Inequality Between and Within Skill Groups: The Curious Case of India

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Abstract

Wage inequality has risen in India over the past three decades. A similar phenomenon has been documented widely for other developing countries. However, unlike in other countries, which saw widening wage structures both between and within skill groups, I show that inequality in India increased between groups but fell within them over the period 1983-2005. Returns to education increased with the wages of college graduates rising relative to high school graduates who, in turn, earned increasingly more than less educated workers. But workers within education groups witnessed lower wage dispersion over time. Defining demographic groups more narrowly, by additionally including characteristics such as experience, gender, industry and state, among others, regression results show that inequality increased between them while simultaneously declining within them, as indicated by a compression of the residual wage inequality. Decomposition analysis attributes the decline in wage dispersion within groups to falling returns to unobservable characteristics. This, previously undocumented, divergent trend in inequality between and within skill groups in India cannot be explained by the three main arguments in the extant literature for why developing countries have witnessed a rise in wage inequality in recent decades following trade liberalization – greater imports of skill-complementary technology, offshoring, and reallocation of skilled labor towards exporting firms. I provide several pieces of suggestive evidence to argue that reduction in labor market frictions and growth in offshored tasks from developed countries that are routine in content, but performed by high-skilled workers, can lead to the divergent trends in inequality between and within groups. Compositional changes in the labor force do not account for the inequality patterns witnessed in India.

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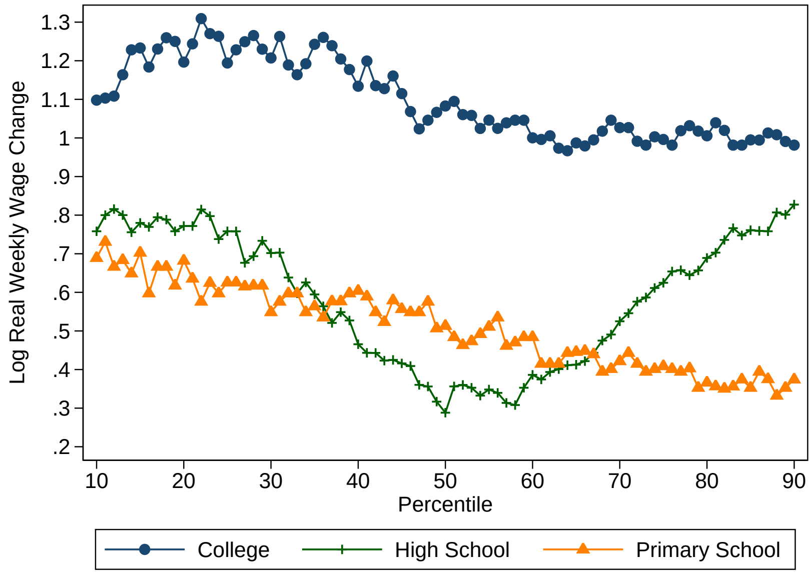

Figure 1: 1983-2005 Wage Change for Education Groups[a]

[a]The figure shows the percentile changes in log real weekly wages over 1983-2005 for three education groups. Data report the highest level of schooling attained. Primary educated and high school graduates typically have five and twelve years of schooling, respectively. The group of college graduates includes those with higher degrees. Sampling weights have been used.

1 Introduction

As in many other developing countries, wage inequality has been increasing in India over the last three decades, especially following trade liberalization in the early 1990s. Between 1983 and 2005, while workers at the 10th percentile saw their real weekly wages increase by 0.7 log points, those at the 90th percentile gained 0.94 log points in real weekly wages.[1] However, while inequality increased *between* observable skill groups, it declined *within* these groups (see Figure 1).[2] This divergent trend in between- and within-group inequality has not been seen in other developing countries and is inconsistent with previously offered explanations for the rise in inequality in these countries. In this paper, I comprehensively document the evolution of wage inequality in India. I argue that these trends may be caused by growth in offshoring of routine tasks from developed countries and reduced labor market frictions.

[1]See Figure 2.

[2]Figure 1 shows the wage gains made by workers with different education levels over the period 1983-2005. Inequality increased between education groups – college graduates gained more than high school graduates, who in turn gained more than the primary educated workers (except around the middle percentiles). However, inequality fell within these groups. College graduates who were at lower percentiles of the college wage distribution gained more than college graduates at higher percentiles. The same holds true for primary educated workers as well as for the middle educated and uneducated (not shown in the figure). For high school graduates, persons around the middle of the high school wage distribution gained less over the 23 year period than those at the two ends of the spectrum. Thus, inequality fell in the lower half of the wage distribution but increased in the upper half (similar to the wage-polarization witnessed in the U.S. since the mid-1990s).

India began deregulating its economy in the 1980s with measures such as industrial delicensing. Following a financial crisis in 1991, its trade regime was phenomenally liberalized. As liberalization and other structural reforms proceeded through the next two decades,[3] India rapidly integrated with the world economy. Using nationally representative household level data for the period 1983-2005, I show that wage inequality increased in India, especially in the post liberalization years, and especially in the upper half of the wage distribution. Defining demographic groups narrowly along several observable characteristics, I show that inequality increased between these groups. Further, relative wages of highly educated groups of workers increased despite an increase in their relative supply, indicating an increase in demand for these workers. The growing demand for skilled workers is also reflected in upgrading of the skill composition of the workforce within all two-digit industries. However, I find that inequality within these observable skill groups declined over time – as reflected in a decline in residual wage inequality. Results also show that this fall in within-group inequality is mainly driven by a decline in returns to unobservable skills.

The rising between-group wage inequality is not unique to India, and can be rationalized by two main theories offered in previous literature. One explanation is trade induced skill-biased technological change (SBTC) or "skill-biased trade" – with more open trade regimes, developing countries increase imports of modern machinery that embodies skill-biased technology, increasing the productivity and wages of skilled relative to unskilled workers.[4] Another explanation is offshoring of tasks from developed countries that are low-skill intensive from their perspective but are performed by relatively skilled workers in developing countries.[5]

However, the falling within-group inequality is unique to India, and stands opposite to the rising trend documented for other developing countries including Brazil (Helpman et al. (forthcoming), Krishna et al. (2012), and Menezes-Filho et al. (2008)), Colombia (Attanasio et al. (2004)), China (Xing and Li (2012)), and Indonesia (Lee and Wie (2013)). As I explain below, this pattern also cannot be explained by the skill-biased trade and offshoring hypotheses. It also goes against the predictions of recent work by Helpman, Itskhoki and Redding (2010a, 2010b, HIR henceforth) and Helpman et al. (forthcoming) who integrate models of firm heterogeneity with search and matching frictions to show that trade liberalization induces a reallocation of higher ability workers towards exporting firms that are more productive and pay higher wages, thereby increasing residual wage inequality among observationally equivalent workers.

Inequality within observable skill groups can exist for several reasons. It may be that workers with the same education and experience level, or other observable characteristics, differ in other valuable skills that are unobservable, such as innate ability, quality of education, etc. Or, workers within observable skill groups may, in fact, be fairly homogeneous but witness wage

[3] See Appendix A for a brief overview of these reforms.

[4] See Robbins (1996), Berman and Machin (2000), Chamarbagwala (2006), Goldberg and Pavcnik (2005), Attanasio, Goldberg and Pavcnik (2004), Mazumdar and Quispe-Agnoli (2004), Pavcnik (2002, 2003), and Burstein, Cravino, and Vogel (2013).

[5] See Feenstra and Hanson (1996) and Zhu and Trefler (2005).

dispersion due to labor market frictions. Thus, a decline in within-group inequality may be caused by (a) falling relative returns to some unobservable skills, (b) compositional changes leading to a decline in the heterogeneity among workers along these unobserved skills, and/or (c) reduction in labor market frictions.[6] I consider each of these possibilities and suggest that a decline in returns to unobservable skills and labor market frictions are plausible explanations for the divergent trends in between- and within-group inequality in India. I also show that compositional changes cannot account for the decline in residual inequality.

Consider why returns to unobservable skills may be falling. The rising between-group inequality and simultaneously falling within-group inequality suggest that while demand for some skills is increasing, it is falling for others. I propose an explanation for this puzzling trend – the routine nature of tasks offshored to India. In particular, while tasks offshored to India increase the demand for easily observable skills such as education and experience, their routine content does not require finer or soft skills, such as problem solving and teamwork, that are also not observable in the data. Thus, while the returns to easily observable skills such as education and experience increase, causing a widening of between-group inequality, the returns to finer skills fall, so that within-group inequality falls. In section 4, I discuss this argument in greater detail and provide supporting evidence.

India's labor market is also likely becoming more efficient over time as a result of substantial improvements in transportation and communication infrastructure and structural reforms. If workers within observable skill groups are fairly homogeneous, then falling wage dispersion can be a consequence of reducing labor market frictions. Thus, while offshoring and skill-biased trade increase demand for observable skills, thereby causing between-group inequality to increase, the growing efficiency of the labor markets reduces frictional wage inequality within groups. I discuss this more in section 4.

A vast literature demonstrates that most advanced countries have witnessed increasing wage inequality, both between and within groups, since the 1980s.[7] Empirical analyses in these papers show that increasing returns to observable skills, such as education and experience, have increased wage dispersion between observable skill groups. The widening residual wage dispersion is taken as evidence that returns to unobservable skills have also increased. The most prominent explanation for increasing between- and within-group inequality is SBTC, i.e., technological changes, aided by the spread of computers, have increased the productivity of skilled relative to unskilled workers, leading to a rising wage gap.

As mentioned earlier, many developing countries that liberalized their trade regimes have also experienced growing inequality.[8] This phenomenon is opposite to the prediction of the textbook Stolper-Samuelson theorem. According to the theorem, developing countries abundant in

[6]Yet another possibility is that residual wage inequality is simply because of measurement error. Then, a decline in within-group inequality may be a result of reducing measurement error.

[7]See Katz and Murphy (1993), Berman, Bound and Machin (1998), Katz (2000), Autor, Katz, and Kearney (2008), among many others.

[8]Goldberg and Pavcnik (2007) and Pavcnik (2011) provide detailed reviews.

unskilled labor export goods and services intensive in relatively unskilled labor to developed economies and import skill-intensive products. Thus, following trade, the demand for unskilled workers should increase relative to skilled workers leading to a reduction in wage inequality. Recent studies (see, among others, Robbins (1996), Tan (1999), Attanasio et al. (2004), and Berman and Machin (2000)) instead argue that as developing countries increasingly liberalize their trade regimes, they import capital equipment that embodies skill-biased technology developed in advanced countries, leading to greater demand and higher wages for skilled relative to unskilled workers. Thus, developing countries are also witnessing SBTC, albeit trade induced. However, since SBTC entails growing inequality both between and within skill groups, this explanation cannot account entirely for the patterns I document for India.[9]

Another channel by which wage inequality can increase in developing countries following trade liberalization is offshoring. Feenstra and Hanson (1996) and Zhu and Trefler (2005) present models with the premise that while developed countries offshore tasks that are less skill intensive from their perspective, they are performed by skilled workers in developing countries. Thus, both papers predict that offshoring leads to greater demand for skilled workers and higher wage inequality in developing countries. However, both models consider only two types of labor – high and low skilled, with no heterogeneity within these types. Thus, they are silent on the effect of offshoring on residual inequality. A few other channels by which trade with advanced countries can lead to skill upgrading and rising skill-premia in developing countries have also been analyzed. See, for example, Verhoogen (2008).

My finding of falling within-group inequality is also inconsistent with recent work by HIR and Helpman et al. (forthcoming), who show that in the presence of firm heterogeneity and labor market frictions, trade liberalization triggers a reallocation of workers across firms leading to greater within-group inequality.[10] The underlying mechanism is as follows. Suppose workers are ex ante identical (i.e., they have the same observable characteristics), but heterogeneous in ex post match specific ability. Since firms cannot observe this ability, they screen workers so as to improve their employee pool. Complementarities between firm productivity and workers' abilities ensure that larger, more productive firms screen more intensively and employ higher ability workers than smaller, less productive firms. They also pay higher wages since there is a higher cost of replacing higher ability workers. A large literature (see Melitz (2003), Bernard et al. (2003), Bernard et al. (1997), and Hanson and Harrison (1999)) shows that trade liberalization increases dispersion in firm revenues, and exporting firms are larger and more productive than non-exporting firms. Building on this evidence, HIR show that with trade liberalization, exporting firms become larger, employ higher ability workers and pay them higher wages. Thus, opening to trade exacerbates the wage dispersion among observationally identical workers.[11]

[9] Parro (2011) and Burstein, Cravino and Vogel (2013) develop models to formalize trade induced SBTC in developing countries, but only consider two types of labor (high and low skilled) with no heterogeneity within these types. Thus, these models highlight between- but not within-group inequality.

[10] Simultaneously, between-group inequality may rise or fall.

[11] A few other studies also reach similar conclusions. See Amiti and Davis (2012), Egger and Kreickermeier

This paper also contributes to the growing empirical literature that examines the labor market trends in India. Previous studies (see, for example, Berman, Somanathan and Tan (2006), Chamarbagwala (2006), and Topalova (2007)) have also found that the overall wage inequality and returns to education are increasing in India. The rising skill premium has been attributed by some studies to skill-biased trade (eg. Kijima (2006)). However, this opinion is contradicted by others who relate it to indigenous skill-biased technological change not influenced by trade (Berman, Somanathan and Tan (2006)), those who relate it to trade in general (Acharya (2006)), and yet others who think of it as explained by trade induced SBTC in combination with other factors like increased foreign direct investment (FDI), deregulation in general (Chamarbagwala (2006)), and capital-skill complementarities (Berman, Somanathan and Tan (2006)). Mishra and Kumar (2005), on the other hand, argue that trade, in fact, led to reduced wage inequality. However, these studies have not considered the trends in within-group inequality.

The rest of the paper is organized as follows. Section 2 provides a brief overview of the data I use for my analysis. Section 3 documents the trends in wage inequality between and within narrowly defined demographic groups. Section 4 discusses possible explanations for these trends. Section 5 concludes and discusses policy implications.

2 Data and Descriptive Statistics

My principal data source is the Employment and Unemployment schedule of the National Sample Survey (NSS) of India – a nationally representative household level survey that is conducted approximately every five years. I use data from repeated cross-sections for the years 1983, June 1987-July 1988, June 1993-July 1994, June 1999-July 2000 and June 2004-July 2005. In presenting results, I refer to these survey years as 1983, 1988, 1994, 2000 and 2005. Wages are deflated by national consumer price index available separately for urban and rural areas (1983=100) and obtained from the online database of the Reserve Bank of India (India's central bank).[12]

Following Katz and Murphy (1992), I create separate wage and employment samples. The wage sample consists of all persons between the ages of 15 and 65 years[13] who were either working or unemployed in the previous year in either a principal or subsidiary capacity[14] and were engaged in regular or casual wage employment in the reference week. Besides requiring

(2009), Felbermayr et al. (2014), Sampson (2014), and Davidson et al. (2008), among others. Also see Grossman (2013) for a review.

[12]As documented by Deaton (2008) and Deaton and Dupriez (2011), there is considerable within country variation in prices. So, instead of using the all India CPI, I use CPI separately for rural and urban areas. This is a step in the right direction. However, Deaton (2008) also shows that between 1999 and 2004-05, the CPI numbers might be understating inflation, more so in rural than in urban areas. Thus, real wages in 2004-05 may be lower in both urban and rural areas, more so in the latter, than they appear in this paper.

[13]In Appendix B.2, I examine robustness of my results when the sample is restricted to individuals aged 20-65 years. Results remain similar.

[14]Principal activity refers to the activity that a person was engaged in for the longest duration of time during the previous year. Subsidiary activity is the activity engaged in for the next longest duration of time.

individuals to be in the labor force in the previous year, I also add this latter qualifier of being gainfully employed in the reference week because the survey reports wages only for the reference week.[15] Self employed workers are excluded from this sample as there is no wage or income measure for them. By restricting my sample to people who were in the labor force in either principal or subsidiary capacity, I include only those who had some degree of continuous attachment to the labor force in the wage analysis. On the other hand, the employment sample consists of all persons between the ages of 15 and 65 years, who worked in either principal or subsidiary capacity during the previous year, or in the reference week, irrespective of whether they worked for wages or were self employed. All workers, regardless of whether or not they were self employed, are included in the employment sample to get as close a measure as possible of the aggregate labor supply in the economy in each year.

The survey asks people to report up to four different economic activities that they were involved in during the reference week. Hence, some persons in the wage and employment samples may appear more than once under different jobs. The survey also reports the amount of time (half or full day) individuals spent on the jobs they held on each day of the reference week. Using this information, I calculate the fraction of the reference week spent on each job by an individual such that these sum up to one over all jobs. I multiply these fractions with the sampling weights so that no person gets, for instance, double the weight because he/she appears twice in the dataset. This procedure also helps assign weights to different jobs held by an individual in proportion to the time spent on them in the reference week.[16]

Wage data are not top or bottom coded. To remove outliers, I drop the top and bottom 1% of the wage sample in each year.[17] Wages are reported for each wage and salaried activity engaged in during the reference week. The survey does not provide information on hours of work. Instead, as mentioned earlier, we know whether the person worked for half or full day, on each of the seven days of the reference week. Half day is recorded if the person worked one to four hours on a day and full day is recorded if the person worked five to eight hours. Since this is, at best, a rough indicator of the number of hours worked in the reference week, I do not

[15] According to the documentation of NSS data, survey (and, hence, reference) weeks are uniformly distributed through each of the four quarters of the year over which the survey is conducted. That means that all seasons are equally represented in the sample. This also makes the data comparable across years.

[16] When calculating summary statistics using the principal activity of individuals in the previous year, the time spent on various jobs in the reference week is not relevant. For these statistics, I give each job a weight equal to the inverse of the number of jobs that the person reports to have held during the reference week. This procedure ensures that all people in the wage and employment samples receive their actual sampling weights, and are not double counted. Using these weights for wage analysis yields results similar to those reported in the paper.

[17] In 1983 and 1988, about 6% and 45% of the persons in the wage sample reported zero wages. In both years, these individuals are disproportionately uneducated (about 60%), males (more than 80%), living in rural areas (around 91%), and predominantly engaged in the primary sector (nearly 55%) or as domestic helps (close to 18%). It is possible that these people are mostly agricultural labor or household servants who are on informal contracts and do not get money wages at regular intervals. In later years, individuals who reported zero wages share similar demographic characteristics. It is not clear, however, why they constitute such large proportions in 1983 and 1988 and comparatively negligible proportions (less than 2%) in later years of the survey. Thus, considerably more than a total of 2% of the sample was dropped in these two years. In Appendix B.1, I present results without dropping any outliers. Results remain close to the main results.

use it to calculate hourly wage. Instead, I use log real weekly wages as the variable of interest.

The survey reports the level of education as the highest level of education completed by an individual. Using this information, I divide all people in the sample into five education categories: uneducated (this includes individuals who are illiterate, or literate without formal schooling, or those who did not complete primary education), primary educated (typically 5 years of schooling), middle schooled (typically 8 years of schooling), high school graduates (typically 12 years of schooling), and college graduates and above (typically 15 years of education for non-technical degrees, and 16 years for technical degrees like engineering).[18] I construct dummies for the highest level of education completed.

I use age as a proxy for labor market experience. The standard measure of potential labor market experience defined as age - years of schooling - six is not suitable for these data. The reason is that a large proportion of the sample consists of uneducated persons so that the measure of potential experience results in implausibly high levels of experience for these individuals.[19] I divide individuals in the sample into five 10-year age groups – 15-15, 26-25, 36-45, 46-55, and 56-65.

Industry codes in the data follow the National Industrial Classification (1970, 1987, 1998). Following Chamarbagwala (2006), I aggregate these to eighteen uniform two-digit industries. Occupation codes follow the National Classification of Occupations, 1968. Using these codes, I group individuals into seven one-digit occupation categories.[20] Marital status is coded using three categories: never married, currently married, and widowed, divorced, or separated. I also construct dummies for gender, the state that the person resides in, whether the person lives in a rural or urban area, religion (hindu, muslim, christian, other), and the caste group (general, scheduled castes, scheduled tribes, other backward classes). Additionally, in all regressions, I control for the quarter in which the person is interviewed to control for any seasonality effects. [21]

[18] The group of college graduates also includes those with vocational and professional degrees.

[19] As a robustness check, I use a modified potential labor market experience measure where the labor market experience acquired between the ages of six and twelve is not counted and that gained between the ages of twelve and eighteen counts as half the potential experience acquired between those ages. Results using this measure are similar to those using age.

[20] In Appendix B.3, I present results with education, age groups, industry and occupation defined more narrowly. Results remain similar.

[21] My analysis abstracts from issues of labor immobility across sectors and geographic regions, the consequent labor market segmentation, and informal employment as they are not critical to the documentation of wage and employment trends in this paper. Topalova (2007) provides evidence to argue that there is considerable geographical and intersectoral labor immobility in India and that it has not reduced over time. Dutta (2005) incorporates labor market segmentation in her analysis using the regular-casual worker dichotomy. Regular workers are defined as those who are on a formal contract receiving wages at periodic intervals. Casual workers are those who do not have any regular employment but instead look for miscellaneous jobs from time to time and get paid intermittently without any formal contracts. Dutta (2005) argues that casual wage workers constitute the informal sector, regular wage workers constitute the formal sector, and that the labor market is segmented along this dimension. Although, given the the National Sample Survey design, this is the only dichotomy one can use to address the issue of segmentation, it may not be an appropriate approach. Fields (2009), summarizing the theoretical literature on segmented labor markets, says that "...for dualism to exist, different wages must be paid in different sectors to comparable workers." In the light of this statement, one cannot justifiably argue that the labor market in India is segmented between regular and casual wage workers. Systematic differences in their skills

Table 1: Demographic Composition

Demographic Group		(1) 1983	(2) 1988	(3) 1994	(4) 2000	(5) 2005
				Percentage		
Class of Worker	Self Employed	32.87	38.19	28.97	28.77	30.20
	Wage Workers	41.70	43.08	43.76	46.49	42.15
Education	No School	68.44	66.39	61.57	55.75	50.31
	Primary School	12.72	12.85	11.90	11.69	13.84
	Middle School	9.30	9.38	11.39	13.69	15.39
	High School	6.92	8.22	10.83	13.32	13.16
	College and above	2.55	3.13	4.28	5.47	7.27
Age Group	15-25	31.45	30.09	28.23	26.01	25.19
	26-35	27.67	28.49	28.93	29.54	28.57
	36-45	20.41	20.78	21.52	23.35	24.19
	46-55	13.60	13.74	14.06	14.00	14.65
	56-65	6.87	6.89	7.26	7.11	7.40
Gender	Male	66.02	67.05	67.19	68.32	66.63
	Female	33.98	32.95	32.81	31.68	33.37
Location	Rural	79.98	80.86	79.02	78.08	77.57
	Urban	20.02	19.14	20.98	21.92	22.43

Notes: All numbers are weighted percentages of the employment sample. Sampling weights have been used. Class of worker is identified on the basis of principal activity in the previous year. Percentages for class of worker do not sum to 100 in each year. The remaining sample is constituted by unpaid family workers, those unemployed or who did not work due to sickness or other reason for most but not all of the year. Education percentages do not sum to 100 due to missing data.

In the final employment sample, there are 1,554,828 observations. These represent the total number of activities during the reference week reported by all individuals included in the sample across all years. Of these individuals, 49% report a single activity and another 47% report two activities. Note that all of these activities may not necessarily be wage-paying. In the final wage sample, there are 441,110 observations, which represent the total number of wage-paying jobs held by all individuals in the reference week across all years. About 75% of this sample is constituted by individuals who report a single job during the reference week, and another 24%

may well be the reason why they find regular or casual wage jobs in the first place. Data show that casual and regular workers are systematically different in their educational and other demographic characteristics. Casual workers are overwhelmingly rural, uneducated males engaged in the primary sector. In contrast, regular workers are predominantly urban males with high school and college degrees, with a majority being employed in services. According to my estimates, on average, casual workers earn around twenty percent less than regular workers, controlling for observable skills and other demographic characteristics.

Table 2: Industrial and Occupational Composition

		Year				
		(1)	(2)	(3)	(4)	(5)
		1983	1988	1994	2000	2005
				Percentage		
Industry	Agriculture, Forestry and Fishing	58.38	57.37	55.15	54.55	50.36
	Mining, Construction and Utlities	3.25	4.81	4.24	5.22	6.48
	Manufacturing	9.94	10.21	9.57	9.91	10.74
	Services	17.66	18.47	20.03	22.22	22.98
Occupation	Professional, Technical and Related	2.82	2.83	3.14	3.46	3.62
	Administrative, Executive and Managerial	1.07	1.42	1.81	2.78	3.18
	Clerical and Related	2.83	2.92	2.97	3.08	2.64
	Sales	5.40	5.92	6.30	6.30	7.38
	Service	3.58	3.43	3.17	3.74	3.82
	Farmers, Hunters and Related	58.29	56.41	55.29	53.55	50.10
	Production and Related	15.20	16.43	16.41	18.21	19.57

Notes: All numbers are weighted percentages of the employment sample. Sampling weights have been used. Industry and occupation are identified on the basis of principal activity in the previous year. Percentages do not sum to 100 for each year due to missing data.

by individuals who held two jobs.

Tables 1, 2, and 3 present descriptive statistics. Table 1 shows the demographic composition of the employment sample for all years of the survey. In terms of the primary activity that individuals reported for the previous year, 32.9% were self employed and 41.7% worked for wages in 1983. Over the years, these proportions stayed stable. By 2005, the percentage of self employed fell slightly to 30.2% while that of wage workers barely increased to 42.2%. Looking at the educational composition of the sample, we see clear evidence of increasing schooling attainment over time. While in 1983, 68.4% of the sample had no formal education, this percentage fell to 50.3%. The proportion of workers with a high school degree increased from 6.9% to 13.2%, and that of college graduates increased from just 2.6% to 7.3%. We also see a steady decline over time in the proportion of individuals in the 15-25 years age group in the employment sample, presumably because people stay in school longer. In all years, the proportion of males in the workforce is twice as much as that of females. The rural/urban composition of the employment sample also stayed stable.

Table 2 reports the broad sectors and occupations that individuals were principally employed in during the previous year. We see that between 1983 and 2005, the workforce in agriculture declined by eight percentage points, and most of this decline was absorbed by services and mining, construction, and utilities. The occupational composition remained quite stable with professional and technical, clerical, and service (for example, janitors) worker shares holding steady, and the share of administrative, executive and managerial jobs increasing by two

Table 3: Educational Composition by Class of Worker, Industry and Occupation

			Education				
			(1)	(2)	(3)	(4)	(5)
Demographic Group		Year	No School	Primary School	Middle School	High School	College & Above
					Percentage		
Class of Worker	Self Employed	1983	65.04	15.72	11.42	6.21	1.55
		2005	44.89	15.11	17.01	15.77	7.19
	Wage Workers	1983	67.60	11.30	8.05	8.70	4.29
		2005	50.80	13.33	14.25	11.70	9.88
Industry	Agriculture, Forestry and Fishing	1983	79.30	10.99	6.68	2.63	0.35
		2005	62.42	13.58	13.52	8.67	1.77
	Mining, Construction and Utlities	1983	63.84	15.27	10.47	7.53	2.84
		2005	49.77	17.14	18.41	9.94	4.74
	Manufacturing	1983	53.58	19.90	13.65	9.90	2.89
		2005	37.04	18.03	20.26	15.95	8.71
	Service	1983	38.04	15.41	15.90	20.17	10.39
		2005	25.37	12.29	17.62	23.64	21.05
Occupation	Professional, Technical and Related	1983	7.59	5.68	11.93	40.99	33.74
		2005	3.87	2.86	5.38	23.27	64.60
	Administrative, Executive and Managerial	1983	24.90	14.76	15.02	24.80	20.48
		2005	18.36	11.53	16.27	24.88	28.96
	Clerical and Related	1983	10.17	8.95	17.07	41.11	22.58
		2005	5.01	5.63	13.39	36.16	39.71
	Sales	1983	43.35	19.51	18.31	14.38	4.36
		2005	26.80	14.43	20.50	26.19	12.06
	Service	1983	62.26	17.12	12.10	7.28	1.15
		2005	46.55	15.99	18.26	15.46	3.71
	Farmers, Hunters and Related	1983	79.25	10.97	6.70	2.67	0.35
		2005	62.48	13.60	13.51	8.64	1.73
	Production and Related	1983	58.34	19.54	13.73	7.51	0.80
		2005	43.09	18.28	21.17	13.66	3.79

Notes: All numbers are weighted percentages of the employment sample. Sampling weights have been used. Class of workers, industry and occupation are identified on the basis of principal activity in the previous year. Percentages do not sum to 100 for each year due to missing data.

percentage points. Production occupations (factory workers) increased from 15.2% to 19.6% while farming and related occupations fell from 58.3% to 50.1%.

Table 3 further documents the educational composition of these demographic groups. In 1983, while wage workers tended to be slightly more educated than the self employed, by 2005, about 23% of workers in both groups had at least a high school degree. All sectors witnessed educational upgrading. In particular, the percentage of manufacturing workforce with a college degree increased from 2.9% to 8.7%, and that with a high school diploma increased from 9.9% to 16%. Services saw a doubling of their college-educated workforce from 10.4% to 21.1%. Similar educational upgrading is evident in all occupation groups. As one would expect, professional and technical occupations employ the most skilled workforce, followed by clerical jobs and administrative and managerial positions. Professional and technical workers also saw the most significant rise in their educational composition – while 41% of these workers had a high school degree in 1983, this percentage fell to 23.3% by 2005. Instead, the proportion of those with a college degree doubled from 33.7% to 64.6%. The next largest increase in college-educated workers occurred in clerical occupations, followed by administrative, executive and managerial positions. However, sales, service, production, and farming, all saw increases in the educational attainment.

3 Wage and Employment Trends

We are now ready to document the evolution of wages and employment of various skill and demographic groups in India.

3.1 Overall Inequality

First, let us consider the evolution of overall wage inequality over the sample period. Figure 2 shows that overall inequality increased in India over the entire sample period, although workers at all percentiles of the wage distribution gained in real terms. Panel A traces the average real weekly wages of people at the ninetieth, fiftieth and tenth percentiles of the wage distribution in each year. It shows that inequality increased the most in the upper half of the real weekly wage distribution. For workers at the 90th percentile, while their real weekly wage stood at nearly Rs. 150 in 1983, it more than doubled to about Rs. 320 by 2005. The 50th and 10th percentile workers also gained in real terms over the period, but their gains were much smaller compared to workers at the 90th percentile. Panel B shows the change in log real weekly wages between 1983 and 2005 for the 10th to 90th percentiles of the log real weekly wage distributions. Workers beyond the 80th percentile increasingly gained much more than workers at the lower percentiles. As a result, inequality increased between the 50th and 90th percentiles, although, it fell between the 50th and the 80th. Looking at the lower half of the wage distribution, we see that inequality fell between the 10th and 50th percentiles. However, the latter is mainly because workers at the lowest percentiles gained more than those at subsequent percentiles.

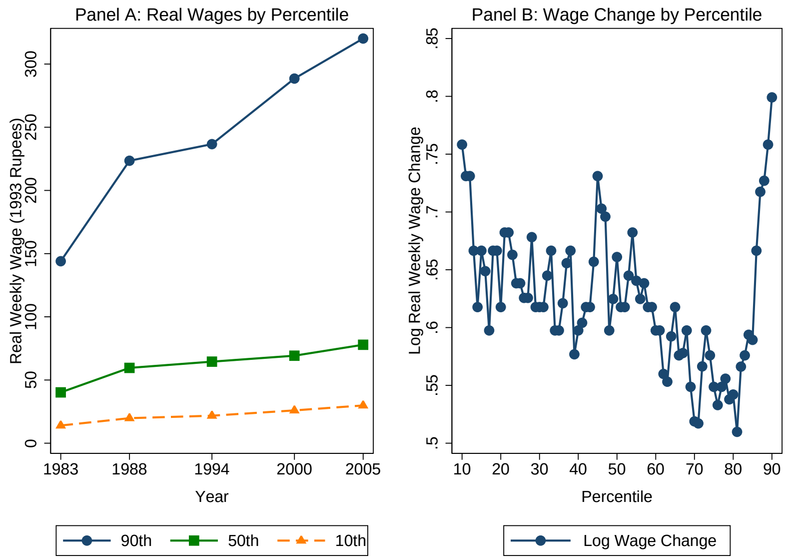

Figure 2: Overall Inequality Over 1983-2005[a]

[a]Panel A shows real weekly wages at the 10th, 50th, and 90th percentiles of the wage distribution in each year. Panel B shows changes in log real weekly wages over 1983-2005 for tenth to ninetieth percentile ranks. Sampling weights have been used.

Overall inequality can be decomposed into inequality between various demographic or skill groups and inequality within them. Consider the regression: $Y_{it} = X_{it}\beta_t + \epsilon_{it}$. Here, Y_{it} refers to the natural logarithm of the real weekly wage of person i in year t. The vector of regressors, X_{it}, includes education dummies, indicators for ten-year age groups, interactions of education and age groups, and dummies for gender, marital status, urban residence, state of residence, religion, caste groups, and quarter of interview. In another specification, I additionally include controls for industry and occupation. Estimating separate regressions for each year allows the coefficients on all variables to vary over time. The residuals are captured in ϵ_{it}. The distribution of Y_{it} reflects the overall inequality in the economy in year t. The distribution of $X_{it}\beta_t$ gives us a measure of between-group inequality where various groups are identified by the included regressors. Then, the distribution of the residuals from the estimated regression equation can be interpreted as a measure of inequality within groups, i.e., inequality due to differences in unobservable characteristics and returns to them. Following this regression approach, I now present results for between- and within-group inequality.

3.2 Between Group Inequality

Table 4 present regression results. Columns (1)-(5) show estimates of the main education and age effects, as well as wage premiums to gender and urban location, obtained from yearly regressions of log real weekly wages on education groups, age groups, interactions of education

Table 4: Yearly Log Wage Regressions

Regressors	(1) 1983	(2) 1988	(3) 1994	(4) 2000	(5) 2005	(6) 1983	(7) 1988	(8) 1994	(9) 2000	(10) 2005
	Dependent Variable: Log Real Weekly Wages									
Primary School	0.080***	0.033	0.038***	0.030**	0.006	0.022*	-0.000	-0.003	-0.015	-0.030**
	(0.013)	(0.022)	(0.015)	(0.015)	(0.015)	(0.013)	(0.021)	(0.015)	(0.015)	(0.015)
Middle School	0.115***	0.068**	0.102***	0.054***	0.065***	0.011	0.001	0.013	-0.025*	-0.000
	(0.017)	(0.027)	(0.015)	(0.014)	(0.014)	(0.016)	(0.026)	(0.015)	(0.014)	(0.014)
High School	0.427***	0.424***	0.318***	0.245***	0.173***	0.233***	0.276***	0.121***	0.068***	0.004
	(0.022)	(0.026)	(0.020)	(0.018)	(0.018)	(0.021)	(0.025)	(0.018)	(0.017)	(0.018)
College	0.814***	0.850***	0.911***	0.681***	0.673***	0.566***	0.635***	0.500***	0.294***	0.264***
	(0.031)	(0.034)	(0.048)	(0.041)	(0.034)	(0.032)	(0.035)	(0.043)	(0.042)	(0.032)
Ages 26-35	0.035***	0.074***	0.061***	0.048***	0.021*	0.029***	0.059***	0.051***	0.040***	0.033***
	(0.009)	(0.014)	(0.010)	(0.010)	(0.012)	(0.009)	(0.014)	(0.010)	(0.010)	(0.012)
Ages 36-45	0.070***	0.115***	0.101***	0.071***	0.035***	0.059***	0.089***	0.087***	0.059***	0.046***
	(0.010)	(0.016)	(0.011)	(0.011)	(0.012)	(0.010)	(0.015)	(0.011)	(0.011)	(0.012)
Ages 46-55	0.037***	0.090***	0.064***	0.059***	0.022	0.035***	0.079***	0.057***	0.060***	0.037***
	(0.012)	(0.020)	(0.013)	(0.012)	(0.015)	(0.012)	(0.019)	(0.012)	(0.012)	(0.014)
Ages 56-65	-0.049***	-0.019	-0.034**	0.004	-0.072***	-0.051***	-0.027	-0.016	0.005	-0.037**
	(0.017)	(0.028)	(0.017)	(0.017)	(0.019)	(0.017)	(0.027)	(0.017)	(0.016)	(0.018)
Male	0.454***	0.568***	0.459***	0.435***	0.464***	0.430***	0.511***	0.423***	0.400***	0.435***
	(0.007)	(0.011)	(0.007)	(0.008)	(0.008)	(0.007)	(0.011)	(0.007)	(0.007)	(0.007)
Urban	0.425***	0.227***	0.336***	0.307***	0.247***	0.266***	0.082***	0.154***	0.121***	0.058***
	(0.007)	(0.011)	(0.007)	(0.008)	(0.008)	(0.008)	(0.012)	(0.008)	(0.010)	(0.008)
Constant	3.792***	3.698***	3.693***	4.250***	3.896***	3.848***	3.773***	3.938***	4.544***	4.308***
	(0.165)	(0.051)	(0.109)	(0.044)	(0.411)	(0.165)	(0.063)	(0.152)	(0.052)	(0.675)
Education Group*Age Group	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry						Yes	Yes	Yes	Yes	Yes
Occupation						Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Caste	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Religion	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Marital Status	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	104,570	65,864	84,923	99,009	86,393	103,965	65,494	83,688	96,486	85,880
R-squared	0.423	0.467	0.468	0.476	0.522	0.456	0.494	0.513	0.528	0.581

*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Omitted education group is workers with no formal schooling. Omitted age group is 15-25 years. Sampling weights have been used.

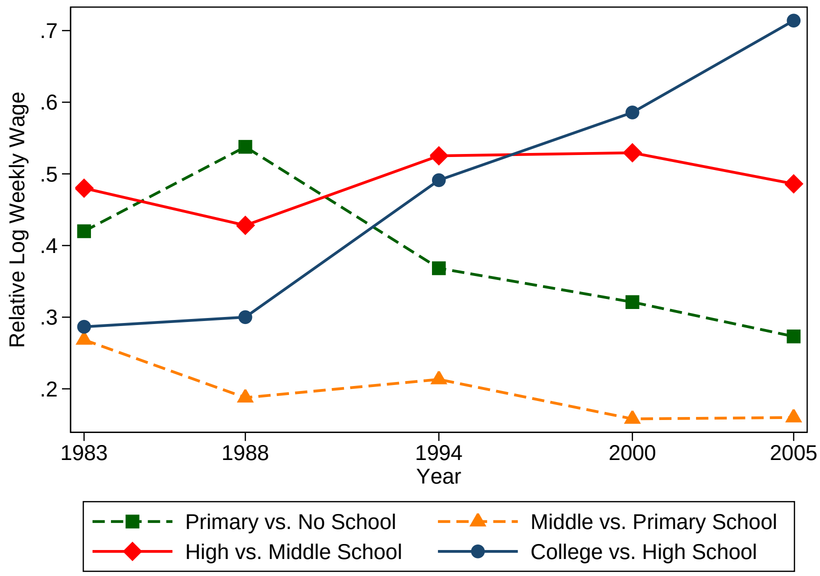

Figure 3: Returns to Education[a]

[a]The figure shows wage gaps between education groups over 1983-2005, as predicted from yearly regressions of log wages on dummies for education groups, age groups, interactions of age and education groups, and controls for state of residence, rural or urban area, gender, marital status, caste, religion, and quarter of interview. Sampling weights have been used.

and age groups, and controls for state of residence, urban or rural area, gender, marital status, caste, religion, and quarter of interview.

Using this specification, the main effects for education dummies show that in each year workers with higher education levels earn substantially more relative to those with lower education levels. Hypothesis tests show that in all years, wages of college relative to high school graduates, high school graduates relative to those who completed middle school, and middle school educated relative to primary educated were significantly higher at the 1% level. Moreover, wage inequality increased between higher education groups over the years. While the table does not show coefficients on the interactions between education and experience and other controls, I plot relative returns to education across years as predicted from these regressions in Figure 3. The figure shows that returns to college education relative to a high school degree grew sharply over the sample period from 0.3 log points to over 0.7 log points. While college premium over high school education was less than the returns to high school education relative to middle school education between 1983 and 1994, it was more than the latter in 2000 and 2005. Wage returns to high school graduates grew relative to those who completed middle school between 1983 and 1994, but declined slightly thereafter. Returns to middle school education relative to primary education and of primary education relative to no schooling fell over the 23-year period. Although not presented in Figure 3, the group of workers with at least a high school degree (i.e., college and high school graduates combined) witnessed steadily rising premiums

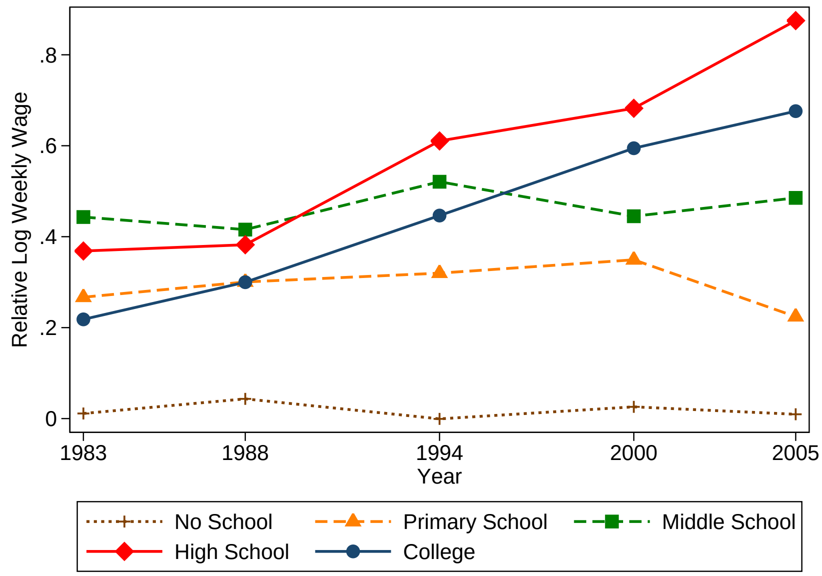

Figure 4: Returns to Experience by Education Levels[a]

[a]The figure shows wage gaps between workers in the age groups 46-55 and 26-35 years over 1983-2005, as predicted from yearly regressions of log wages on dummies for education groups, age groups, interactions of age and education groups, and controls for state of residence, rural or urban area, gender, marital status, caste, religion and quarter of interview. Sampling weights have been used.

over those who did not complete high school.

Looking at experience, results show that older workers also earn higher returns than younger workers in each year, although this advantage disappears for the oldest workers in the sample, i.e., those in the 56-65 age group. Hypothesis tests show that in all years, wages of workers aged 26-35 years relative to those aged 15-25 years, 36-45 years old relative to 26-35 years old, and 46-55 years old relative to 36-45 years old were significantly higher at the 1% level. Over time, inequality also increased between experience groups with the same education levels. Figure 4 presents relative wages of workers aged 46-55 years relative to younger workers between the ages of 26 and 35, separately for each education level. These are estimated using the regressions in columns (1)-(5) of Table 4. Relative wages of older workers were higher among high school graduates than among college graduates, but rapidly grew for both education groups. Returns to age increased by a small amount among middle school educated, grew but then declined for the primary educated, and stayed roughly constant for those with no formal schooling.

Columns (6)-(10) of Table 4 present estimates from regressions that additionally add controls for industry and occupation that the individual was employed in during the reference week. I present results with and without occupation controls, in particular, because occupations may essentially be titles for wages. (See Lemieux (2011).) Nonetheless, since regression estimates in Table 4 are not causal, including occupational dummies provides useful information about the evolution of returns to occupations over time, intra-occupation inequality, and whether changes

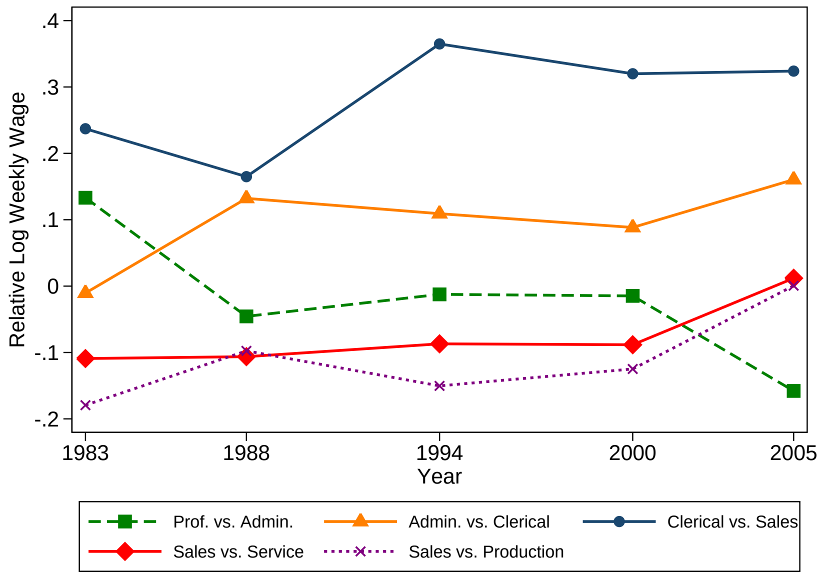

Figure 5: Returns to Occupation[a]

[a]The figure shows wage gaps between workers in different occupations over 1983-2005, as predicted from yearly regressions of log wages on dummies for education groups, age groups, interactions of age and education groups, industry, occupation, and controls for state of residence, rural or urban area, gender, marital status, caste, religion and quarter of interview. Sampling weights have been used.

in relative returns to occupations contribute to the evolution of between-group inequality. As expected, the main effects for education and age groups are quantitatively smaller than those from the first specification, but remain highly statistically significant, except for lower education groups.

Inequality between several occupation groups increased over the years. Figure 5 plots relative returns to occupations as estimated from regressions in columns (6)-(10) in Table 4. We see that the wage gap between clerical and sales workers was the highest in all years and increased by about 0.1 log points. The gap between administrative, executive, and managerial workers and clerical workers also increased by nearly 0.2 log points over 1983-2005. While in 1983, professional and technical workers earned more than administrative and managerial workers, this relationship was reversed by 2005. Wage gaps between sales and service workers, and between sales and production workers closed over the years.

In both specifications, the male-female wage gap fluctuates with no significant upward or downward trend. The wage premium of urban areas declined from 0.4 log points to 0.3 log points in the first specification and from 0.3 log points to 0.1 log points in the second specification.

Variance decomposition shows that changes in returns to education and education composition of the labor force are the most important factors driving the growth in inequality. I decompose the change in the variance of the log real weekly wage distribution between 1983 and 2005 into changes in variances of observable quantities (keeping prices constant at their mean levels over the sample period) and changes in variances of estimated coefficients (keeping quantities constant). The variance of log real weekly wages increased by 0.11 between 1983 and 2005. Decomposing this into variances of quantities and prices, I find that the largest contribution to this change in dispersion came from the change in the variance of returns to education (0.095). The distribution of education levels across the sample was the next largest contributor (0.06). Dispersion in returns to age also increased, contributing 0.029 points to the overall inequality growth.

In Appendix B.3, I present results with education, age groups, industry and occupation defined more narrowly. In particular, individuals are classified into seven education groups – not literate, literate without formal schooling, literate but below primary education (these are combined into the category of "no school" in the results presented above), primary school, middle school, high school, and college and above. This is the narrowest classification of education levels that can be uniformly identified across all years of the survey. Individuals are classified into five-year age groups. I also define industry and occupation of employment more narrowly. In particular, I classify workers into 45 two-digit industries. This is the narrowest two-digit industry classification that can be uniformly used across all survey years. Finally, I classify workers into 100 two-digit occupational categories. Columns (1)-(5) of Appendix Table B.5 present the main education and age coefficients estimated from regressions of log real weekly wages on education, five-year age groups, interactions of education with ten-year age groups,[22] state of residence, rural or urban location, and additional controls for gender, marital status, caste, religion, and quarter of interview. Columns (6)-(10) additionally include controls for industry and occupation. For both specifications, we see that workers with higher education levels earn large and statistically significant returns relative to those with lower education levels. Similarly higher age groups also earn significantly large wage premiums.

3.3 Employment

Section 3.2 shows that over 1983-2005 inequality increased between various skill groups. Before analyzing within-group inequality, I show that the growth in returns to education occurred despite a significant increase in the supply of higher educated workers – a finding consistent with the previously offered explanations of skill-biased trade and offshored tasks being performed by skilled workers. Table 1 showed substantial educational upgrading of the labor force between 1983 and 2005. Further, both males and females acquired higher education levels. Figure 6 shows trends in the labor supply of all education groups separately by gender.[23] It is evident that for both males and females, the proportion of middle, high school, and college educated workers consistently increased over the sample period. The share of the male labor force constituted by college graduates increased from about 3% in 1983 to nearly 10% in 2005. For

[22]Including interactions of education groups with five-year age groups yields large standard errors.

[23]Women have always constituted a very small fraction of the labor force in India. However, their participation in the labor market increased over the sample period.

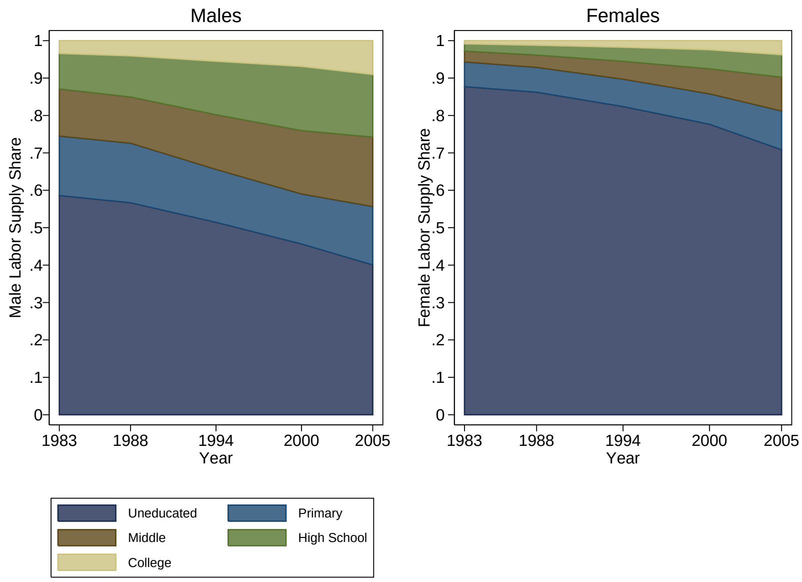

Figure 6: Educational Composition of Labor Force[a]

[a]The figure shows proportions of male and female labor force constituted by various education groups. The figure is based on the employment sample. Sampling weights have been used.

females, college graduates grew from 1% of the female labor force to about 5%. The supply of uneducated workers fell substantially over the 23-year period, although the vast majority of both men and women in the labor force remained uneducated.

The fact that the relative wages of more highly educated workers grew even as their supply increased indicates increased demand for such workers. Indeed, the equilibrium levels of employment of high school and college educated workers increased over time. Furthermore, this occurred disproportionately within two digit industries rather than through movements of workers between them.[24] Table 5 decomposes the overall shift in employment of workers in different education groups into shares caused by shifts between and within two digit industries. The table shows that between 1983 and 2005, the employment of uneducated workers fell by 17.39% while that of primary educated workers increased slightly. Employment of middle school, high school, and college educated workers increased by 5.8, 6, and 4.8 percent, respectively. Except for primary educated workers (for whom employment shifts both within and between industries were small and similar in magnitude), these shifts were driven overwhelmingly by shifts within two digit industries. For example, the employment share of college graduates increased 4.76 points between 1983 and 2005, out of which only 0.36 was due to between industry shifts and 4.40 was due to within industry shifts.

Similar trends in wage inequality, returns to education and experience, and employment

[24]According to Berman, Somanathan and Tan (2006), the increased employment of higher educated groups of workers in the manufacturing sector was overwhelmingly due to increased employment within even 3 digit manufacturing industries.

Table 5: Industry Based Employment Shift Indices: 1983-2005

Education group	Employment Shares in 1983	Overall Shift	Between Industry Shift	Within Industry Shift
No School	66.64	-17.39	-2.06	-15.33
Primary School	13.15	0.86	0.50	0.36
Middle School	9.78	5.79	0.57	5.22
High School	7.55	5.99	0.64	5.35
College	2.89	4.76	0.36	4.40

are also documented in two other studies for India (see, Berman, Somanathan and Tan (2006) and Chamarbagwala (2006)). However, these studies did not consider the evolution of residual inequality, which I examine next.

3.4 Within Group Inequality

Figure 1, presented in the introduction, showed that while inequality increased between various education groups, it fell within them. Results in section 3.2 further showed that even after controlling for several demographic characteristics, inequality grew between education groups, between experience groups, and between occupations. Next, I analyze the evolution of inequality within groups. As explained earlier, the distribution of residuals obtained from a regression is a measure of within-group inequality, where the "group" is defined by all the demographic characteristics that are included as regressors. The difference between the raw wage distribution and the residual wage distribution gives us a measure of inequality between groups.

Panels A, B, and C of Figure 7 plot the difference in the 90th and 10th, 90th and 50th, and 50th and 10th percentiles of the raw and residual wage distributions of each year. These residuals are obtained from year-wise regressions presented in columns (1)-(5) in Table 4. The vertical gaps between the the raw and residual wage differentials yield measures of between group inequality. In all three panels, we see that between-group inequality increased. Between 1983 and 2005, the 90-10 wage dispersion between groups increased by 0.16 log points, the 90-50 differential increased by 0.12 log points, and the 50-10 differential increased by 0.04 log points. Thus, between-group inequality increased mainly in the upper half of the wage distribution. On the other hand, the 90-10 wage dispersion within groups fell by 0.12 log points, from 1.63 to 1.51. This decline is driven mainly by compression in the lower half of the distribution, where it fell from 0.95 log points to 0.81 log points. The large decline in the 50-10 within-group inequality more than offset the rise in the corresponding between-group inequality, so that overall 50-10 wage dispersion fell over the sample period.

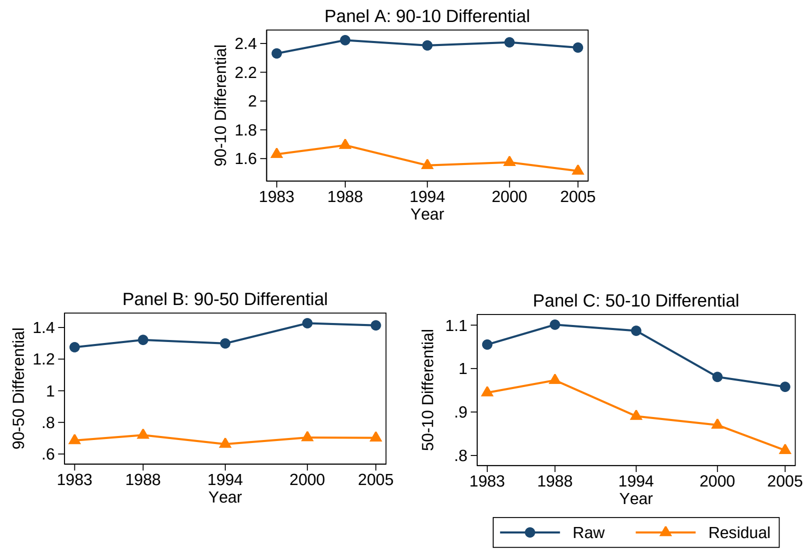

Figure 7: Raw and Residual Wage Inequality[a]

[a]The figure shows the 90-10, 90-50, and 50-10 percentile differences in log real wages and residual wages obtained from yearly regressions of log wages on education categories, 10-year age groups, interactions of education and experience groups, state of residence, rural or urban area of residence, gender, marital status, caste, religion, and quarter of interview.

Similar inequality trends are obtained from estimates of the second specification (columns (6)-(10) of Table 4), which additionally controls for industry and occupation. The 90-10 between-group inequality increased from 0.76 in 1983 to 0.94 in 2005, while the corresponding within-group differential fell from 1.57 to 1.43. Wage dispersion between groups increased by 0.13 points in the upper half of the distribution and by 0.05 points in the lower half. Dispersion within groups again stayed stable at 0.64 in the upper half of the dispersion, and fell by 0.15 points in the lower half.

Next, I follow Lemieux (2003) to decompose changes in overall inequality into components attributable to changes in observable quantities (included regressors), observable prices (estimated coefficients on the included regressors) and unobservable prices (returns to unobservable characteristics). The unexplained remainder is a combination of unobservable quantities, measurement error and noise. Table 6 presents these decomposition results for changes in 90-10, 90-50, and 50-10 percentile differences in overall inequality. Results presented in Panel A are from regressions for years 1983 and 2005 of log real weekly wages on a vector of education categories, 10-year age groups, interactions of education and age groups, state of residence, whether the individual lives in a rural or urban area, gender, caste, religion, marital status, and a control for the quarter in which the individual was interviewed. Results in Panel B additionally control for industries and occupations that the individual was employed in during the reference week. In both panels, we see that changes in observable quantities led to an increase in the overall

Table 6: Decomposition of Changes in Overall Inequality
1983 - 2005

Differential	Total Change	Observed Quantities	Observed Prices	Unobserved Prices	Unexplained
			Panel A		
90-10	0.041	0.159	-0.022	-0.238	0.143
90-50	0.138	0.118	0.051	-0.080	0.050
50-10	-0.097	0.041	-0.073	-0.158	0.093
			Panel B		
90-10	0.041	0.097	0.048	-0.218	0.114
90-50	0.138	0.053	0.114	-0.085	0.056
50-10	-0.097	0.044	-0.066	-0.133	0.057

90-10 wage differential. While observable prices decreased this differential by a small amount in Panel A, they increase it slightly when industry and occupation are controlled for in Panel B.[25] The main dampening effect on this inequality measure, however, was caused by a decline in unobservable prices. In both panels, they reduced the 90-10 differential by 0.2 log points. Thus, returns to unobservable skills declined over this time period, leading to a compression of wage inequality.

The results for the 90-10 differential mask the somewhat different patterns in the upper and lower halves of the wage distribution. We see that while changes in observable quantities contributed to exacerbating both the 90-50 and 50-10 differentials, observable prices contributed to increasing only the 90-50 differential. For both halves of the distribution, however, changes in unobservable prices reduced the overall inequality. Thus, results in Table 6 reinforce the finding that while between-group inequality increased in India, within-group inequality fell at the same time.

Appendix Table B.6 presents decomposition results for demographic groups defined more narrowly along education, age, industry, and occupation, as described earlier. Panel A presents results using regressions without industry and occupation controls and Panel B presents results using regressions that do include them. Results are close to those in Table 6. Inequality increases even between these narrowly defined groups and falls within them. The increase in between-group inequality is driven by changes in observable quantities and the decline in within-group inequality is driven by a decline in unobservable prices.

[25] Using another decomposition approach proposed by Juhn, Murphy, and Pierce (1993) and the same regressions as in Panel B of Table 6, I decompose the total contribution of observable quantities to overall 90-10 inequality growth into those coming from individual quantities. Results from this analysis show that education is the biggest contributing factor, followed by age. More specifically, this decomposition shows that changes in observable quantities increased the overall 90-10 wage inequality by 0.173 points. Of this, 37% (0.064) was due to education, 24.3% (0.042) was because of age composition, and the two jointly (main effects plus interactions) contributed 67% (0.117).

4 Potential Explanations for Declining Within Group Inequality

The evidence presented in the previous section establishes that although the wage gap between observable skill or demographic groups in India is widening, it is shrinking within them. This divergent trend in between- and within-group inequality stands in contrast to other developing countries that have witnessed rising inequality both between and within groups. As explained in the introduction, this can also not be rationalized by previously offered explanations for growing wage inequality in these countries – skill-biased trade, offshored tasks being performed by skilled workers, and reallocation of more able workers towards exporting firms. Thus, we need to think of other potential causes for rising between-group inequality accompanied by falling within-group inequality.

Inequality within observable skill groups may decline due to one or more of the following possibilities. (1) Compositional changes: Workers within groups are heterogeneous in unobservable skills that are valuable in the labor market, but over time this heterogeneity falls. (2) Decline in returns to unobservable skills: Workers within groups are heterogeneous in unobservable skills, with higher levels of these skills fetching higher returns, but over time the relative returns to these skills fall. (3) Smaller frictions in labor markets: Workers within groups are homogeneous in unobservable skills but get different wages due to labor market frictions. In this case, a decline in frictions over time reduces the wage dispersion among otherwise identical workers.

Below, I consider each of these possibilities and discuss whether they can potentially account for the divergent movements in between- and within-group inequality in India.

4.1 Compositional Changes

If workers are heterogeneous along dimensions that we cannot observe in the data, then a decrease in this heterogeneity could contribute to falling within-group inequality even as between-group inequality increases in response to rising demand for observable skills. However, I provide arguments based on previous literature and evidence from data suggesting that such a decline in unobservable heterogeneity is unlikely to be driving the inequality patterns we see in India.

First, from previous literature, we know that wage dispersion is higher among more educated workers (see Lemieux (2003, 2006) and Flinn and Mullins (2015)). According to the standard human capital accumulation function (see, for example, Heckman, Lochner and Taber (1998)), the underlying reason for this is greater heterogeneity in unobservable skills among more educated labor. For example, higher educated workers invest more in on-the-job training, which if unobservable, increases inequality among these workers. In a recent paper, Bonfiglioli and Gancia (2015) show that higher wage dispersion among more educated groups can result from a complementarity between innate ability and effort. In this case, acquiring more education would increase the dispersion in innate ability or talent. As shown in Table 1 and Figure 6, India's labor force has become more educated over time. If the predictions of this literature applied in India, then it would mean that workers within higher education groups become more, not less, heterogeneous in their unobservable talent. This compositional change will lead to a higher within-group inequality over time, contradicting the evidence I document.

Second, note that Lemieux's (2003) decomposition approach that I follow in this paper accounts for any unobserved compositional change that is correlated with or induced by observable changes. Thus, this method allows me to control for changes in factors (such as on-the-job training) that influence residual inequality either positively or negatively, but are correlated with the included regressors. Results from this decomposition method presented in Table 6, however, show that the contribution of these unobservable changes (which is calculated as part of observed quantities) is more than offset by the decline in unobserved prices. This implies that within-group inequality fell despite such changes. Moreover, any other unobserved compositional change uncorrelated with observed changes constitutes part of the unexplained component, which is again smaller in absolute magnitude than the contribution of unobserved prices.

Further, Helpman et al. (2010b) and Krishna et al. (2012) show that in response to trade liberalization, inequality increases more among higher skilled workers. In autarky, low skilled labor is only employed at low productivity firms, but high skilled individuals may be employed by a wider range of firms, causing their wages to be more dispersed than the former's. Following trade liberalization, low skilled workers may still be employed at low productivity firms. However, high skilled labor gets reallocated to exporting firms, that also increase their wages compared to non-exporting firms. This mechanism yields no increase in wage dispersion among low skilled labor while inequality increases within the group of high skilled workers. Since I do not have information on firms that individuals are employed by, this is an example of an unobserved compositional change that is induced by trade liberalization and not by the observable individual characteristics included in the regressions presented in sections 3.2 and 3.3. Therefore, my decomposition results do not control for this possibility. Nonetheless, since this unaccounted for compositional change would increase within-group inequality, it is still likely not the factor driving the within-group inequality decline in India.

But there can be other unobservable compositional changes within groups that are uncorrelated with the included regressors and work to reduce residual inequality. For example, the quality of education could improve over time. If the quality improvement is higher at schools at the lower end of the quality distribution, then individuals with the same education level would witness reduced variation in their wages. I provide suggestive evidence that indicates that this is again an unlikely driving force for the inequality trends in India.

One way of eliminating these compositional changes, at least partially, is to track cohorts in the data. If unobservable compositional changes are reducing residual inequality, which would otherwise have increased, then we expect to see rising residual inequality within cohorts. To examine if this is the case, I divide the sample into six synthetic six-year birth cohorts - 1936-

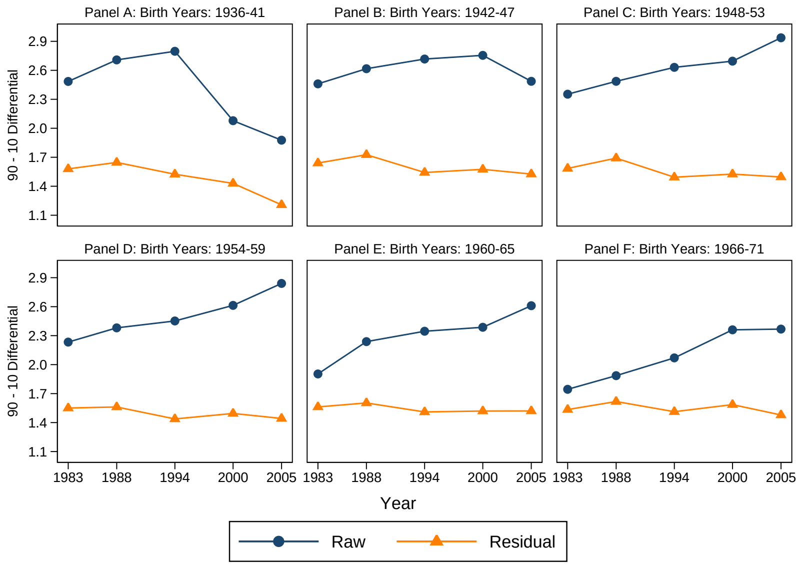

Figure 8: 90-10 Raw and Residual Wage Percentile Differentials for Cohorts[a]

[a]The figure shows the 90-10 percentile differences in log real wages and residual wages obtained from yearly regressions of log wages on education categories, 10-year age groups, interactions of education and experience groups, industry of employment, occupation, state of residence, rural or urban area of residence, gender, marital status, caste, religion, and quarter of interview, estimated for each six-year birth cohort.

41, 1942-47, 1948-53, 1954-59, 1960-65, and 1966-71. I estimate the same regressions as before and examine the evolution of 90-10 raw and residual wage-differentials over the years for each cohort separately. Results are presented in Figure 8. As is clear from all panels of the figure, each of these cohorts saw a decline, even if small, in residual wage inequality. The oldest cohort (born 1936-41) in Panel A saw a relatively larger decline. With the exception of this cohort, all others also experienced rising between-group inequality. Thus, we see a similar pattern of growing inequality between groups and shrinking inequality within groups even when we track cohorts, which are not subject to the same compositional changes as the total labor force. Thus, changing compositions of observable skill groups do not seem to be the factor underlying wage compression within skill groups.

Of course, there are compositional changes within these synthetic cohorts too. Data show that overtime, higher proportions of younger cohorts, born after 1948, lived in urban areas, worked in services and mining, construction, and utilities, were employed in higher skilled occupations such as professional and technical, administrative and managerial, and clerical. However, controlling for unobservable compositional changes that are correlated to changes in observed characteristics, as is accomplished by Lemieux's (2003) decomposition method, I find that in all cohorts, unobserved prices still fall between 1983 and 2005, causing a decline in residual inequality.[26]

Finally, I consider the possibility that the within-group inequality decline is a consequence of decreasing variation in hours worked during a week – a compositional change thus far omitted from the analysis (and, therefore, varying within groups). As explained in section 2, the household survey does not provide precise information on hours worked on a job held during the reference week. Instead, it assigns a half-day to the job when an individual reports working 1-4 hours on it, and a full day when he/she reports working 5-8 hours. Summing these over all seven days of the reference week gives the total number of days spent on each job. Examining changes in this variable over time, I find that the variance between groups (where groups are defined by the first specification in Table 4) in days worked per job stayed stable over the sample period, changing from 1.43 in 1983 to 1.45 in 2005. However, dispersion in this variable did decline considerably within groups – the 90-10 differential fell from 2.01 in 1983 to 0.73 in 2005.

Note that changes in hours worked are likely correlated with the included regressors, and, hence, already accounted for by the decomposition analysis presented in Table 6, Panel A. To investigate this issue further, I regress log wages on days spent per job in addition to all other variables included in the first specification in Table 4. I use results from these regressions to calculate between- and within-group inequality over the years and also conduct decomposition analysis. I still find divergent trends – between 1983 and 2005, while the 90-10 between-group wage dispersion increased from 1.1 log points to 1.2 log points, the corresponding dispersion within groups fell from 1.3 to 1.2. Results remain similar when I additionally control for industry and occupation.

4.2 Decreased Relative Returns to Unobservable Skills

Next, I examine the possibility that workers within groups are heterogeneous in skills valuable in the labor market, but over time the relative returns to these skills fall. This is a likely factor since the decomposition results in Table 6 demonstrate that unobservable prices were the dominant force contributing to dampening inequality in India over 1983-2005. In this section, I provide one potential channel for such a decline.

Consider the task content of offshored jobs that India may receive from developed countries. A growing literature establishes that multinational firms tend to offshore inputs and jobs that are intensive in routine tasks to developing countries. The literature makes this argument in three ways. Some studies argue that occupations that are intensive in routine task content and processes that can be easily summarized in a set of instructions or do not require face-to-face interaction are most likely to be offshored (see Blinder (2009), Acemoglu and Autor (2011), and Firpo, Fortin, and Lemieux (2011)). Other studies infer that the offshored tasks are those that are routine in nature by establishing that offshoring firms shift activities in their home country towards more non-routine, face-to-face communication intensive, and problem solving activities

[26]Results are available on request.

(see Becker et al. (2013), Oldenski (2012), Jensen and Kletzer (2010), and Goos, Manning and Salomons (2014)). Finally, Oldenski (2012) uses actual data on offshoring by multinational firms to document that these firms are, in fact, more likely to offshore occupations that are intensive in routine tasks. This is true for both service and manufacturing sector offshoring (Oldenski (2012)).

Further, routine occupations exist for both high- and low-skilled workers. A few studies (see Jensen and Kletzer (2010), Acemoglu and Autor (2011), and Oldenski (2012)) show that firms offshore both high-skill and low-skill intensive tasks if they can be easily routinized, summarized in a few instructions, and/or monitored. This suggests that transaction and monitoring costs of tasks (besides transportation and other trade costs) constitute an important factor determining the set of tasks that are offshored. Routine tasks may have lower monitoring costs than non-routine tasks, and therefore, be more likely to be offshored. Hogrefe (2013) presents a model that explicitly assumes that routine tasks have a lower cost of offshoring.

I build on the above two pieces of evidence to hypothesize that offshoring can drive the divergent wage inequality trends that we see in India. Suppose that tasks require two types of skills – "observable" (like education and experience), and "unobservable" (like problem solving and analytical skills). Firms in advanced countries offshore the set of tasks that minimizes the total cost of production. This means that offshored tasks should have low monitoring costs, which can, in part, be because they can be performed by workers with easily observable skills. On the other hand, tasks that are intensive in unobservable skills, will have high monitoring costs, rendering them less likely to be offshored. Since existing evidence indicates that offshored tasks are routine in nature, I hypothesize that they are also intensive in observable skills. In this case, greater offshoring can lead to increased demand for easily observable skills like education, increasing between-group inequality, but reduced demand for softer, analytical or problem solving skills that are not easily observable. Reduced demand for such skills can reduce within-group inequality as I argue below.

Consider two scenarios. First, suppose workers that are observationally equivalent in the data (i.e. workers within narrowly defined demographic groups) also appear identical to employers at the time of forming the match. In this case, individuals at the highest percentiles in the wage distribution within a group are those with the highest level of skills that are valuable to the employers and are revealed to them over time. But these skills remain unobservable in the data (for example, ability to troubleshoot or think critically). If returns to these skills fall over the years due to increased content of routine tasks, then we would see a decline in within-group inequality.

Second, suppose workers that appear observationally equivalent in the data are not identical to the employers. Then, within a demographic group, some workers have higher levels of skills that employers can observe and value (for instance, quality of education). Hence, these workers get higher wages than others. If these skills, observable to the employer, are positively correlated with skills such as problem solving, as argued by previous studies (see Lemieux (2003) and

Bonfiglioli and Gancia (2016), among others),[27] then individuals at the highest percentiles of the wage distribution within groups also have the highest levels of these latter skills which are unobservable in the data. If returns to these skills decline over time, we would again see reduced wage dispersion within groups.

Note that while extensive trade liberalization began only in the 1990s, some liberalizing reforms were also introduced during the 1980s. For example, import licenses were removed on many capital goods and intermediate products so that imports without any license requirements increased from 5% in 1980-81 to 30% in 1987-88. Many export incentives were also introduced such as tax exemptions on export income, cuts in interest rates on export credit, etc. (Panagariya (2004)). These reforms may have given some boost to offshoring activity, but it really increased starting in the 1990s. Akhtar (2013) shows that while India did receive FDI during the 1980s, it grew sharply starting in the 1990s. Hence, offshoring can be a potential factor underlying India's inequality trends mainly during the 1990s and 2000s. Indeed, in Figure 7, we see greater divergence in between- and within-group inequality in the post liberalization years.

This hypothesis fits the stylized facts presented in this paper but needs to be examined rigorously. While such an examination lies beyond the scope of this paper, I present some supportive evidence below.

Some industries are more likely to receive offshored activities than others. Although I do not have data on offshoring, we know that services and manufacturing received the bulk of FDI over the sample period. While manufacturing received the highest FDI in the 1990s, services have received the highest share of FDI since then. As detailed in Akhtar (2013), during the 1990s engineering, electronics and electrical equipment received the highest FDI share of 32% while services (including finance) accounted for 17%. Between 2000 and 2010, services, computer software (which received 8.5%), and telecommunication together accounted for nearly 37% of all FDI.

I divide my sample into four broad sectors of employment – agriculture, manufacturing, mining, construction and utilities, and services. Although there are myriad differences between these sectors, we can examine whether patterns of inequality across these sectors are consistent with the offshoring hypothesis. In Table 7, I present decomposition results for these sectors. We see that in services, observed prices and quantities increased inequality sharply between 1983 and 2005, contributing 145% of the total 90-10 increase, while the decline in relative returns to unobservable skills worked to compress the overall 90-10 inequality by 113%. In manufacturing, the 90-10 wage differential fell by 0.22 log points, most of it concentrated in the lower half of the distribution. While observed quantities and prices contributed 7% of this decline, within-group inequality reduced it by 132%. However, in the upper half of the wage distribution in manufacturing, observed quantities and prices increased inequality while unobserved prices reduced it. Adding the unexplained component to unobserved prices, we can conclude that in all sectors, within group inequality declined, with a larger proportion of this

[27] Refer to discussion of these studies in section 4.1.

Table 7: Decomposition of Changes in Inequality by Sector
1983 - 2005

Differential	Total Change	Observed Quantities	Observed Prices	Unobserved Prices	Unexplained
		Panel A: Services			
90-10	0.220	0.063	0.256	-0.249	0.150
90-50	0.471	0.008	0.238	-0.108	0.334
50-10	-0.251	0.055	0.018	-0.141	-0.184
		Panel B: Manufacturing			
90-10	-0.216	0.077	-0.092	-0.286	0.085
90-50	-0.020	0.045	-0.008	-0.087	0.031
50-10	-0.196	0.032	-0.084	-0.196	0.054
		Panel C: Mining, Construction and Utilities			
90-10	-0.156	0.032	-0.078	-0.336	0.226
90-50	-0.038	0.011	-0.082	-0.188	0.221
50-10	-0.118	0.021	0.004	-0.148	0.005
		Panel D: Agriculture			
90-10	-0.139	-0.042	-0.006	-0.107	0.016
90-50	0.015	0.003	0.080	-0.030	-0.038
50-10	-0.155	-0.045	-0.086	-0.076	0.053

decline attributable to falling returns to unobservable skills. Thus, the divergent movement in between- and within-group inequality is the most pronounced in services, as one would expect under my offshoring hypothesis. In manufacturing, these divergent trends were visible in the upper half of the wage distribution.

In the case of mining, construction and utilities, and agriculture, this divergence is either less pronounced or absent. In mining, construction and utilities, both between- and within-group inequality fell in the overall (90-10 percentile differential) and the upper half (90-50 percentile differential) of the wage distribution. In the lower half of the distribution, between-group inequality contributed 20% to the overall increase in inequality while within-group inequality declined to reduce it by 120%. In agriculture, we similarly see a small divergent pattern in the upper half but not in the lower half of the wage distribution. However, the decline in within-group inequality is pervasive across all sectors, suggesting a role for additional factors underlying the inequality trends in India.

Next, I examine occupations. Chamarbagwala (2006) and Berman, Somanathan and Tan (2006) documented educational upgrading within industries in India. Table 5 above also confirms this. However, educational upgrading occurred even within occupations. Two occupation groups stand out in terms of their educational upgrading, rising shares within various industries, and their rising returns – administrative, executive and managerial, and professional and technical. Administrative, executive and managerial occupations witnessed significant educa-

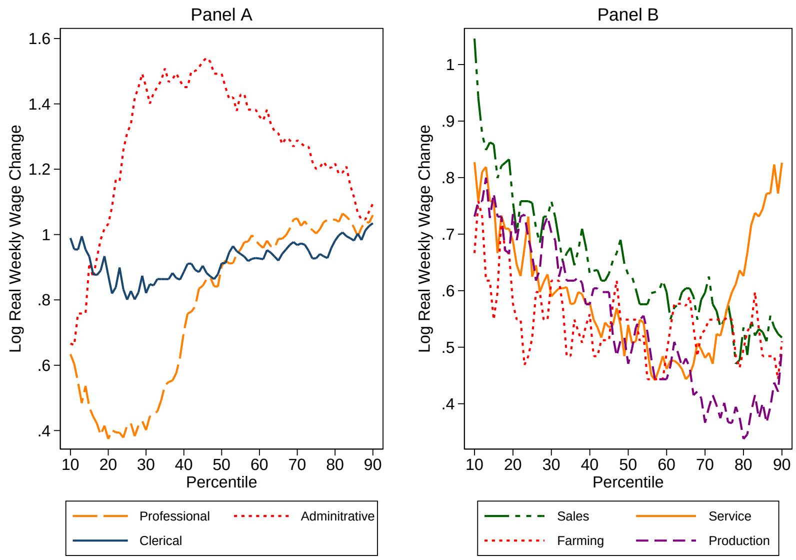

Figure 9: Wage Changes Within Occupation Groups[a]

[a]The figure shows changes over 1983-2005 in log real wages at the tenth to the ninetieth percentiles of the wage distributions for all occupation groups. Sampling weights have been used.

tional upgrading of their workforce, with the proportion of college graduates increasing from 25% to 33% in services, and from 16% to 21% in manufacturing. Their share also increased the most in both manufacturing and services – about 5 percentage points over the sample period. The 20% increase in returns to this group (as estimated from the regression specification in Table 4, columns (6)-(10)) was also the largest among all occupation groups. Professional and technical occupations witnessed the most significant educational upgrading, with the share of college graduates increasing more than 30 percentage points. The share of this occupation group increased nearly 10 percentage points to 21% in finance and real estate, and computer related service sectors. Absolute returns in these occupations increased 11%. Clerical and sales workers experienced 15.5% and 14% increase in returns, respectively. The smallest increases in returns were seen by service workers (such as janitors), production workers, and farmers and related labor.

Thus, not only did more educated workers flow into higher paying occupations, they also saw significant wage growth. As shown in Figure 5, inequality also increased *between* these and other occupation groups. If these occupations received large proportions of offshored tasks, these trends are consistent with Feenstra and Hanson's (1996) argument that offshored tasks are performed by skilled workers in developing countries, raising inequality.

However, I find that *within* occupation groups, workers witnessed reduced wage dispersion over time. As decomposition results using regression specifications that include industry and occupation controls show (Table 6, Panel B), unobservable prices declined substantially, and drove the decline in inequality even intra-industry and intra-occupation. Also, Figure 9 shows that raw wage inequality fell sharply within several occupation groups. The largest declines were experienced between the 30th and 90th percentiles in the wage distributions of administrative, executive, and managerial jobs, and throughout the distribution for sales workers. For both groups, wage dispersion fell by nearly 0.5 log points. Inequality within the group of professional and technical occupations fell in the lower part of the distribution but increased between the 30th and 90th percentiles. The decline in wage inequality within occupations may be because, over time, the task content of occupations has become more routine, leading to a decline in returns to skills such as problem solving or social interactions.[28]

In the absence of data on offshoring, we do not know which occupations were engaged the most in offshored activities.[29] However, the patterns of educational upgrading of occupations, increasing inequality between occupation groups, and falling inequality within them, driven by declining unobservable prices, are all consistent with the offshoring hypothesis I propose.

4.3 Fall in Labor Market Frictions

Finally, I consider the possibility that observationally identical workers are, in fact, homogeneous in unobservable skills but experience wage dispersion due to labor market frictions. Then, reduced frictions and greater efficiency in the labor market cause a compression in wage inequality within groups.

Besides trade liberalization, the period 1983-2005 witnessed many other structural reforms. During the 1980s, industrial licensing was abolished, eliminating or reducing restrictions on entry and expansion of firms, as well as changes in their product-mix. Other industrial reforms were also introduced. The tax system was reformed so as to reduce taxes on firm inputs. During the 1990s, investment licensing was removed and entry of private firms was allowed in several sectors that were thus far dominated by government owned firms. Many state-owned enterprises were privatized, and banking reforms were introduced with the aim of increasing competition in the financial sector and improving the allocation of credit (see Panagariya (2004) and Ahluwalia (2002)).

Over the sample period, infrastructure also improved along many dimensions. According to data from the World Bank, electricity consumption increased from 166 kWh per capita in 1983 to 469 kWh in 2005. The percentage of population with access to improved water source increased from 71% in 1990 to 86% in 2005. The length of roads increased from 1485.4 thousand kms in 1981 to 3373.5 thousand kms in 2001 (Central Statistics Office). As Dun & Bradstreet report, teledensity witnessed a significant increase from just above 2% in 1999 to 36.98% by end of 2009 (when urban teledensity was 89%).

These economic reforms and infrastructural developments may have contributed to the

[28] For the United States, Ross (2016) shows a within-occupation change in task content in the opposite direction - becoming more non-routine and interactive over time.

[29] To the best of my knowledge, there is no information on the occupation-mix of offshoring to India. Lack of data on occupations offshored is a common limitation of research on offshoring.

patterns of between- and within-group inequality documented in this paper. I leave a systematic investigation of these potential factors to future work.

One general consequence, however, of these industrial reforms and improvements in transportation and communication infrastructure is likely to be a reduction in labor market frictions.[30] A large literature shows that search frictions can cause wage dispersion among observationally identical workers. See Rogerson et al. (2005) and Mortensen (2005) for reviews. It follows, therefore, that as frictions reduce, frictional wage dispersion will also decline, causing within-group inequality to fall. Search models would predict this under the condition that workers within groups are homogeneous. However, it is difficult to predict ex ante how within-group inequality will respond to reduced frictions if workers in these groups are heterogeneous. Between-group wage inequality will also be impacted, but it is again unclear ex ante, whether it will rise or fall.[31]

This possibility allows for another explanation for the divergent movements in between- and within-group inequality. As shown in sections 3.1 and 3.2, the evolution of between-group inequality, rise in returns to observable skills, and within-industry skill upgrading are consistent with previously suggested mechanisms of skill-biased trade, offshored tasks performed by skilled workers, and trade-induced positive assortative matching of workers and firms within industries. While these channels may underlie rising inequality between groups, simultaneously growing efficiency of the labor market can drive the wage compression within groups (if workers in these groups are otherwise homogeneous).

One suggestive evidence of this possibility can be seen from looking at variation in inequality trends across states with different labor regulations. While these laws are widely considered to be too restrictive in India, they have substantial cross-state variation since both federal and state governments can amend them. Besley and Burgess (2004) classify ten major states as pro-worker or pro-employer on the basis of various amendments passed by these states over the period 1958-1992 to the Industrial Disputes Act – an important set of labor regulations in India. Using their classification, Aghion et al. (2008) show that industries in pro-worker states grew slower than in others following industrial delicensing. In another study, Topalova (2010) shows that the poverty incidence following trade liberalization decreased more slowly in pro-worker states. These studies, therefore, point to lower efficiency of labor markets in states with pro-labor regulations. In Figure 10, I present 90-10 differentials in log real and residual

[30]For instance, improvements in transportation and communication infrastructure may contribute to increasing the size of labor markets by increasing information flows and mobility of labor. As Harmon (2013) shows, larger labor markets improve job-match quality.

[31]For instance, suppose both college and high school graduates face search frictions, causing both to be equally mismatched. When frictions fall, they could fall more for college (high school) graduates causing their wages to increase more than high school (college) graduates, thereby increasing between-group inequality. On the other hand, suppose initially high school graduates faced greater search frictions than college graduates so that their wages were disproportionately reduced. Now if frictions are eliminated for both groups of workers, high school graduates could see a relatively larger wage gain than college graduates leading to a reduction in between-group inequality. Analogous logic applies when workers are heterogeneous in unobservable skills. However, if the effects of trade liberalization dominate those of declining labor market frictions, we may not see this result.

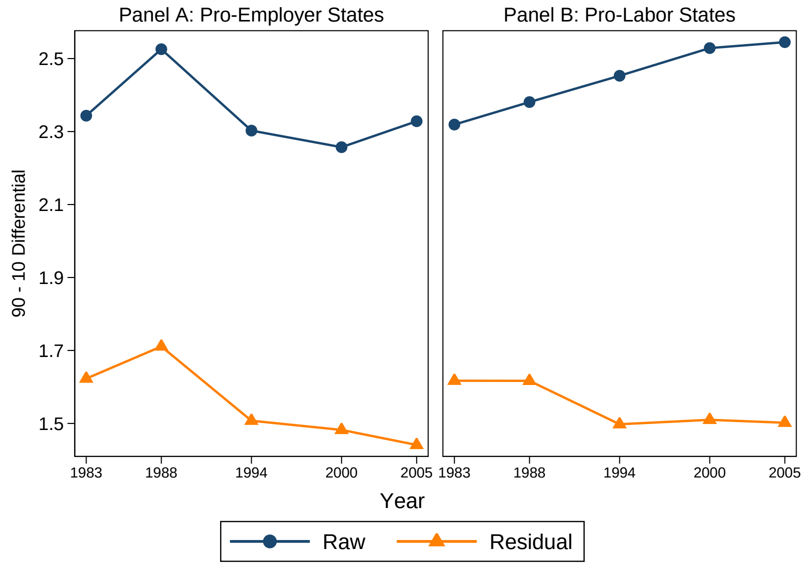

Figure 10: 90-10 Raw and Residual Wage Percentile Differentials for States[a]

[a]The figure shows the 90-10 percentile differences in log real wages and residual wages obtained from a regression of log wages on education categories, 10-year age groups, interactions of education and experience groups, industry of employment, occupation, rural or urban area of residence, gender, marital status, caste, religion, and the quarter of interview. Regressions are estimated separately for pro-employer and pro-labor states. Pro-employer states include Andhra Pradesh, Karnataka, Kerala, Madhya Pradesh, Rajasthan and Tamil Nadu. Pro-labor states are Gujarat, Maharashtra, Orissa, and West Bengal.

wages separately for pro-employer and pro-labor states. We see that in the post liberalization years (1994-2005), residual inequality fell steadily in states with pro-employer regulations while that in states with pro-labor laws stayed stagnant at 1.5 log points. This is consistent with the argument that lower labor market frictions are associated with lower levels of residual inequality. I leave a more rigorous investigation of the role of labor market frictions in India's inequality trends to future work.

5 Conclusion

This paper comprehensively documents trends in employment and wage inequality between and within observable demographic groups in India for the period 1983-2005. I demonstrate that while inequality is growing between these groups, it is falling within them, and that this decline is not an artifact of unobservable compositional changes across cohorts. To the best of my knowledge, this decline in residual inequality is unique among developing countries that have been studied. Previously offered explanations for widening wage structures in these countries also cannot account for this decline. I propose that the routine nature of offshored tasks and greater efficiency of labor markets potentially underlie these inequality trends in India.

The offshoring hypothesis, if true, has important policy implications. Policies that limit offshoring with the aim of reducing inequality in developing countries must recognize that offshoring may, in fact, decrease inequality along some skill dimensions. Moreover, as returns to the finer or soft skills fall, the supply side of the labor market may respond by investing less in these and more in education and experience, with important long term consequences. If reduced labor market frictions underlie declining within-group inequality, then this should constitute another incentive for further policy changes and infrastructure development besides macroeconomic growth and poverty alleviation. It should also inform reform of India's labor laws that continue to be complex and restrictive.

This study has several natural extensions that I leave to future research. The explanations that I propose can both be theoretically formalized and empirically tested. Also, it is important to investigate if a similar phenomenon is being witnessed in other developing countries that are increasingly attracting offshored tasks or whose labor markets are becoming more efficient.

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Appendices

Appendix A India Until 1991, The Crisis, and the Reforms of 1990s

Until 1991, India followed highly protectionist international trade policies. As of 1991, all imports either required licenses or were prohibited, despite some liberalization in the 1980s. All bulk items like cereals, petroleum, metals, and fertilizers, were 'canalized', i.e., they could be imported only by the government. Tariffs on imports were extremely high; the highest rate was 355% (Krueger and Chinoy (2002)), the simple average was 113% (Panagariya (2008)), and the import weighted average was 87% (Panagariya (2008)). Exports from India were also subject to several restrictions like prohibition, licensing, quantity ceilings, canalization, and pre-specified terms and conditions. Foreign direct investment (FDI) was severely restricted, allowing entry only into specific priority areas or when it provided technology transfer. There was an upper limit of 40% (Krueger and Chinoy (2002)) foreign equity in firms unless they were high-tech or export oriented. Firms receiving FDI also had to increase the domestic content of their output.

The industrial policy of the Indian government until early 1980s had also been extremely interventionist. While heavy industry was a state monopoly, other industries either required licenses (that regulated scale, technology, and location of projects, and the outputs and inputs of plants) or were reserved for the small-scale sector. Public sector enterprises were specimens of wasteful and inefficient activity and "acted as a brake on private sector development." (Srinivasan (2000)).

Until the late 1980s, the financial sector was also highly regulated. Public sector banks dominated commercial banking and the financial sector. National banks accounted for 92% of total deposits. Interest rates were controlled and substantial parts of credit had to be directed to priority sectors.

Between late 1940s and 1980 the real GNP of India grew around 3.8% annually while the rate of growth of real per capita income was about 2% per annum. In the mid 1980s, the fiscal and monetary policies in India became substantially more expansionary than previous policies. The government had to borrow from domestic and foreign sources to finance its investment as well as current expenditure. The Gulf war caused oil prices to spike and workers' remittances to plummet, further worsening the situation. In 1990-91 the central government's fiscal deficit stood at 10.4% of GDP (Panagariya (2008)), inflation rose to 13.5% (Krueger and Chinoy (2002)) and in mid-1991 foreign exchange reserves were only enough to finance two weeks of imports despite an IMF loan of \$1.8 billion in January 1991 and sharp cuts in imports.

At this time there was a change in governments and a long term stabilization process was initiated, unlike the previous short term measures. Besides the usual stabilization measures, several unprecedented economic reforms were carried out that were aimed at changing the underlying structure of the economy.

In the first two years of reforms that began in July 1991, several measures were implemented with regard to India's trade policy. The rupee was devalued 19% in real terms (Krueger and Chinoy (2002)). A market exchange rate was established in 2002 and by 2003 the official exchange rate was unified with it. Later, the rupee was made officially convertible on the current account. More recently, many capital account transactions have also been freed up. Licensing was abolished for most imports except consumer goods (license requirements on these were removed a decade later). Tariffs rates were slashed so that by 1995 the peak rate was 50% (Krueger and Chinoy (2002)). At the turn of the century, the import weighted average tariff rate stood at 30.2%. By 2004, the highest tariff rate on industrial goods was 20%, although there were some exceptions (Panagariya (2008)). These tariff reductions applied only to non-agricultural goods. In March 1992, the number of export items subject to control was brought down from 439 to 296, only 16 of which remained prohibited. FDI was also liberalized. The approval process was simplified and the percentage shares of domestic firms that could be owned by foreigners were increased. In May 2001, 100% foreign ownership of firms was permitted in several industries.

Another set of reforms was aimed at liberalization of industrial policy. In the late 1980s, the licensing system was abolished and the business environment was significantly deregulated.

The financial sector also witnessed changes. Beginning in 1992, interest rates were gradually freed and directed credit was reduced. Competition in the banking industry was encouraged in various ways and more foreign and private banks were allowed to operate. Agriculture was largely left out of the reform process, mainly because of political economy constraints.

Appendix B Robustness

Appendix B.1 Results for Sample Without Outlier Trimming

Table Appendix B.1: Yearly Log Wage Regressions

	(1)	(2)	(3)	(4)	(5)
Regressors	1983	1988	1994	2000	2005
			Dependent Variable: Log Real Weekly Wages		
Primary School	0.041**	0.014	0.040**	0.026*	0.003
	(0.018)	(0.027)	(0.016)	(0.016)	(0.015)
Middle School	0.042*	0.131***	0.097***	0.050***	0.065***
	(0.023)	(0.033)	(0.017)	(0.014)	(0.015)
High School	0.331***	0.339***	0.316***	0.239***	0.155***
	(0.039)	(0.041)	(0.021)	(0.018)	(0.019)
College	0.708***	0.812***	0.917***	0.684***	0.689***
	(0.048)	(0.069)	(0.049)	(0.040)	(0.035)
26-35 Years	0.041***	0.069***	0.050***	0.051***	0.021*
	(0.012)	(0.021)	(0.011)	(0.010)	(0.012)
36-45 Years	0.080***	0.101***	0.094***	0.074***	0.035***
	(0.013)	(0.023)	(0.012)	(0.011)	(0.013)
46-55 Years	0.028	0.074***	0.052***	0.060***	0.020
	(0.019)	(0.027)	(0.014)	(0.013)	(0.015)
56-65 Years	-0.043**	0.004	-0.029	0.006	-0.079***
	(0.021)	(0.034)	(0.018)	(0.017)	(0.019)
Male	0.423***	-1.050***	0.450***	0.442***	0.485***
	(0.009)	(0.016)	(0.008)	(0.008)	(0.008)
Urban	0.402***	3.153***	0.332***	0.303***	0.248***
	(0.010)	(0.015)	(0.008)	(0.008)	(0.009)
Constant	3.503***	3.463***	3.718***	4.259***	3.905***
	(0.426)	(0.097)	(0.111)	(0.047)	(0.418)
Education Group*Age Group	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes
Caste	Yes	Yes	Yes	Yes	Yes
Religion	Yes	Yes	Yes	Yes	Yes
Marital Status	Yes	Yes	Yes	Yes	Yes
Quarter	Yes	Yes	Yes	Yes	Yes
Observations	112,628	121,661	86,612	101,129	88,268
R-squared	0.255	0.554	0.427	0.484	0.531

*** p<0.01, ** p<0.05, * p<0.10 Robust standard are errors in parentheses. Omitted education group is workers with no formal schooling. Omitted age group is 15-25 years. Sampling weights have been used.

Table Appendix B.2: Decomposition of Changes in Overall Inequality
1983 - 2005

Differential	Total Change	Observed Quantities	Observed Prices	Unobserved Prices	Unexplained
90-10	0.03	0.19	0.10	-0.25	-0.01
90-50	0.17	0.17	0.08	-0.08	-0.01
50-10	-0.14	0.02	0.02	-0.18	0.00

Appendix B.2 Results for Sample with Age Group 20-65 Years

Table Appendix B.3: Yearly Log Wage Regressions

Regressors	(1) 1983	(2) 1988	(3) 1994	(4) 2000	(5) 2005
	Dependent Variable: Log Real Weekly Wages				
Primary School	0.110***	0.075***	0.078***	0.075***	0.039**
	(0.016)	(0.026)	(0.018)	(0.020)	(0.019)
Middle School	0.128***	0.084***	0.128***	0.106***	0.097***
	(0.020)	(0.032)	(0.019)	(0.017)	(0.018)
High School	0.422***	0.406***	0.347***	0.284***	0.182***
	(0.024)	(0.027)	(0.022)	(0.021)	(0.021)
College	0.764***	0.781***	0.863***	0.651***	0.657***
	(0.032)	(0.035)	(0.048)	(0.042)	(0.035)
26-35 Years	0.014	0.053***	0.047***	0.044***	0.015
	(0.010)	(0.015)	(0.011)	(0.011)	(0.013)
36-45 Years	0.048***	0.094***	0.089***	0.071***	0.029**
	(0.011)	(0.017)	(0.012)	(0.011)	(0.013)
46-55 Years	0.015	0.068***	0.051***	0.058***	0.016
	(0.013)	(0.021)	(0.013)	(0.013)	(0.016)
56-65 Years	-0.073***	-0.042	-0.045***	0.001	-0.078***
	(0.017)	(0.029)	(0.017)	(0.017)	(0.019)
Male	0.471***	0.580***	0.470***	0.439***	0.469***
	(0.007)	(0.012)	(0.008)	(0.008)	(0.008)
Urban	0.447***	0.236***	0.357***	0.314***	0.268***
	(0.007)	(0.011)	(0.008)	(0.009)	(0.009)
Constant	3.786***	3.754***	3.638***	4.284***	3.889***
	(0.166)	(0.053)	(0.110)	(0.047)	(0.416)
Education Group*Age Group	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes
Caste	Yes	Yes	Yes	Yes	Yes
Religion	Yes	Yes	Yes	Yes	Yes
Marital Status	Yes	Yes	Yes	Yes	Yes
Quarter	Yes	Yes	Yes	Yes	Yes
Observations	94,417	62,017	77,804	91,163	79,555
R-squared	0.435	0.473	0.483	0.486	0.530

*** p<0.01, ** p<0.05, * p<0.10 Robust standard are errors in parentheses. Omitted education group is workers with no formal schooling. Omitted age group is 20-25 years. Sampling weights have been used.

Table Appendix B.4: Decomposition of Changes in Overall Inequality
1983 - 2005

Differential	Total Change	Observed Quantities	Observed Prices	Unobserved Prices	Unexplained
90-10	0.11	0.14	-0.02	-0.22	0.22
90-50	0.23	0.10	0.11	-0.07	0.09
50-10	-0.11	0.04	-0.13	-0.15	0.13

Appendix B.3 Results with Narrower Classifications of Education, Age, Industry and Occupation

Table Appendix B.5: Yearly Log Wage Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Regressors	1983	1988	1994	2000	2005	1983	1988	1994	2000	2005
	Dependent Variable: Log Real Weekly Wages									
Literate Without Formal Schooling	0.215**	0.315***	0.226***	0.187*	0.135	0.117	0.230**	0.145**	0.109	0.057
	(0.086)	(0.118)	(0.083)	(0.110)	(0.103)	(0.073)	(0.110)	(0.068)	(0.108)	(0.099)
Below Primary School	0.234***	0.237***	0.269***	0.245***	0.102*	0.145***	0.125*	0.165***	0.135***	0.061
	(0.048)	(0.081)	(0.044)	(0.042)	(0.061)	(0.045)	(0.071)	(0.040)	(0.039)	(0.049)
Primary School	0.321***	0.529***	0.391***	0.150**	0.191***	0.195***	0.385***	0.213***	0.043	0.072
	(0.056)	(0.061)	(0.058)	(0.066)	(0.053)	(0.049)	(0.057)	(0.050)	(0.055)	(0.048)
Middle School	0.682***	0.636***	0.670***	0.690***	0.636***	0.437***	0.395***	0.323***	0.389***	0.345***
	(0.055)	(0.091)	(0.076)	(0.068)	(0.076)	(0.050)	(0.084)	(0.080)	(0.053)	(0.062)
High School	1.005***	0.993***	1.219***	1.358***	1.439***	0.679***	0.692***	0.688***	0.810***	0.840***
	(0.057)	(0.060)	(0.060)	(0.051)	(0.062)	(0.057)	(0.057)	(0.057)	(0.043)	(0.053)
College	1.083***	1.126***	1.499***	1.644***	1.828***	0.727***	0.771***	0.949***	1.068***	1.126***
	(0.103)	(0.081)	(0.109)	(0.055)	(0.053)	(0.095)	(0.079)	(0.094)	(0.055)	(0.056)
Ages 21-25	0.118***	0.171***	0.131***	0.127***	0.121***	0.097***	0.146***	0.092***	0.090***	0.095***
	(0.010)	(0.016)	(0.011)	(0.011)	(0.012)	(0.010)	(0.015)	(0.011)	(0.010)	(0.011)
Ages 26-30	0.318***	0.410***	0.400***	0.527***	0.602***	0.269***	0.355***	0.332***	0.400***	0.522***
	(0.038)	(0.040)	(0.053)	(0.052)	(0.040)	(0.035)	(0.038)	(0.048)	(0.052)	(0.036)
Ages 31-35	0.379***	0.484***	0.467***	0.606***	0.694***	0.318***	0.414***	0.381***	0.461***	0.596***
	(0.038)	(0.041)	(0.053)	(0.052)	(0.041)	(0.035)	(0.038)	(0.048)	(0.050)	(0.036)
Ages 36-40	0.478***	0.548***	0.629***	0.912***	0.980***	0.404***	0.473***	0.532***	0.741***	0.830***
	(0.038)	(0.043)	(0.054)	(0.050)	(0.041)	(0.037)	(0.041)	(0.049)	(0.047)	(0.037)
Ages 41-45	0.518***	0.582***	0.682***	0.965***	1.061***	0.435***	0.494***	0.575***	0.776***	0.885***
	(0.039)	(0.043)	(0.054)	(0.050)	(0.041)	(0.037)	(0.041)	(0.050)	(0.047)	(0.037)
Ages 46-50	0.502***	0.668***	0.807***	1.087***	1.235***	0.433***	0.580***	0.676***	0.869***	1.044***
	(0.049)	(0.045)	(0.056)	(0.049)	(0.042)	(0.046)	(0.044)	(0.053)	(0.048)	(0.038)
Ages 51-55	0.483***	0.646***	0.811***	1.120***	1.255***	0.414***	0.563***	0.678***	0.885***	1.053***
	(0.050)	(0.047)	(0.058)	(0.050)	(0.042)	(0.047)	(0.046)	(0.054)	(0.049)	(0.039)
Ages 56-60	0.366***	0.501***	0.727***	1.145***	1.285***	0.364***	0.453***	0.673***	0.965***	1.084***
	(0.107)	(0.084)	(0.119)	(0.068)	(0.061)	(0.098)	(0.082)	(0.102)	(0.066)	(0.061)
Ages 61-65	0.239**	0.150	0.542***	0.936***	1.049***	0.260***	0.168*	0.529***	0.814***	0.909***
	(0.109)	(0.094)	(0.121)	(0.072)	(0.067)	(0.101)	(0.090)	(0.104)	(0.070)	(0.066)
Constant	3.169***	3.287***	2.949***	3.181***	2.584***	3.114***	3.759***	3.459***	3.316***	3.323***
	(0.225)	(0.100)	(0.165)	(0.081)	(0.405)	(0.203)	(0.141)	(0.219)	(0.139)	(0.567)
Education Group*Age Group	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry						Yes	Yes	Yes	Yes	Yes
Occupation						Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Caste	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Religion	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Marital Status	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	104,639	65,885	84,923	99,009	86,393	103,906	65,352	82,959	96,486	85,880
R-squared	0.427	0.474	0.473	0.481	0.526	0.485	0.521	0.551	0.565	0.616

*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses. Omitted education group is illiterate workers. Omitted age group is 15-20 years. Education groups are interacted with 10-year age groups. Sampling weights have been used.

Table Appendix B.6: Decomposition of Changes in Overall Inequality
1983 - 2005

Differential	Total Change	Observed Quantities	Observed Prices	Unobserved Prices	Unexplained
			Panel A		
90-10	0.041	0.167	-0.002	-0.230	0.107
90-50	0.138	0.123	0.051	-0.071	0.035
50-10	-0.097	0.043	-0.052	-0.159	0.072
			Panel B		
90-10	0.041	0.098	0.099	-0.242	0.086
90-50	0.136	0.040	0.154	-0.080	0.022
50-10	-0.096	0.057	-0.055	-0.162	0.064