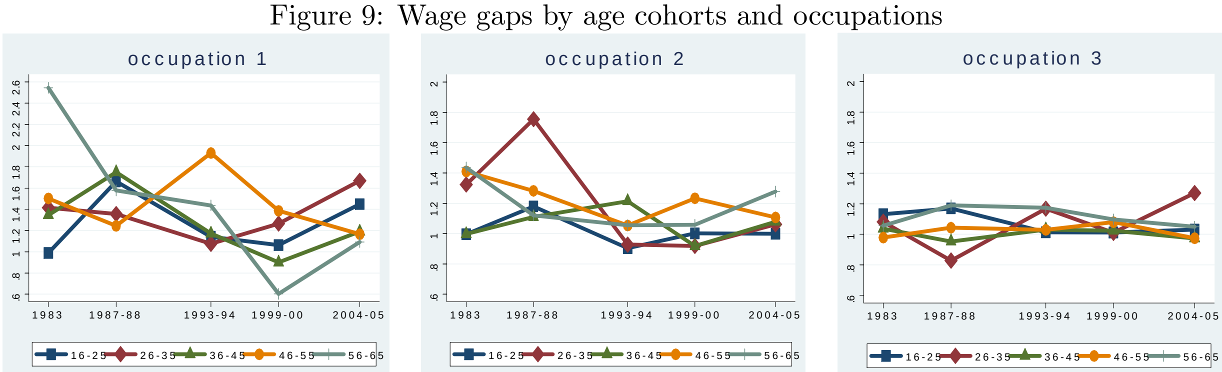


(a) (b) (c)

Notes: The figures show the evolution of the relative wage gap between non-SC/STs and SC/STs over time for different age groups. Panel (a) presents the results for the overall sample, while panels (b) and (c) report the results for rural and urban households separately.

is for occupation 2, while panel (c) is for occupation 3. It can be seen that the relative wage premia in occupations 1 and 2 have declined across most age cohorts. In agricultural jobs (occupation 3) the convergence is a bit muted, but the wage gaps there are very small to begin with. As with educations gaps, we see that wage gaps are the most spread out in occupation 1, and to a smaller extent in occupations 2 and 3. Overall, the data suggests that SC/ST wages have been converging toward non-SC/ST levels, and this trend is most pronounced for higher-skill occupations.

Figure 9: Wage gaps by age cohorts and occupations



(a) (b) (c)

Notes: The figures show the evolution of the relative wage gap between non-SC/STs and SC/STs over time for different age and occupation groups. Occ 1 collects white collar workers, Occ 2 collects blue collar workers, while Occ 3 refers to farmers and other agricultural workers.

The evolution of the wage gaps between SC/STs and non-SC/STs provides an interesting counterpoint to the racial wage gaps that are typically reported in the USA. Thus, during the period 1980-2006 the median wage of black males relative to white male workers has fluctuated between

70 and 80 percent with an average of around 75 percent. During the same period the median wage of Hispanic men relative to white men has declined from 71 percent to under 60 percent.[12] In contrast, our computations above imply that the median wage of SC/STs relative to non-SC/STs has increased from 80 percent in 1983 to 95 percent in 2004-05.[13] Amongst the younger cohorts the wage catch-up has been even faster with the relative median wages of SC/ST children having risen from 88 percent to 101 percent during this period. Clearly, the rate of wage convergence for SC/STs since 1983 has been quite striking both at an absolute level as well as in comparison to historically disadvantaged minority groups in more developed countries like the USA.

3.4.1 Conditional Wages

The trends we documented above suggest that the wage gap between SC/STs and non-SC/STs has been declining over the past 22 years. We now examine this impression more closely using formal statistical tests. In particular, for each census round we estimate a linear log wage regression on the following characteristics: individual age and age squared, dummies for his education category, SC/ST dummy, Muslim dummy, region and occupation specific dummies.

We control for differences in reservation policies across states by including state-level SC/ST reservation quotas (*quota SC/ST*). The introduction of reservations for SC/STs in public sector employment and in higher education institutions was a key policy initiative in India. The reservations were provided in proportion to the population shares of SCs and STs.[14] We also include a Muslim dummy in our regression specification. This is intended as a control for the fact that Muslims, on average, have done poorly in modern India (post independence in 1947). If we do not control for a Muslim fixed factor explicitly, then part of the decline in wage and economic inequality that we find in the data may be attributed to the poor performance of Muslims who would be assigned into non-SC/ST group.

We control for regional differences by grouping states into five regions – North, South, East, West, Central and North-East – and include region dummies in the regression specification.[15] In

[12] These numbers are from US Current Population Survey.

[13] For ease of comparison with the typical wage gap numbers reported for the USA, the SC/ST wage gaps reported here are the inverses of the non-SC/ST to SC/ST relative wage gaps we reported above.

[14] 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 increased OBC relative wages 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.

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

combination with the state-level reservation policy, this allows us to decompose state-level differences into those attributable to reservations policy, and those due to other time-invariant factors that are common to all states within a given region. The identifying assumption behind this strategy is that the states within a region are broadly similar but differ in terms of the reservation quota they implement.

Table 5: Conditional wage regressions

	1983 (i)	1987-88 (ii)	1993-94 (iii)	1999-00 (iv)	2004-05 (v)
age	0.0350***	0.0732***	0.0358***	0.0327***	0.0289***
	(0.0034)	(0.0067)	(0.0046)	(0.0031)	(0.0035)
age sqr	-0.0004***	-0.0007***	-0.0004***	-0.0003***	-0.0002***
	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
1-SC/ST, 0-non SC/ST	-0.0522***	-0.0664**	-0.0303	-0.0013	-0.0586***
	(0.0162)	(0.0336)	(0.0208)	(0.0144)	(0.0161)
1-rural, 0-urban	0.0473**	0.2659***	0.1670***	0.1930***	0.2497***
	(0.0235)	(0.0677)	(0.0274)	(0.0223)	(0.0234)
edu 2 dummy	0.0855***	0.1586***	0.0861***	0.1025***	0.1296***
	(0.0192)	(0.0428)	(0.0273)	(0.0184)	(0.0209)
edu 3 dummy	0.1825***	0.1765***	0.1270***	0.1468***	0.1106***
	(0.0237)	(0.0372)	(0.0296)	(0.0206)	(0.0217)
edu 4 dummy	0.2424***	0.2921***	0.1894***	0.1492***	0.1251***
	(0.0292)	(0.0459)	(0.0335)	(0.0210)	(0.0253)
edu 5 dummy	0.5553***	0.6409***	0.3207***	0.3715***	0.3527***
	(0.0388)	(0.0479)	(0.0376)	(0.0277)	(0.0311)
1-muslim, 0-other	-0.0041	-0.0302	-0.0560	0.0159	-0.0844***
	(0.0235)	(0.0344)	(0.0365)	(0.0212)	(0.0228)
quota SC/ST	-0.0145***	-0.0118***	-0.0032	-0.0140***	-0.0094***
	(0.0013)	(0.0026)	(0.0020)	(0.0013)	(0.0012)
R-sqr	0.359	0.376	0.201	0.356	0.320
N	8313	3807	8287	9354	8453

Notes: This table presents estimation results from a regression of log real wages on a set of individual-level, household-level and aggregate control variables for five NSS survey rounds ((i)-(iv)). Refer to the text for model specification details. Standard errors are in parenthesis. * p-value≤0.10, ** p-value≤0.05, *** p-value≤0.01.

Table 5 reports the key results. We find that the coefficient on the SC/ST dummy variable is negative and significant throughout except for the 1993-94 and 1999-2000 rounds. The negative estimates for the SC/ST dummy indicate that the conditional wages of SC/STs were significantly lower than similarly endowed non-Muslim non-SC/STs. Interestingly, the size of this negative SC/ST effect declined over the first four rounds – in fact becoming insignificant in 1993-94 and 1999-2000 before returning to its initial 1983 level in the last round. Our results also suggest that reservations have been associated with lower average wages for all groups.[16]

Table 5 also shows a significant positive coefficient on the rural dummy for all rounds except for the first which indicates a positive wage effect of living in rural areas after one accounts for all our controls. We find this to be an interesting feature of the Indian experience during this period.

[16] Prakash (2009) focuses on the role of reservations for India's lower castes. He finds broadly insignificant effects of reservations on wages of all except the very poorly educated SC/STs.

From the perspective of this study though, it is worth noting that this differential rural wage effect is common to both SC/STs and non-SC/STs.[17] While a more detailed investigation of this issue is beyond the scope of this paper, it is also worth noting that both the rural-urban wage differential and rural-urban education differential declined during the period under study. However, the wage differential declined at a faster rate than the education differential. Put differently, relative to the corresponding urban levels, wages in rural areas grew faster than education levels in rural areas. What factors can account for this feature of the data is an intriguing issue which we intend to study in greater detail in future work.

As we saw earlier, relative wage gaps have been declining and this decline has coincided with a decline in the gaps in education attainment levels between SC/STs and non-SC/STs. So, how much of the wage gap between the two groups arises due to differences in education? We answer this question by using the Oaxaca-Blinder decompositions.

We employ a two-fold Oaxaca-Blinder procedure which involves running wage regressions separately for the two groups on a list of controls including education levels. One then decomposes the wage gaps into the part coming from the different coefficients on the controls for the two groups, and the part due to differences in endowments between the two groups. To obtain the reference coefficients we use a pooled approach which allows for a group membership indicator (as in Fortin, 2006). Our controls are the same as in the regression specification above. Table 6 reports the results for the overall sample.

Columns (i) and (ii) report average log wages of non-SC/STs and SC/STs, respectively; while column (iii) reports the wage gap for the two groups over different survey rounds.[18] Column (iv) attributes a fraction of this gap to group differences in measured endowments, while column (v) reports the size of the gap usually attributable to discrimination or potentially to group differences in unobserved characteristics. Finally, the last column of Table 6 reports the fraction of the explained log wage difference that is accounted for by differences in education endowments alone. The column shows that differences in education accounted for 56 percent of the explained wage gap in 1983 which increased to 95 percent in 2004-05. The detailed results from Oaxaca-Blinder decomposition and for the regressions that will follow are reported in the supplemental tables available from

[17] In particular, when we include an interaction term between rural dummy and SC/STs dummy, we find the coefficient on it to be insignificant for all survey rounds. These results are available upon request.

[18] Wage gap reported in Oaxaca-Blinder decomposition is computed as a difference between average log wages of non-SC/STs and SC/STs. The relative wage gaps we reported earlier were obtained as the ratios of average wages (in levels) of non-SC/STs to SC/STs. As a result, the magnitudes of the gaps from these two approaches are different, but the trends are the same.

Table 6: Oaxaca-Blinder decomposition

	non-SC/ST	SC/ST	difference	explained	unexplained	fraction to edu
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
1983	2.13	1.93	0.20	0.15	0.05	0.59
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	
1987-88	2.46	2.21	0.25	0.18	0.07	0.77
	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)	
1993-94	2.32	2.15	0.17	0.14	0.03	0.37
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	
1999-00	2.54	2.38	0.16	0.16	0.00	0.40
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	
2004-05	2.60	2.49	0.10	0.05	0.06	0.93
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	

Notes: This Table presents a two-fold Oaxaca-Blinder decomposition of the log-wage gap between non-SC/STs and SC/STs for the five NSS survey rounds, as identified in the first column. Columns (i) 'non-SC/ST', (ii) 'SC/ST' and (iii) 'difference' present the average real log-wages for non-SC/STs, SC/STs and the gap between them, respectively. Columns (iv) 'explained' and (v) 'unexplained' refer to the size of the wage gap attributable to differences in endowments between non-SC/STs and SC/STs, and to the differences in the returns to those endowments, respectively. Column (vi) 'fraction to edu' reports the share of the explained wage gap coming from education attainment differences between the two groups. Standard errors are in parenthesis.

http://faculty.arts.ubc.ca/vhnatkovska/research.htm.

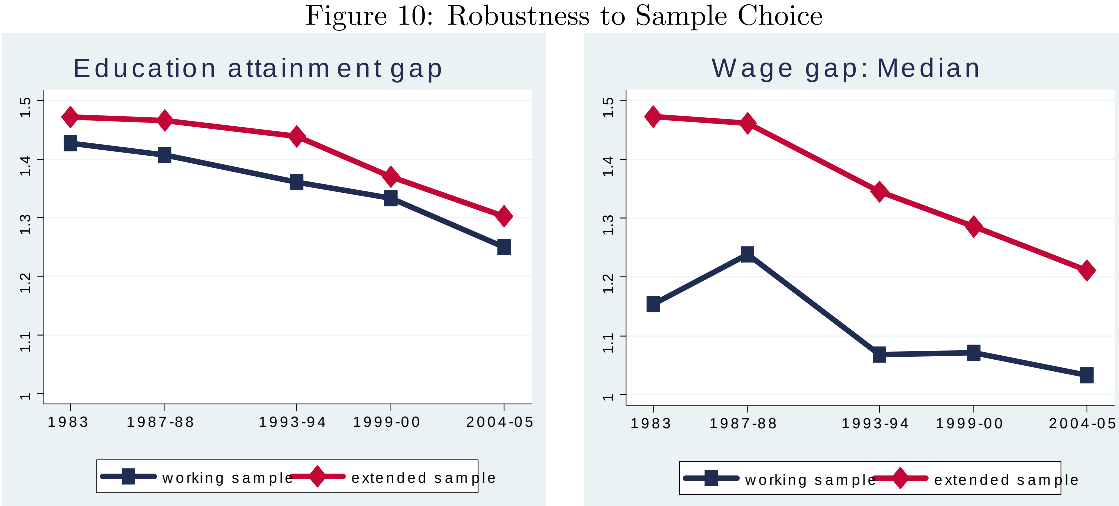
These results, in conjunction with the facts that both wage and education differences have been declining over time, suggest that the major part of the decline in the wage differences between SC/STs and non-SC/STs between 1983 and 2004-05 is due to a decline in the education differences between them.

3.5 Sample and Robustness

A key restriction underlying our working sample is that we have only considered joint households consisting of a head of household and at least one child or grandchild. This restriction allowed us to construct the groups of Parents and Children which will allow us to study the time trends in inter-generational mobility patterns within SC/ST and non-SC/ST households (see below). The imposed restriction did however reduce the sample size by dropping brothers/cousins of the head of the household as well as their children. Moreover, the restriction also dropped households with only one generation of full-time working males. Does this sample restriction matter for our results? To check this we compared the relative education and wage gaps from the extended sample (without the joint-household restrictions) with the results reported above using the working sample (which reflects the restrictions).

Panel (a) of Figure 10 shows the average education attainment levels of non-SC/STs relative to SC/STs for both the extended sample and the working sample. Similarly, Panel (b) of Figure 10 plots the median wages of non-SC/STs relative to median SC/ST wages for the two samples. Clearly, the same pattern of convergence emerges in both samples. Both figures show, however, that the non-SC/ST to SC/ST gaps are larger for all years in the extended sample. This is due to the fact that the larger sample includes a number of older individuals (like brothers of the head of household living in a joint household) who get dropped in the working sample. Recall that the measured gaps in both education and wages are larger for older cohorts. We conclude from this exercise that our results on education and wage convergence are not an artifact of the sample selection imposed by our joint household condition.

Figure 10: Robustness to Sample Choice



(a) (b)

Notes: Panel (a) depicts the ratio of the mean education attainment level of non-SC/STs to SC/STs for the working and extended samples. Panel (b) presents the ratio of the median wages of non-SC/STs to SC/STs for the same two samples.

We also checked for the robustness across samples of our regression estimates from the conditional wage regression by running the wage regressions on the extended sample as well. We found that the coefficient on the SC/ST dummy declines over the five rounds from -0.07 to -0.03. Hence, the trend in the extended sample is the same as in the working sample. However, as in the unconditional gaps plotted above, the greater presence of older individuals with larger wage gaps implies that the overall estimate for the SC/ST dummy is, on average, slightly larger in the extended sample relative to that in the working sample.

4 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? Are children changing occupation, industry, education and income status relative to their parents more frequently than before? Our primary interest is in studying how the occupation and industry 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/ industry switch as a binary variable that takes a value of one if the child's or grandchild's education level/ occupation/ industry of employment is different from his parent's (who is the head of the household) education achievements/ occupation/ industry of employment; and zero otherwise. We label education switch variable as **switch-edu;** occupation switch variable as **switch-occ;** and industry switch variable as **switch-ind.** We also distinguish *education improvement*, which is another binary variable equal to one if the child's education is higher than that of his parent and zero otherwise, from *education reduction* which is a binary variable that takes a value of one if the child's education is below his parent's education and zero otherwise.

4.1 Education Mobility

We begin by analyzing intergenerational education switches. Our main interest is in determining the degree to which children are changing their education levels relative to their parents and by how much. We are also interested in determining whether or not the switches reflect increases in educational attainment by the children.

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 state-level characteristics, such as state-level reservation quota for SC/STs, and region-specific fixed effects. Thus,

$$x_i\beta = \beta_0 + \beta_1 age_i + \beta_2 age_i^2 + \beta_3 SC/ST_i + \beta_4 muslim_i + \beta_5 rural_i + \beta_6 hh\_size_i + \beta_7 quota\_scst_j + \sum_{j=1}^{6} \alpha_j region\_dummy_j. \quad (4.1)$$

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.[19,20]

Panel (a) of Figure 11 depicts the computed probabilities of intergenerational switches in education attainment together with the ± 2 std error confidence bands (dashed lines).[21] The remarkable feature highlighted by the Figure is that 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.

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 11 reveals that the average size of the switch has been increasing over time for both groups. Moreover, 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 that positive numbers for the size of the switch indicate improvements in education categories.

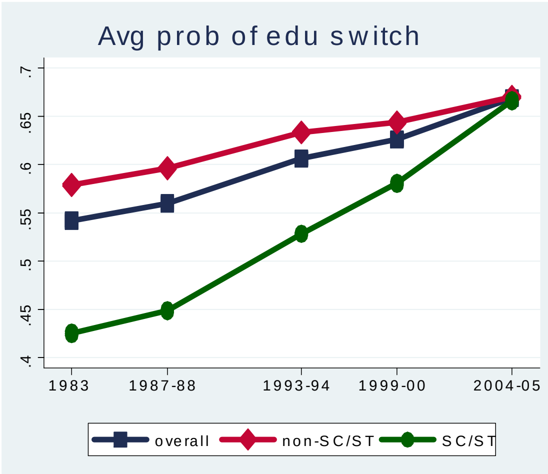
We also find that most of the intergenerational education switches are in fact increases in educational attainment levels. The estimated probability of an SC/ST child increasing his level of education attainment relative to the parent was just 36 percent in 1983 but rose sharply to 59 percent by 2004-05. The corresponding probabilities of an increase in education attainment for

[19] The detailed regression results for this Section are available in supplemental tables from http://faculty.arts.ubc.ca/vhnatkovska/research.htm.

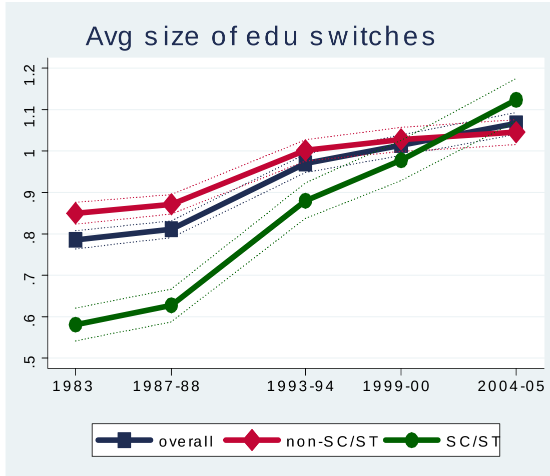
[20] We choose to proceed with the regression approach as we are also interested in the effect of caste on the probability of switching conditional on other controls. As we show in the Supplemental Tables, the marginal effects of caste on these probabilities are always significant.

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

Figure 11: 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 non-SC/ST 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. Hence, a majority of the increase in the education switch probability for SC/STs relative to the non-SC/STs is accounted for by an increase in the probability of an improvement in the education attainment level. Detailed summary of these results is available in the Appendix Table A3.

4.2 Occupation Mobility

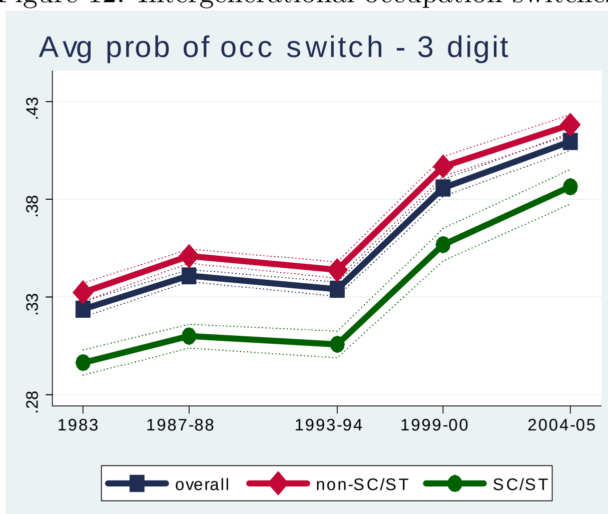
We now turn to intergenerational occupation switches. The conditional probability of an occupation switch is obtained in a similar manner to the education switch probabilities. Now, y_i is a binary variable for occupation switch as defined above (*switch-occ*) while x_i is a vector of controls:

$$\begin{aligned} x_i\beta &= \beta_0 + \beta_1 age_i + \beta_2 age_i^2 + \beta_3 SC/ST_i + \beta_4 muslim_i \\ &\quad + \beta_5 rural_i + \beta_6 hh\_size_i + \beta_7 quota\_scst_j + \sum_{j=1}^{4} \theta_j edu\_dum_j \\ &\quad + \sum_{j=1}^{6} \alpha_j region\_dummy_j + \sum_{j=1}^{9} \gamma_j occup\_dummy_j. \end{aligned} \tag{4.2}$$

In our model, the occupation switch for individual i depends on three sets of controls. The first set includes individual characteristics such as age, age squared, belonging to an SC/ST group ($SCST$), and religion ($muslim$). Second, we control for household-level characteristics such as household size (hh_size_i), and his rural location ($rural_i$). Third, we allow for occupation-specific fixed effects, region-level fixed effects, and state-level SC/ST reservation quotas.

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. We compute this measure of intergenerational occupational mobility for the overall sample as well as for SC/STs and non-SC/STs separately.

Figure 12: Intergenerational occupation switches



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.

Figure 12 depicts the computed probabilities of occupation switches at the three-digit level (dotted lines plot the $\pm$ 2 std error confidence bands). As the Figure shows, 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 subgroups with the switch probabilities rising for both. 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.[22]

[22] We also estimated the occupation switch probabilities at the one-digit and two-digit levels and found that the

4.2.1 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 are switching are most likely to have parents working in which sector? 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} where i denotes the occupation of the household head and j denotes the occupation of the child. Thus, p_{ij} is the probability of a household head working in occupation i having a child working in occupation j. Clearly, high p_{ii} would reflect relatively little intergenerational occupational mobility while large p_{ij} where $i \neq j$ would indicate high mobility.

We report the results for the three broad occupation categories we defined earlier in Table 7. Each row of the Table denotes the occupation of the parent while columns indicate the occupation of the child. Thus, going across columns along any row i would indicate the probability of a household head working in occupation i to have a child working in the relevant occupation column. 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. The Table has two panels: Panel (a) gives the numbers for 1983 and Panel (b) for 2004-05.

Table 7 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.

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

Table 7: 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.

Second, the probability of the son of a farmer (working in occupation 3) switching to occupations 1 or 2 has risen for both groups. This probability is of interest to us 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% for non-SC/STs and 11% for SC/STs. By 2004-05 these numbers had risen to 23% for non-SC/STs and 21% 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.

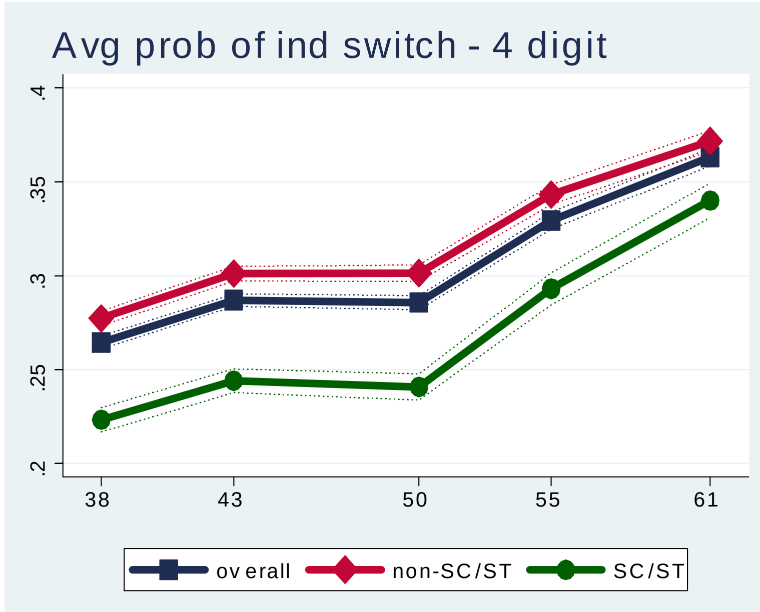
Third, the probability of a child working in occupation 3 conditional on his father being employed in occupation 1 or 2 has declined from 50% to 31% for SC/STs and from 30% to 23% for non-SC/STs over our sample period. We believe that this reflects a significant reduction in regress prospects of SC/ST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

4.3 Industry Mobility

Given the large sectoral changes in India during the period under study, an issue of independent interest is the degree of industry mobility in India between 1983 and 2004-05. We define intergenerational industry switch in the same manner as occupation switches and estimate the conditional probability of industry switches using equation (4.2).

Figure 13 presents the overall probability of industry switches at the four-digit level as well

Figure 13: Intergenerational industry switches



Notes: This figure presents the average predicted probability of intergenerational industry 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.

as the probability of switches for SC/STs and non-SC/STs (dotted lines plot the $\pm$ 2 std error confidence bands). The figure shows that the overall probability of children switching the industry of employment relative to their parent has risen from 26 percent in 1983 to 36 percent in 2004-05 period. The industry mobility trends of both SC/STs and non-SC/STs have been similar although the level of the switching probability has remained significantly higher for non-SC/STs. We also estimated the probability of industry switching at the three-, two-, and one-digit levels and found similar time-series trends, with little convergence across the two groups. As with the occupation mobility estimates, the main difference when considering more aggregated industry categories is that the probability of an industry switch is universally lower.[23]

4.3.1 Industry Transition Matrix

We now turn to the industry choices of the two groups. Using the same approach that we employed to evaluate occupation mobility, we compute industry transition probabilities and summarize them in Table 8. As with occupation transition probabilities, each row of the Table denotes the industry of the parent's employment while columns indicate the industry of the child's employment. Thus,

[23]The results for three-, two- and one-digit industry categories are available upon request.

Table 8: Intergenerational industry transition probabilities

(a). Average mobility in the 1983 round									
Non-SC/ST	To				**SC/ST**	To			
From	Ind **1**	Ind **2**	Ind **3**	size	From	Ind **1**	Ind **2**	Ind **3**	size
Ind **1**	0.87	0.04	0.09	0.67	Ind **1**	0.90	0.04	0.06	0.78
	(0.00)	(0.00)	(0.00)	(0.00)		(0.01)	(0.00)	(0.00)	(0.01)
Ind **2**	0.09	0.75	0.16	0.11	Ind **2**	0.16	0.68	0.16	0.08
	(0.01)	(0.01)	(0.01)	(0.00)		(0.02)	(0.03)	(0.02)	(0.00)
Ind **3**	0.15	0.12	0.73	0.22	Ind **3**	0.22	0.09	0.69	0.14
	(0.01)	(0.01)	(0.01)	(0.00)		(0.02)	(0.01)	(0.02)	(0.01)

(b). Average mobility in the 2004-05 round									
Non-SC/ST	To				**SC/ST**	To			
From	Ind **1**	Ind **2**	Ind **3**	size	From	Ind **1**	Ind **2**	Ind **3**	size
Ind **1**	0.77	0.05	0.18	0.60	Ind **1**	0.79	0.05	0.17	0.68
	(0.01)	(0.00)	(0.01)	(0.01)		(0.01)	(0.00)	(0.01)	(0.01)
Ind **2**	0.07	0.70	0.23	0.11	Ind **2**	0.09	0.66	0.25	0.08
	(0.01)	(0.01)	(0.01)	(0.00)		(0.02)	(0.03)	(0.03)	(0.00)
Ind **3**	0.12	0.12	0.76	0.29	Ind **3**	0.13	0.14	0.73	0.24
	(0.01)	(0.01)	(0.01)	(0.00)		(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 working in industry i having a child working in industry j. Ind 1 refers to agriculture, Ind 2 collects manufacturing and mining&quarrying, while Ind 3 refers to services. Column titled 'size' reports the fraction of parents employed in industry 1, 2, or 3 in a given survey round. Standard errors are in parenthesis.

going across columns along any row i would indicate the probability that a household-head working in industry i has a child working in the relevant industry column. Off-diagonal elements measure the degree of intergenerational industry mobility. Column "size" reports the average share of parents employed in each of the industries in a given round. Panel (a) gives the numbers for 1983 and Panel (b) for 2004-05.

Not surprisingly, Ind 1 (agriculture) has remained the primary industry of employment for both SC/STs and non-SC/STs throughout, although its share has declined significantly between 1983 and 2004-05. Ind 1 also has the highest persistence of the three industry groups. The numbers indicate that intergenerational industry persistence has decreased sharply for Ind 1. Children are switching from agriculture into other industries more frequently in 2004-05 in comparison with 1983. While most of this move is primarily into service industries, the probability of moving into manufacturing has increased, especially for SC/STs. At the same time, the probabilities of moving from Ind 2 or Ind 3 into Ind 1 have declined and more so for SC/STs. We interpret these results as evidence of upward industry mobility, especially for SC/STs.

4.4 Income Mobility

Our fourth, and probably the most typical, measure of intergenerational mobility is on income. We turn to this issue next. The goal of this exercise 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. The intergenerational elasticity 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.

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 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. Hence, our regression specification is

$$\begin{aligned} w_{ic} &= \alpha + \beta w_{ip} + \gamma_1 A_{ip} + \gamma_2 A_{ip}^2 + +\gamma_3 A_{ip}^3 + \delta_1 \tilde{A}_{ic} + \delta_2 \tilde{A}_{ic}^2 \\ &\quad + \delta_3 \tilde{A}_{ic}^3 + \theta_1 w_{ip} \tilde{A}_{ic} + \theta_2 w_{ip} \tilde{A}_{ic}^2 + \theta_3 w_{ip} \tilde{A}_{ic}^3 + \varepsilon_i \end{aligned} \tag{4.3}$$

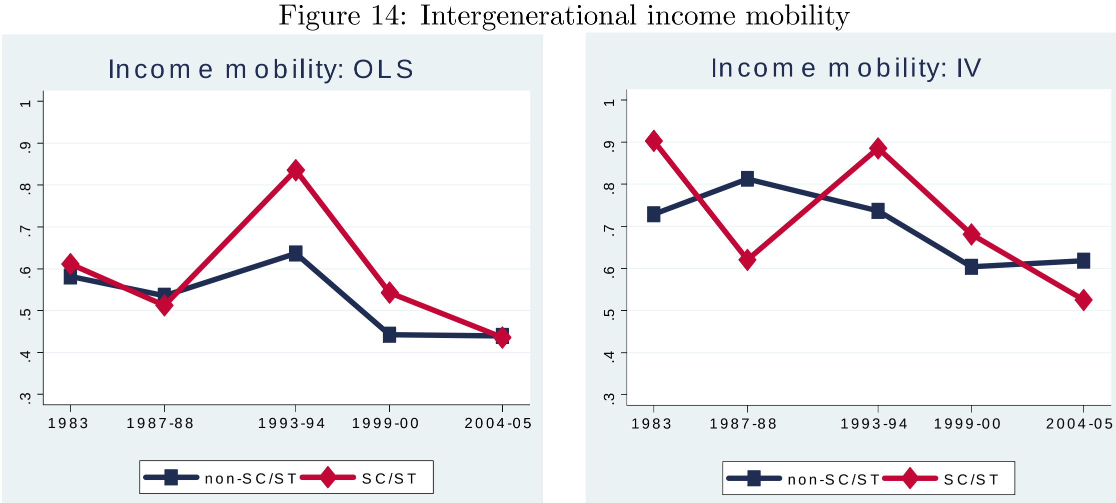
where w_{ic} denotes the log daily wage of the child of household i and w_{ip} is the log daily wage of the male head of the same household. A_{ip} denotes the head of household i's age while $\tilde{A}_{ic}$ is the child's age, which we normalized to equal zero at age 23 which is the mean age of children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

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. As pointed out in Haider and Solon (2006), the short run proxy for long run income of parents will bias the estimated β downward. However, as long as the bias is stable over time it will not alter the interpretation of how the intergenerational elasticity of income has evolved over time.

We run this regression separately for each NSS sample year. Note that the constant α picks up any sample year specific factors. The key parameter of interest is β. We estimate a different β for each NSS round and focus on how the estimated β's have changed over the sample period.

We plot the OLS estimates in panel (a) of Figure 14 below, while panel (b) of the Figure presents our estimates from an instrumental variable (IV) regression.[24] We should note that all the point estimates in both figures are significant at the 1 percent level except for the OLS estimate for 1987-88 which is significant at the 5 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 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 14: Intergenerational income mobility



(a) (b)

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 Appendix.

[24] As with the other regressions, the complete estimation results are available in supplemental tables from http://faculty.arts.ubc.ca/vhnatkovska/research.htm.

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, they confirm our findings from the OLS estimation. In fact, IV estimates suggest that SC/STs' intergenerational income persistence has declined from a whopping 0.87 to 0.45 and, by the end of our sample period, was below that for non-SC/STs.

Overall, our results suggest that there has indeed been an upward trend in the degree of intergenerational mobility in education, occupation, industry and income. However, there are significant differences in the convergence patterns of these mobility indicators for SC/STs relative to non-SC/STs. While intergenerational educational and wage mobility of the two groups have tended to converge, occupational and industry mobility rates have not converged similarly.

5 Conclusion

In this paper we have studied the evolution of occupation and industry choices, education attainment rates and wages in India between 1983 and 2004-05 with a special focus on the fortunes of scheduled castes and scheduled tribes (SC/STs). We have found that the 22-year period under study has been a period of dramatic changes for these historically disadvantaged groups. SC/STs have systematically reduced the gap with non-SC/STs in education attainment levels and have been changing occupation and industry of employment at increasingly faster rates. Moreover, the wage gap between SC/STs and non-SC/STs has narrowed sharply during this period. We have also found that the majority of the wage gap is accounted for by differences in education whose contribution has been rising over time. The caste effect on wages appears to have almost disappeared. Crucially, we find that these trends are the sharpest amongst the younger cohorts and in urban areas. The last two features are especially uplifting since they are potentially indicative of the types of changes one may expect in the future since India has been becoming increasingly urbanized and younger over time.

It is worth reiterating that SC/ST wages have been converging toward non-SC/ST levels across cohorts, education and occupation categories. Moreover, the speed of this convergence is impressive not just at an absolute level but also when compared to the wage convergence experienced by historically disadvantaged minority groups elsewhere such as Blacks and Hispanics in the USA. We find this evidence particularly reassuring in terms of the future prospects of SC/STs in India.

What explains these significant changes in the Indian social landscape? We believe that the rapid structural changes in the Indian economy over the past 25 years are at the heart of this progress. The liberalization of the previously restricted economy has opened up new opportunities for the private sector. While the increase in potential opportunities is common to all segments of the population, the more rapid response of SC/STs probably reflects a confluence of factors. One factor may be the competitive pressures that were unleashed on markets by the economic liberalization. As argued by Becker (1957), increasing competition raises the losses to businesses from pursuing discriminatory labor market practises. This reduces the degree of wage discrimination. The resultant decline in the wage gap could then also induce these disadvantaged groups to increase their education attainment rates since the returns to education rise. A second factor may be that the rapidly changing socioeconomic environment in India has presented SC/STs with a historic opportunity to break out of a centuries-old cycle of illiteracy and poverty, and they have been acting proactively to take advantage of it. A strengthening of community based networks of SC/STs along the lines suggested in Munshi (2010) may have also been at play in accelerating this process. The third possibility is that the reservations policy in place since 1950 for public sector jobs and higher education seats may have played a role in the declining wage gaps. The first two possibilities imply that caste may be becoming a less important factor in economic allocations in India while the third factor would put caste-based policies at the center of the explanation. We intend to examine these potential explanations in future work.

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A Appendix

A.1 Data Appendix

A.1.1 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 the time.

A.1.2 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. We are also interested in studying the patterns of industry employment for different social groups. We employ 5-digit National Industry Classification (NIC) – 1998 industry code that is reported for each individual over the previous year (relative to the survey year).

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.[25] We drop observations if total number of days worked in the reference week is more than seven.

To summarize, our working sample imposes the following restrictions on the data:

1) The overall sub-sample includes all households with a male head of household in the 16-65 age group with at least one other directly related male member of a younger generation (son or grandson) also in the 16-65 age group, where neither is enrolled in an educational institution, both

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

have education and occupation information and are working full-time. Within included households, we only consider the head of the household and his direct male descendants.

2) The wage sub-sample includes only those households from the overall sample for which wage data for head and at least one of his descendants are non-missing and non-zero.

The working sample is further subdivided into two generational groups – children and parents. Only household heads are considered as parents in our analysis. Any members from younger generations are considered as children (therefore it includes grandchildren).

A.1.3 Occupation and Industry 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

Table A2 summarizes one-digit industry codes in our dataset. In the presentation in the text we group these codes further into three broad industry categories: Ind 1 refers to Agriculture, Hunting, Forestry and Fishing; Ind 2 collects all tradable industries; while Ind 3 refers to all non-tradable industries. These groupings are detailed in Table A2.

A.2 Intergenerational education mobility

Table A3 presents average conditional probabilities of education improvements (panel (a)) and education reductions (panel (b)) for the overall sample and separately for non-SC/STs and SC/STs over different survey rounds. These probabilities were estimated following the procedure we used to obtain average conditional probabilities of education switches, which is described in details in the main text.

Table A2: Industry categories

Industry code	Industry description	Group
A	Agriculture, Hunting and Forestry	Ind 1
B	Fishing	Ind 1
C	Mining and Quarrying	Ind 2
D	Manufacturing	Ind 2
E	Electricity, Gas and Water Supply	Ind 3
F	Construction	Ind 3
G	Wholesale and Retail Trade; Repair of Motor Vehicles, motorcycles and personal and household goods	Ind 3
H	Hotels and Restaurants	Ind 3
I	Transport, Storage and Communications	Ind 3
J	Financial Intermediation	Ind 3
K	Real Estate, Renting and Business Activities	Ind 3
L	Public Administration and Defence; Compulsory Social Security	Ind 3
M	Education	Ind 3
N	Health and Social Work	Ind 3
O	Other Community, Social and Personal Service Activities	Ind 3
P	Private Households with Employed Persons	Ind 3
Q	Extra Territorial Organizations and Bodies	Ind 3

Table A3: Intergenerational education improvements and reductions

	(a) education improvements			**(b) education reductions**		
	overall	non-SC/STs	SC/STs	overall	non-SC/STs	SC/STs
1983	0.4557	0.4874	0.3552	0.0863	0.0915	0.0700
	(0.0008)	(0.0008)	(0.0011)	(0.0003)	(0.0003)	(0.0004)
1987-88	0.4684	0.5014	0.3676	0.0915	0.0949	0.0811
	(0.0007)	(0.0007)	(0.001)	(0.0002)	(0.0003)	(0.0004)
1993-94	0.5234	0.5449	0.4621	0.0827	0.0885	0.0664
	(0.0006)	(0.0006)	(0.0008)	(0.0002)	(0.0003)	(0.0004)
1999-00	0.5363	0.5488	0.5035	0.0900	0.0951	0.0767
	(0.0006)	(0.0007)	(0.0012)	(0.0003)	(0.0003)	(0.0004)
2004-05	0.5806	0.5779	0.5880	0.0884	0.0921	0.0785
	(0.0006)	(0.0007)	(0.0011)	(0.0003)	(0.0004)	(0.0005)

Notes: This table presents average probabilities of education improvements (Panel (a)) and education reductions (Panel (b)) for the overall sample and separately for SC/STs and non-SC/STs. These probabilities were estimated using equation (4.1), except we used a binary variable denoting education improvements or education reductions as the left-hand-side variable. Standard errors are in parenthesis.