Convergence Across Castes*

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Abstract

India has witnessed a remarkable wage catch-up by the historically disadvantaged scheduled castes and tribes (SC/STs) towards non-SC/ST levels during the period 1983-2012. To provide a structural explanation for the catch-up, we develop a multi-sector, heterogenous agent model where individuals differ in innate ability as well as their caste identity. Castes differ in their costs of schooling and accessing sectoral labor markets. This induces caste-based talent misallocations of agents in schooling and employment. Using the model, we show that sectoral productivity growth during 1983-2012 can explain 72 percent of the observed wage convergence between the castes. Rising education and sectoral reallocation of workers induced by the productivity growth are the primary drivers of this predicted convergence. We estimate significant welfare costs of the talent misallocations induced by the caste distortions.

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1 Introduction

A perennial challenge of managing the development process is to balance the macroeconomic goals of growth and development with the microeconomic goals of equity and distributional fairness. These

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challenges often come to the fore during periods of rapid economic changes in growing economies. An example of this phenomenon is India over the past 30 years. This period has witnessed a rapid takeoff of the Indian economy with average annual growth rates doubling relative to the pre-1991 phase. What were the distributional consequences of the growth take-off? Did growth lift all groups or were there tradeoffs? What are the mechanisms that linked the two?

We approach the issue by focussing on the experience of Scheduled Castes and Scheduled Tribes (SC/STs) – an historically underprivileged section of Indian society.[1] SC/STs experienced a rapid wage catch-up towards non-SC/ST levels between 1983 and 2012 with the mean wage gap shrinking by 10.5 percentage points and the median wage gap declining by 14 percentage points. This wage convergence was accompanied by convergence in education attainment levels, occupation choices, and consumption levels (see Hnatkovska et al. (2012)).[2]

The goal of this paper is to assess the roles of growth and affirmative action programs in driving the declining economic gaps between non-SC/STs and SC/STs. Constitutionally mandated affirmative action programs that carved out reserved seats in higher education, legislative houses and public sector jobs for SC/STs have been a key feature of public policy in India since the 1950s. How important have these protections been in accounting for the changes in the observed caste disparities since 1983 relative to the role of faster productivity and economic growth in India?

To answer these questions, we first review the evidence on the evolution of gaps between SC/STs and non-SC/STs in wages, education attainment rates as well as sectoral employment. A key finding from this exercise is that the period 1983-2012 was characterized by simultaneous decreases in the caste gaps in education attainment and sectoral employment rates.

As a next step, we conduct a statistical decomposition of the change in the overall wage gap between non-SC/STs and SC/STs during 1983-2012. In a multi-sector economy, caste wage gaps could change either due to changes in the employment distribution of castes across sectors or due to changes in sectoral caste wage gaps or some combination of the two. Our decomposition exercise reveals that the relatively faster entry of SC/STs into the service sector during this period was the most important driver of the caste wage convergence.

Based on this evidence, we develop a three-sector model (agriculture, manufacturing and ser-

[1] SC/STs comprise a list of castes that have been listed in a schedule of the Indian constitution as being historically disadvantaged and consequently eligible for affirmative action programs. Crucially, caste identities are inherited by birth and hence immutable over time. Moreover, the extent of affirmative action reservations for SC/STs have also remained constant over time.

[2] There has also been sharp convergence in the intergenerational mobility rates in these three indicators (see Hnatkovska et al. (2013)).

vices) of an economy with heterogenous agents. Agents differ along two dimensions. First, agents are different in their innate ability endowment which they all draw from a common ability distribution. Second, individuals in the model belong to one of two castes: non-SC/STs and SC/STs. Caste identities are immutable and given.

Castes differ on two dimensions: (a) the cost of acquiring schooling; and (b) the cost of accessing sectoral labor markets. These differential costs imply that even though the ability distributions of individuals in the two castes are identical, there is a misallocation of ability in schooling and sectoral employment. These misallocations induce caste gaps in sectoral employment and wages.

We use the model to quantitatively assess the effect of changes in sectoral productivities on the schooling and sectoral misallocations during 1983-2012. Specifically, we examine the explanatory power of these productivity changes for the observed decline in the sectoral caste employment gaps, the sectoral caste wage gaps as well as the overall caste wage convergence observed in the data.

The model is calibrated to match the 1983 levels of the sectoral caste employment gaps, sectoral caste wage gaps and the average education levels of the two castes. Our baseline calibration identifies higher schooling costs for SC/STs as the primary cause of the large sectoral caste gaps in employment and wages in 1983.

Armed with the calibrated model for 1983, we conduct a sequence of quantitative experiments to examine the importance of productivity growth. Our experiments yield five key results. First, sectoral productivity growth during 1983-2012 accounts for 72 percent of the percentage decline in the caste wage gap during this period. Moreover, as in the statistical decomposition results, the key drivers of the overall wage convergence in the model are decreases in the caste gaps in employment and wages in the service sector.

Importantly, while the empirical and analytical focus of the paper is on ***relative*** wage gaps, we show that the model also reproduces the observed dynamics of the ***absolute*** wage gaps between the groups during this period.

Second, the measured productivity growth causes the model to reproduce the observed thickening tails of the schooling distribution for the two castes (a higher shape parameter for the fitted Pareto distribution for schooling) during 1983-2012. Since schooling is the key underpinning of economic disparity in the model, we interpret this as evidence of the model's success in reproducing the changing heterogeneity within and across groups in India during this period.

Third, the observed sectoral labor productivity growth induce dynamics of sectoral output shares in the model that reproduce the patterns in the data. We view these aggregate features of the model, including its structural transformations predictions, as indicative of the model being a good fit to the data.[3]

Using counterfactual experiments we show that the key to the caste convergence is the endogenous rise in education along with a re-sorting of workers into sectors that was induced by the differential sectoral productivity growths.

There are three important aspects of the worker re-sorting in the model. The first is the net movement of workers across sectors; the second is the changing education attainment of workers; and the third is the selection by ability of the workers that choose to move. We find that selection effects quantitatively account for just 10 percent of the wage convergence in the baseline model. The remaining 90 percent of the convergence is due to the joint impact of greater education attainment and net flows of worker across sectors.

We then conduct additional counterfactual experiments to show that it is rising education attainment that accounts for most of the 90 percent of the caste wage convergence that is jointly explained by education attainment and net flows of worker across sectors. Intuitively, non-SC/STs in the model start with higher absolute levels of schooling. Since there is an upper bound to schooling, the average non-SC/STs education response to the productivity shock is smaller than the corresponding education response of SC/STs. This drives most of the wage convergence in the model.

Fourth, we assess the importance of affirmative action programs for jobs in India. In the baseline calibration, the sectoral entry costs of SC/STs are lower than those for non-SC/STs. We view this to be the consequence of job reservations for SC/STs. When we equalize these sectoral entry costs across castes while leaving all other parameters in the baseline model unchanged, the caste wage gap rises by 13 percentage points in 1983 and by 5 percentage points in 2012 relative to the corresponding gaps under the baseline calibration. This suggests to us that affirmative action was likely important in lowering the ***levels*** of the caste wage gaps.

However, our quantitative experiments also suggest that affirmative action likely did not materially affect the ***dynamics*** of caste wage gaps between 1983 and 2012. The predicted decrease in the wage gap during 1983-2012 in the baseline case where reservations exist throughout, is 7.5 percent. When reservations are removed in the model by equalizing entry costs across castes at all times, the same productivity growth causes the caste wage gap to decline by a much sharper

[3]Interestingly, while the model allows for non-homothetic preferences, our quantitative exercises reveal that it is differential sectoral productivity growth that accounts for the sectoral dynamics of prices and the structural transformation in the model. Non-homothetic preferences, by themselves, imply counterfactual sectoral price movements.

17.1 percent. The higher rate of decrease without reservations is due to low "base" effects: without reservations, SC/STs localize in the low wage agriculture sector which reduces their 1983 wages. Most importantly however, growth appears to drive a reduction in caste wage gaps, with or without reservations.

Fifth, the model allows us to compute the welfare costs of caste distortions. We do this by equalizing both the schooling costs and the sectoral entry costs across castes. Recall that these are the only two sources of differences across castes. We find that equalizing all schooling and sectoral entry costs across castes increases average per capita consumption by 10.2 percent in 1983 and 10.3 percent in 2012. Correspondingly, removing all caste distortions results in per capita output rising by 11.4 percent in 1983 and 8.5 percent in 2012. The gains for SC/STS are obviously larger than these overall numbers. Importantly however, when the caste distortions are modelled as pure deadweight losses, their elimination is a Pareto improvement as per capita consumption of both SC/STs and non-SC/STs rise in response.

Overall, we interpret our results as suggesting that the primary driver of the caste wage convergence during 1983-2012 was a relatively faster increase in the education attainment rates of SC/STs in response to the sectoral productivity growth. More generally, the rapid growth take-off in India over the past three decades appears to have causally sparked a dramatic narrowing of the historical economic disparities faced by SC/STs.

The paper is related to three distinct bodies of work. The first is the work on castes in India and their impact on economic outcomes. Aside from the contributions of Hnatkovska et al. (2012). and Hnatkovska et al. (2013) cited above, notable other contributors to this literature are Banerjee and Knight (1985), Madheswaran and Attewell (2007) and Borooah (2005) who examined the discrimination against SC/STs in labor markets in urban India. On a related theme, Ito (2009) studied labor market discrimination in two Indian states – Bihar and Uttar Pradesh. Exploring the theme of castes as networks, Munshi and Rosenzweig (2006) and Munshi and Rosenzweig (2016) show how castes induce network effects that impact labor mobility, education choices and employment.[4]

A second literature that is related to our work is the extensive work on structural transformation of countries along the development path wherein countries gradually switch their economic focus

[4]Another paper that is related to our work is Banerjee and Munshi (2004). They examined the differences between entrants belonging to the incumbent traditional community of *Gounders* in the garment industry in Tirupur in India in the early 1990s relative to entrants from other communities. They found evidence of sharp catch-up of capital and output of outsider firms to the levels of entrants from the Gounder community.

from agriculture to non-agricultural sectors. This is a voluminous literature that spans both empirical and theoretical work. Key contributions in this are are Matsuyama (1992), Kongsamut et al. (2001), Ngai and Pissarides (2007) and Acemoglu and Guerrieri (2008). An excellent overview can be found in Herrendorf et al. (2014) who describe both the empirical regularities as well as the theoretical explanations for this phenomenon. Our paper shares the focus on structural transformation with these papers but differs in its focus on the distributional effects of this transformation.

Our work also relates to the literature that has examined the sources of productivity differences between countries. Two lines of research in this broad tent are closely connected with this paper. The first is the work on misallocation of talent by Hsieh et al. (2019) who analyze the consequences of misallocating talent by gender and race on productivity and growth in the USA. We share their interest in the implications of misallocating labor across sectors due to discrimination or other factors. A second branch of work in this area has focused on the role of occupation selection in accounting for income differences between rural and urban workers (see Young (2013)) and between agricultural and non-agricultural workers (see Lagakos and Waugh (2013)). This list is illustrative rather than being exhaustive.

The next section describes the key facts on caste economic gaps and structural transformation in India. Section 3 conducts a decomposition exercise to determine the statistical drivers of the caste wage convergence while Section 4 presents the model and some analytical results. Section 5 presents the calibration and quantitative results while Section 6 presents the counterfactual experiments. Section 7 discusses our welfare results while the last section concludes.

2 Empirical regularities

Our data comes from different sources. The primary data source is the National Sample Survey (NSS) rounds 38 (1983), 43 (1987-88), 50 (1993-94), 55 (1999-2000), 61 (2003-04), 66 (2009-10) and 68 (2011-12).[5] The NSS provides household-level data on approximately 600,000 individuals on education, employment, consumption, and wages as well as other social characteristics. We consider individuals between the ages 16-65 belonging to male-headed households who were not enrolled full time in any educational degree or diploma. The sample is restricted to those individuals who provided their 4-digit industry of employment information as well as their education information.[6]

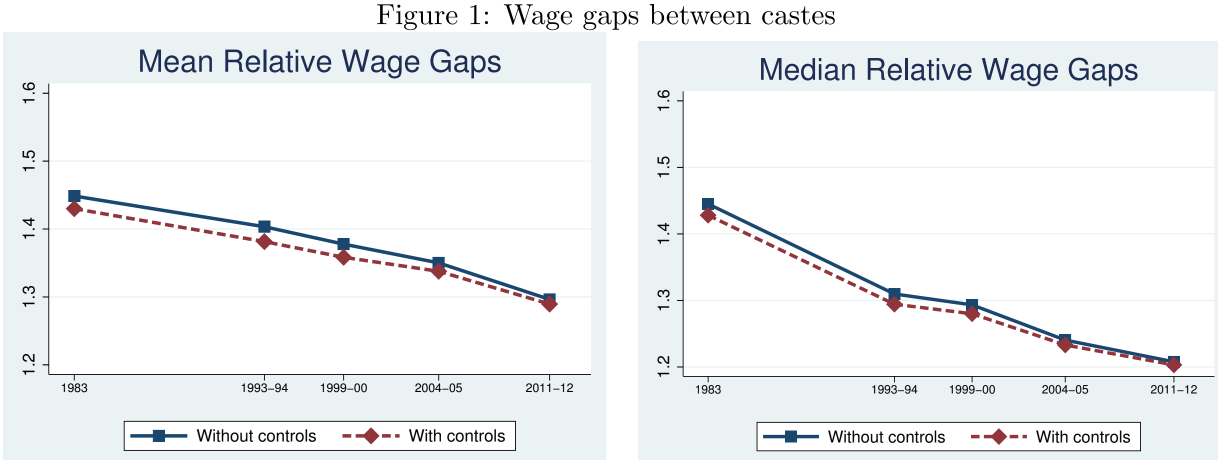
[5] The 68th NSS round is the latest available and released by the Indian government.

[6] We also consider a narrower sample in which we restrict the sample to only males and find that our results remain robust.

Our focus is on full-time working individuals who are defined as those that worked at least 2.5 days per week. This selection leaves us with a working sample of around 165,000-182,000 individuals, depending on the survey round. The wage data is more limited. This is primarily due to the prevalence of self-employed individuals in rural India who do not report wage income. As a result, the sub-sample with wage data is limited to about 48,000 individuals on average across rounds. Details on the data are contained in the Data Appendix to this paper.

We start by reporting some aggregate facts regarding the education and wage gaps between SC/STs and non-SC/STs since 1983. These facts are extensions of the results reported in Hnatkovska et al. (2012). Figure 1 reports the wage gaps between the castes. Panel (a) shows the mean wage gaps between the groups across the NSS rounds while panel (b) shows the corresponding median gaps. The solid lines depict the unconditional wage gaps while the dashed lines show the wage gaps after controlling for the age characteristics of workers.[7] Both plots reveal an unambiguous pattern of wage convergence between the two groups since 1983, with the mean wage gap declining by 10.5% and the median gap falling by 14%.

Figure 1: Wage gaps between castes



(a) (b)

Notes: Panel (a) of this Figure presents the mean wage gaps between SC/STs and non-SC/STs (expressed as a ratio of non-SCST to SCST) from the 1983 to the 2011-12 NSS rounds. Panel (b) shows the corresponding median wage gaps. The dashed lines in the two panels show the computed wage gaps after controlling for the age characteristics of workers (age, age squared) while the solid lines are the gaps without such controls.

Next we examine the education patterns of the two groups during this period. Figure 2 shows the relative gaps in the years of education between non-SC/STs and SC/STs. Panel (a) of the

[7]Specifically, to obtain unconditional wage gaps we estimated an OLS regression (for mean) and a RIF regression (for median) of log wages on a constant and an SC/ST dummy. The conditional gaps are computed from the same regression with age and age squared controls.

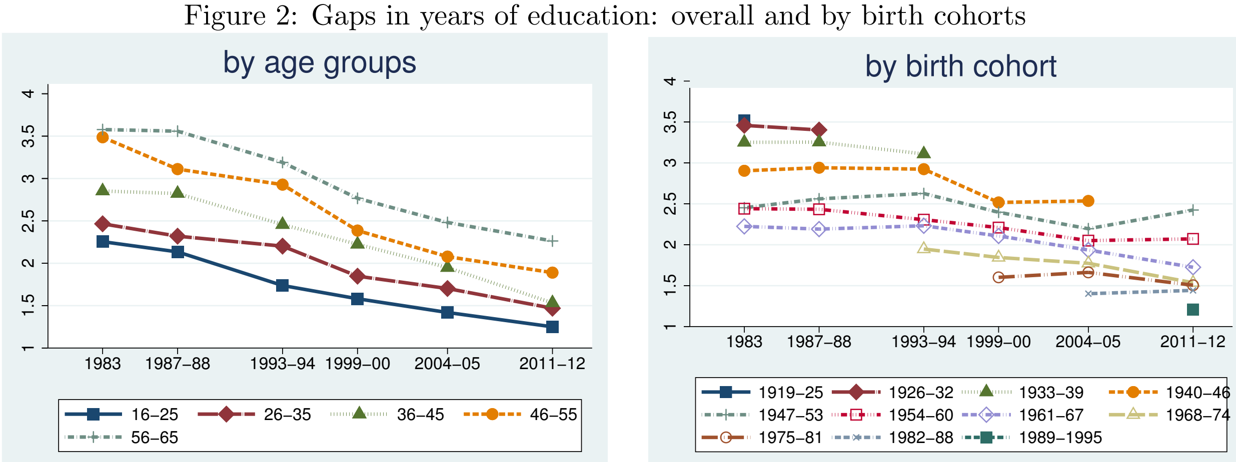
Figure shows the gaps for different age cohorts while panel (b) shows the corresponding gaps in the average years of schooling by birth cohorts.

Both panels reveal a pattern of convergence in education attainment rates between the two groups. Panel (a) shows that the education gap for every ten-year age cohort declined over time, suggesting that education attainment rates of SC/STs increased faster than that for non-SC/STs over time.

This impression from Panel (a) is corroborated by Panel (b) of Figure 2 which shows that the relative gap in years of education between the two groups was systematically lower for younger birth cohorts as compared to older birth cohorts. Thus, SC/STs born in later years had education attainment rates that were closer to their non-SC/ST peers. This is especially stark for the cohort born in 1989-1995 where the education gap has virtually disappeared.

The primary takeaway from Figure 2 is that the period 1983-2012 witnessed a sharp convergence of education attainment rates between SC/STs and non-SC/STs.

Figure 2: Gaps in years of education: overall and by birth cohorts



(a) (b)

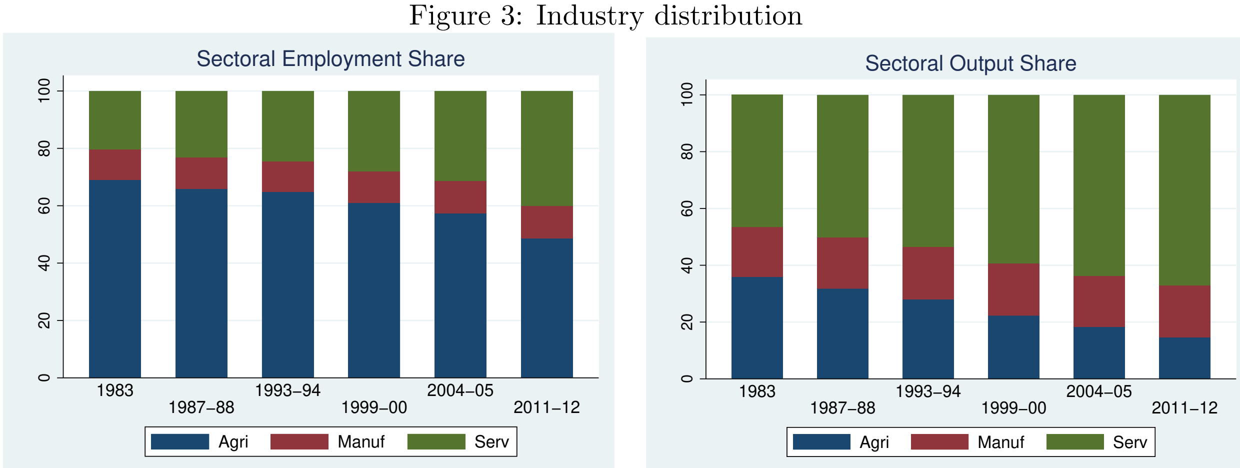
Notes: Panel (a) of this Figure shows the unconditional relative gap in average years of education (non-SCST/SCST) across the NSS rounds for different age cohorts while Panel (b) shows the gaps by birth cohorts.

Given the trends in Figures 1 and 2, the natural question to ask is how much of the wage convergence between the two groups is due to convergence in education attainment. Hnatkovska et al. (2012) examined precisely this question and found that most of the wage convergence is, in fact, due to education convergence.

These trends, while interesting by themselves, raise the logical question about the deeper reasons behind the observed convergence between the groups during this period. While there may have been multiple factors operating simultaneously, in this paper we focus on the two biggest changes that occurred in the Indian economy during this period. As is well known, this period – 1983 to 2012 – was a period of major changes in economic policy which was accompanied by a sharp economic take-off in India. There were large scale trade and industrial reforms carried out in the mid-1980s and in the 1990s. Economic growth in India took off from an average of around 3 percent in the period between 1950 and 1985 to consistently being above 6 percent by the end of the 1990s. Second, this period was also marked by a very sharp structural transformation of the economy.

Below we document some of the key data facts related to the structural transformation of the economy since the early 1980s. In order to present the structural transformation facts, we combine 4-digit industry categories in the data into three broad categories: Agriculture, Manufacturing, and Services. See Appendix 9.1 for more details on the industry grouping.

Figure 3: Industry distribution



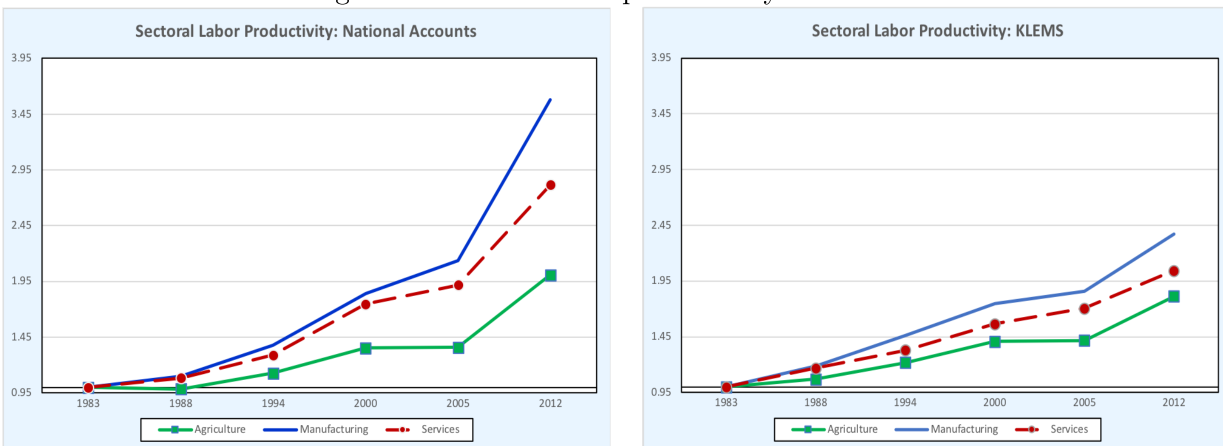
(a) (b)

Notes: Panel (a) of this Figure presents the distribution of workforce across three industry categories for different NSS rounds. Panel (b) presents distribution of output (measured in constant 1980-81 prices) across three industry categories.

Figure 3 shows that the period 1983-2012 was marked by a gradual contraction in the traditional agricultural sector while the service sector expanded both in terms of its share of output as well as employment (there was an expansion in the manufacturing sector too but much more tepid relative to that of the service sector).

This process of structural transformation coincided with rapid growth in productivity at the aggregate and sectoral levels. Figure 4 reports labor productivity in each sector. Panel (a) is measured as output per worker computed from the national accounts data, while panel (b) reports the sectoral labor productivity numbers that are reported in the KLEMS dataset for India. All series are normalized by their values in 1983.

Figure 4: Sectoral labor productivity measures



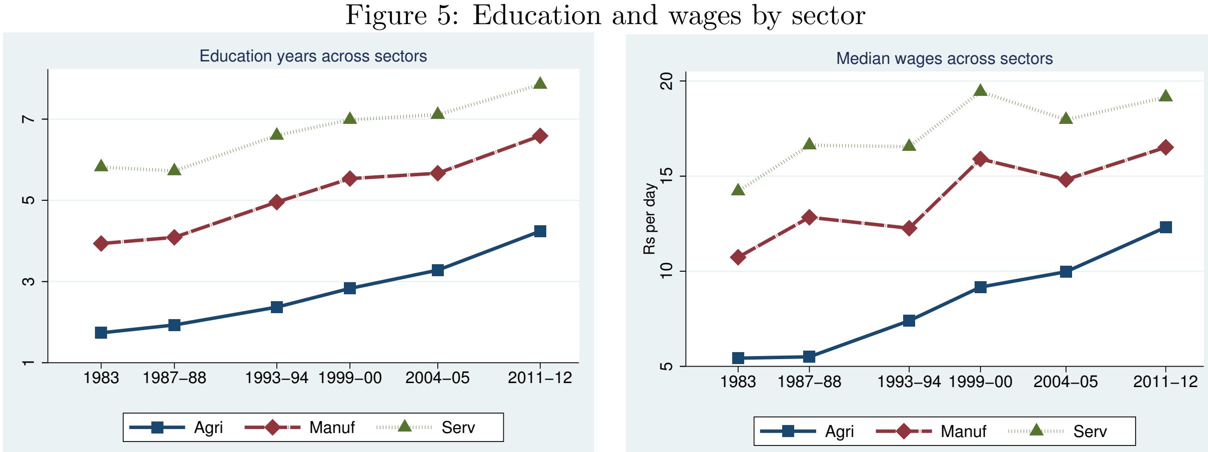
(a) (b)

Notes: Panel (a) of this Figure presents labor productivity, measured as GDP (in constant 1980-81 prices) divided by number of workers in each sector. Panel (b) shows the sectoral labor productivity computed from the KLEMS database for India. All series are normalized by their 1983 values.

Figure 4 shows that productivity growth across the three sectors, especially in the non-agricultural sectors, is a feature of both the national income accounts and KLEMS data. Both datasets also reveal a common rank-ordering of sectoral labor productivity growth during 1983-2012: manufacturing grew the fastest, followed by services, with agriculture being the slowest growing sector.

Sectoral education and wages also exhibited rapid but differential growth, with the two rising the fastest in services, followed by manufacturing and agriculture (see Figure 5).

Figure 5: Education and wages by sector

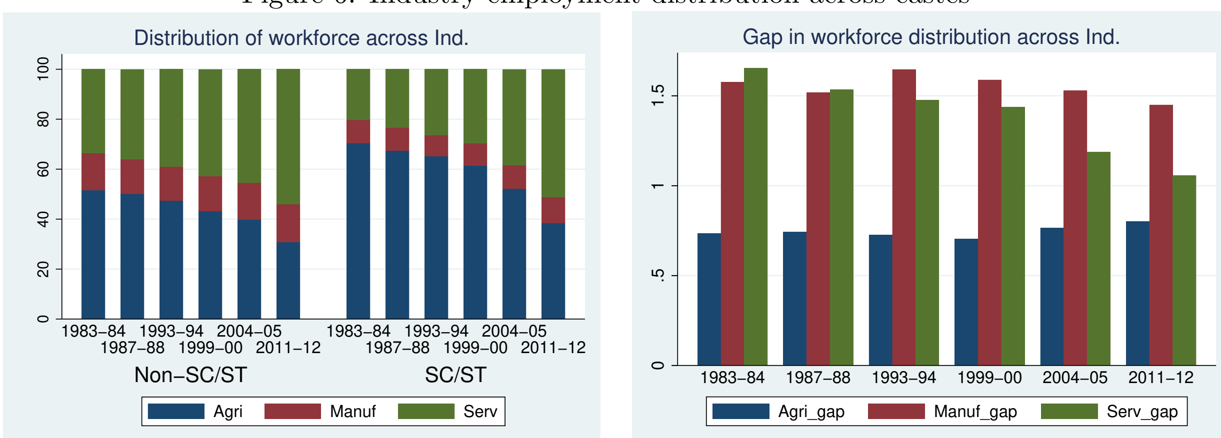


(a) (b)

Notes: Panel (a) of this Figure presents average years of education of workers employed in each of the three sectors. Panel (b) reports median wages in the three sectors.

So, how did this overall transformation of the economy affect the two social groups? Figure 6 reports the industry distribution of working individuals among SC/STs and non-SC/STs, and the relative gaps in this distribution. SC/STs were and remain more likely to be employed in agriculture and other farming activities than non-SC/STs. However the gap narrowed somewhat in the last ten years of our sample. The second largest industry of employment for both social groups is services, whose share has risen steadily over time. Interestingly, services also exhibits the sharpest convergence pattern between non-SC/STs and SC/STs. Specifically, the relative gap between non-SC/STs and SC/STs in employment shares in services has shrunk from 60 percent in 1983 to 21 percent in 2012. Manufacturing shows relatively little changes in the employment shares of the two groups over time.

Figure 6: Industry employment distribution across castes



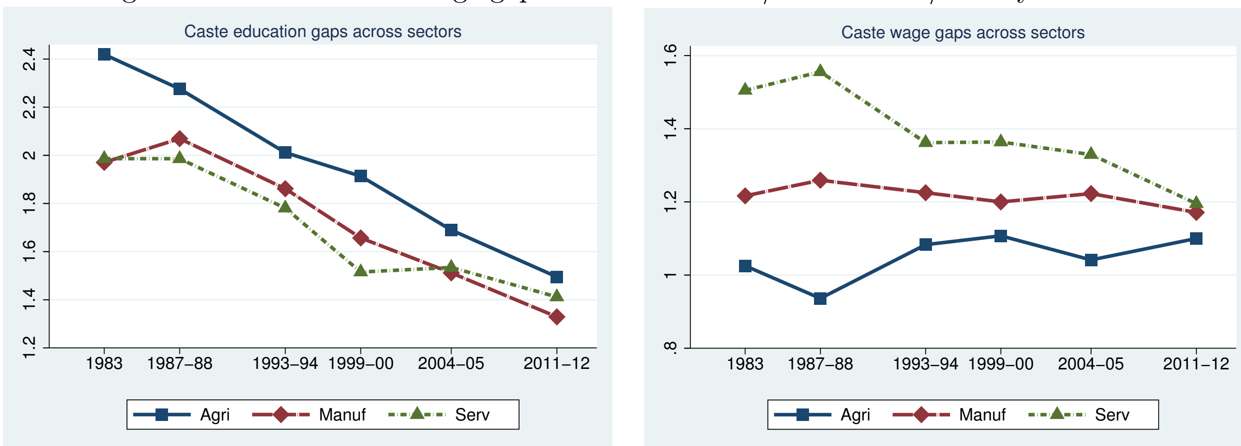
(a) (b)

Notes: Panel (a) presents the distribution of workforce across the three industry categories for different NSS rounds. The left set of bars on each Figure refers to non-SC/STs, while the right set is for SC/STs. Panel (b) presents relative gaps in the distribution of non-SC/STs relative to SC/STs across three industry categories.

Figures 7 reports the relative gaps in education attainments and median wages between non-SC/STs and SC/STs employed in each sector. The education gaps have narrowed significantly over time between the two caste groups across all sectors. Median wage gaps, on the other handm declined in Services, stayed unchanged in Manufacturing, but widened somewhat in Agriculture.

To summarize the data features documented above, the period 1983-2012 was characterized by high aggregate growth in the economy, rising output per worker in all three sectors and productivity growth across the sectors. Concurrently, there was a gradual transformation of the economy with services becoming a larger share of the economy both in terms of output and employment, while the corresponding agriculture shares shrank.

Figure 7: Education and wage gaps between non-SC/STs and SC/STs by sector



(a) (b)

Notes: Panel (a) presents relative gap in years of education between non-SC/STs and SC/STs in three sectors. Panel (b) presents the ratio of non-SC/STs median wages to SC/STs median wages in three sectors.

In terms of the caste distributions, both SC/STs and non-SC/STs exited from agricultural employment during this period. The education gap between the castes declined in all three sectors. Moreover, while wages were converging *overall* between the castes, there were interesting contrasts in the patterns across the sectors. The wage convergence was strong in the service sector. The agricultural sector however saw a divergence in wages between the castes. Interestingly, the wage gaps in the manufacturing sector remained relatively stable over this period.

3 Decomposing the Wage Convergence

How much of the overall caste wage convergence documented above was due to convergence in the sectoral employment distributions versus due to differential movements in the sectoral wages of the castes? This would provide guidance for the margins to focus on in building a structural explanation. In this section we conduct precisely this kind of decomposition using a three-sector structure.

3.1 Notation

We use the following notation for our sectoral decomposition exercise:

Let s denote SC/STs and n denote non-SC/STs individuals. Also let a, m, h denote, respectively, agriculture, manufacturing and services.

- $w^{j,k}$: Average wage of caste $j = s, n$ in sector $k = a, m, h$
- w^j: Average wage of caste $j = s, n$
- w^k: Average wage of sector $k = a, m, h$
- $\ell^{j,k}$: Employment of caste j in sector k
- $l^{j,k} = \frac{\ell^{j,k}}{\sum_k \ell^{j,k}}$: Share of sector k in total employment of caste j
- $\Delta w = \frac{w^n}{w^s}$: Overall caste wage gap
- $\Delta w^k = \frac{w^{n,k}}{w^{s,k}}$: Caste wage gap in sector k
- $\Delta s^k = \frac{l^{n,k}}{l^{s,k}}$: Sectoral caste labor gap

3.2 Decomposition of the wage gap

The overall caste wage gap at any date t can be written as:

$$\Delta w_t \equiv \frac{w_t^n}{w_t^s} = \frac{\sum_{k=a,m,h} w_t^{n,k} l_t^{n,k}}{\sum_{k=a,m,h} w_t^{s,k} l_t^{s,k}} = \sum_{k=a,m,h} \Delta w_t^k \Delta s_t^k \underbrace{\frac{w_t^{s,k} l_t^{s,k}}{w_t^s}}_{\equiv \omega_t^{s,k}}$$

Using the above, we can write the change of the overall wage gap between dates $t-1$ to t as

$$\frac{\Delta w_t}{\Delta w_{t-1}} = \frac{\sum_{k=a,m,h} \Delta w_t^k \Delta s_t^k \omega_t^{s,k}}{\Delta w_{t-1}} = \sum_{k=a,m,h} \left(\frac{\Delta w_t^k \Delta s_t^k}{\Delta w_{t-1}^k \Delta s_{t-1}^k} \right) \left(\omega_t^{s,k} \frac{\Delta w_{t-1}^k \Delta s_{t-1}^k}{\Delta w_{t-1}} \right)$$

The expression above shows that the change in the overall wage gap between dates $t-1$ and t can be decomposed into changes in (a) the three sectoral wage gaps between castes; and (b) the three sectoral labor share gaps between the castes. These are the terms in the first bracket on the right hand side of the equation above. The terms in the second bracket on the right hand side of this equation are weights on these sectoral changes.

The decomposition above allows us to quantitatively assess the individual contribution of each of the six margins identified above to the overall wage convergence. Table 1 reports these results.

Column 1 of Table 1 lists the caste gaps in sectoral labor shares and sectoral mean wages. The second column reports the actual changes in these caste gaps between 1983 and 2012. The third

Table 1: Overall wage convergence: Contributions of sectoral gaps

Caste Gap	$\frac{Gap_{2012}}{Gap_{1983}}$	$\frac{\Delta w_{2012}}{\Delta w_{1983}}$ Predicted	Data
Δs^A	0.98	0.98	0.895
Δs^M	1.09	1.00	0.895
Δs^H	0.76	0.88	0.895
Δw^A	1.04	1.00	0.895
Δw^M	0.95	0.98	0.895
Δw^H	0.92	0.95	0.895

Notes: 1. Each row of this table shows the change in a specific sectoral caste gap between 1983 and 2012 as well as the predicted change in the overall caste *wage* gap if the other five sectoral caste gaps had remained unchanged at 1983 level during this period.

column reports the predicted counterfactual change in the overall caste *wage* gap if the caste gap for that row was the only gap to have changed between 1983 and 2012. The last column compares this counterfactual change with the actual change in the overall caste mean wage gap equal to 10.5%.

As an example, the 0.98 entry in column 2 next to Δs^A indicates that relative caste labor share gap in Agriculture declined by 2 percent between 1983 and 2012. The other two entries for the row labelled Δs^A show that while the overall relative caste wage gap declined by 10.5 percent in the data between 1983 and 2012 (last column), the wage gap would have declined by just 2 percent had the caste labor gap in agriculture been the only gap to have changed during this period.

The main takeaway from Table 1 is that convergence in the caste gaps in services were key for the overall wage convergence. The measured decline in the services labor share gap alone reduces the overall wage gap by 12 percent between 1983 and 2012, while wage convergence in the service sector contributed another 5 percent to the overall wage convergence. In comparison, the other sectoral caste gaps had relatively minor effects on the overall wage gap. Consequently, any structural explanation for the observed wage convergence has to generate a big convergence in the caste labor gap in services.

4 Model

We now ask whether productivity shocks can have a differential impact on the two groups and cause the education and wage gaps between the castes to fall? If so, what are the conditions under which that can happen? Would such an environment also induce sectoral outcomes that are consistent with the facts that we just outlined above, in particular the large changes in the caste labor gap in services?

Consider a one-period lived closed economy that is inhabited by a continuum of agents of measure L. A measure S of these agents belong to caste s (for scheduled castes and tribes or SC/STs) while a measure $N = L - S$ belong to caste n for non-SC/ST.

Individuals belonging to different castes will be distinct along two margins: the cost of acquiring schooling and the cost of accessing sectoral labor markets. We shall elaborate on each of these features below.

An agent i belonging to caste $j = n, s$ maximizes utility from consumption of the final good

$$u\left(c_{ij}\right) = \frac{c_{ij}^{1-\rho}}{1-\rho}$$

Agents produce a final good by combining three intermediate goods using the technology

$$y_{ij} = \left(y_{ij}^{a} - \bar{y}\right)^{\theta} \left(y_{ij}^{m}\right)^{\eta} \left(y_{ij}^{h}\right)^{1-\theta-\eta}$$

where y^k is intermediate good $k = a, m, h$. In the following we shall refer to the a good as the agricultural good, the m good as the manufacturing good and the h good as the high skill good. $\bar{y}$ is the minimum required level of the a good.

Intermediate goods are acquired by agent i using her income w_i. Specifically, an agent i of caste $j = n, s$ with income w_{ij} chooses y^a, y^m, y^h to maximize production of the final good y subject to the budget constraint

$$p^a y_{ij}^a + p^m y_{ij}^m + p^h y_{ij}^h = w_{ij}$$

The optimal expenditures on intermediate goods by an agent i are[8]:

$$p^a y_{ij}^a = \theta\left(w_{ij} - p^a \bar{y}\right) + p^a \bar{y} \tag{4.1}$$

$$p^m y_{ij}^m = \eta\left(w_{ij} - p^a \bar{y}\right) \tag{4.2}$$

$$p^a y_{ij}^a = \left(1 - \theta - \eta\right)\left(w_{ij} - p^a \bar{y}\right) \tag{4.3}$$

[8]The detailed derivations of these and other results below are provided in the Appendix that accompanies the paper.

Substituting the optimal intermediate goods purchases into the production function for the final good gives

$$y_{ij} = \frac{\theta^{\theta}\eta^{\eta}(1-\theta-\eta)^{1-\theta-\eta}}{p^{a\theta}p^{m\eta}p^{h(1-\theta-\eta)}}(w_{ij} - p^{a}\bar{y})$$

We define the aggregate price index in this economy (the unit cost of producing the final good) as

$$P = \frac{(p^{a})^{\theta}(p^{m})^{\eta}(p^{h})^{1-\theta-\eta}}{\theta^{\theta}\eta^{\eta}(1-\theta-\eta)^{1-\theta-\eta}} \tag{4.4}$$

Since we use the final good as the numeraire, with no loss of generality, we set $P = 1$ throughout the model. Hence, the optimal production of the final good by agent i belonging to caste $j = n, s$ is

$$y_{ij} = w_{ij} - p^{a}\bar{y} \tag{4.5}$$

The non-homotheticity in production of the final good due to a minimum use of the agricultural good will be one source of structural transformation in the model.

4.1 Ability and Human Capital

Each agent is born with with an endowment of ability a_i and one unit of labor time that is supplied inelastically to the labor market. Ability is drawn from an $i.i.d.$ process that follows the cumulative distribution function $G(a)$, $a \in [\underline{a}, \bar{a}]$. The ability distribution is identical for both castes.

Ability is a productive input in building human capital. Human capital, in turn, determines the agent's labor productivity as well as the cost of accessing sector specific labor markets. Specifically, human capital of an agent i is determined by

$$e_{ij} = a_{ij}q_{ij}^{\chi}, \ \chi \in (0, 1) \tag{4.6}$$

where q denotes schooling acquired by the agent and χ denotes the schooling elasticity of human capital.

Acquiring human capital is expensive with the cost given by

$$E(q_{ij}) = \lambda_j q_{ij}$$

Note that the marginal cost of education, λ_j, $j = n, s$ is constant and caste specific. This is the first difference between individuals belonging to different castes.

4.2 Human Capital and Sectoral Employment

An agent can work in any of the three sectors conditional on paying the entry costs of accessing those sectors. With no loss of generality, we normalize the entry cost in sector-a to zero. Access to sectors m and h however are costly. Agent i can access sector-$k = m, h$ by spending f_{ij}^k units of the final good. Notice that this specification allows the sectoral entry costs to be caste specific.

In what follows we shall make the following assumptions:

Assumption 1:

$$f_{ij}^k = \begin{cases} 0, & k = a;\ j = n, s \\ \phi(\gamma_j^k - \alpha e_{ij}), & k = m, h;\ j = n, s \end{cases}$$

Assumption 2: $\gamma_j^h > \gamma_j^m, \quad j = n, s$

Assumption 1 says that sectoral entry costs only apply for entry into sectors m and h. The entry costs have two components. The first, γ_j^k, is a fixed cost that is specific to sector and caste. The second component, αe_{ij}, is decreasing in the human capital of the individual but where the marginal effect of human capital on the entry cost is identical across castes. ϕ is a scaling factor that has no qualitative effect on the results but is useful for quantitative purposes.

Assumption 2 implies that the fixed cost of entry into sector-h is greater than that for entry into sector-m for both castes. This ensures an ability rank order where the highest ability individuals work in sector-h (which is consistent with the evidence on the sectoral distribution of human capital).

The preceding makes clear that there are two fundamental sources of differences across castes: the cost of education λ and the fixed costs of entry into sectors m and h. We shall explore the implications of these differences below.

4.3 Sectoral Production Technologies

The technologies for producing the three goods are all linear in the human capital of the worker. In particular, a worker with ability e_i supplying one unit of labor time to sector a produces

$$y_i^a = Ae_i$$

An m-sector worker with ability e_i produces the manufacturing good m according to

$$y_i^m = Me_i$$

Lastly, an $h-$sector worker with ability e_i produces the high skill good according to

$$y_i^h = He_i$$

Note that labor supply is inelastic and indivisible. So each worker supplies one unit of labor time to whichever sector she works in.

4.4 Sector and Schooling Choice

The decisions about which sector to work in and what human capital level to acquire are joint in this model since the schooling decision is contingent on the returns to human capital which, in turn, is dependent on the sector of employment of the worker since human capital impacts both the direct returns to work as well as the sectoral entry costs.

4.4.1 The schooling choice

An agent belonging to caste $j = n, s$ who intends to work in sector-a will choose schooling q to maximize to maximize consumption:

$$c_{ij}^a = y_{ij}^a - \lambda_j q_{ij}$$

Similarly, an agent planning to work in sector-m will choose her schooling to maximize

$$c_{ij}^m = y_{ij}^m - \lambda_j q_{ij} - \phi\left(\gamma_j^m - \alpha a_{ij} q_{ij}^\chi\right)$$

while an agent headed for work in sector-h would choose schooling q to maximize

$$c_{ij}^h = y_{ij}^h - \lambda_j q_{ij} - \phi\left(\gamma_j^h - \alpha a_{ij} q_{ij}^\chi\right)$$

where $y_{ij}^k = w_{ij}^k - p^a \bar{y}, k = a, m, h$. w_{ij}^k denotes wages for the individual contingent on the sector that she chooses to work in. These sectoral wages are given by

$$w_{ij}^k = \begin{cases} p^a A a_{ij} \left(q_{ij}^a\right)^{\chi} & \text{if } i \text{ works in } a \\ p^m M a_{ij} \left(q_{ij}^m\right)^{\chi} & \text{if } i \text{ works in } m \\ p^h H a_{ij} \left(q_{ij}^h\right)^{\chi} & \text{if } i \text{ works in } h \end{cases}$$

Notice that the schooling choice contingent on working in sector $k = a, m, h$ internalizes the effects of schooling on the sectoral entry costs.

The optimal schooling choices for an agent i belonging to caste j who chooses to work in sector-$k = a, m, h$ are:

$$q_{ij}^a = \left(\frac{\chi a_{ij} p^a A}{\lambda_j}\right)^{\frac{1}{1-\chi}} \tag{4.7}$$

$$q_{ij}^m = \left(\frac{\chi a_{ij} \left(p^m M + \phi\alpha\right)}{\lambda_j}\right)^{\frac{1}{1-\chi}} \tag{4.8}$$

$$q_{ij}^h = \left(\frac{\chi a_{ij} \left(p^h H + \phi\alpha\right)}{\lambda_j}\right)^{\frac{1}{1-\chi}} \tag{4.9}$$

The optimal schooling functions above reflect two key features. First, within each sector higher ability agents acquire more schooling and hence, greater human capital. Second, controlling for ability, sectors with higher labor productivity will have workers with greater human capital since schooling is increasing in sectoral productivity.

4.4.2 Sectoral employment choice

The decision regarding the sector of employment is then based on choosing the sector associated with the highest consumption: $max\left\{c_{ij}^a, c_{ij}^m, c_{ij}^h\right\}$ where c_{ij}^k denotes the consumption of an agent i of caste j working in sector $k = a, m, h$. Since both schooling and sectoral entry costs are paid out of the household final good, the household budget constraint dictates that $c_{ij}^k = y_{ij}^k - \lambda_j q_{ij}^k - f_{ij}^k$ where y_{ij}^k is given by equation 4.5 and f_{ij}^k is given by Assumption 1.

The sector-specific schooling levels in equations 4.7-4.9 above imply consumption levels for agents contingent on their decisions regarding schooling and sector of employment:

$$c_{ij}^{a} = (1-\chi)\left(\frac{\chi}{\lambda_j}\right)^{\frac{\chi}{1-\chi}} (a_{ij} p^a A)^{\frac{1}{1-\chi}} - p^a \bar{y} \tag{4.10}$$

$$c_{ij}^{m} = (1-\chi)\left(\frac{\chi}{\lambda_j}\right)^{\frac{\chi}{1-\chi}} \left\{a_{ij}\left(p^m M + \phi\alpha\right)\right\}^{\frac{1}{1-\chi}} - \phi\gamma_j^m - p^a \bar{y} \tag{4.11}$$

$$c_{ij}^{h} = (1-\chi)\left(\frac{\chi}{\lambda_j}\right)^{\frac{\chi}{1-\chi}} \left\{a_{ij}\left(p^h H + \phi\alpha\right)\right\}^{\frac{1}{1-\chi}} - \phi\gamma_j^h - p^a \bar{y} \tag{4.12}$$

As in the schooling decisions, consumption of agents is also increasing in their ability a within each sector. Note that the consumption levels associated with working in each sector are net of the costs of schooling and sectoral entry costs since those are paid by the agent out of the household final good y_{ij}.

To describe the distribution of agents into the different sectors it is useful to define three ability thresholds:

$$\hat{a}_j^m = \left[\frac{\phi\gamma_j^m}{(1-\chi)\left(\frac{\chi}{\lambda_j}\right)^{\frac{\chi}{1-\chi}}\left\{(p^m M+\phi\alpha)^{\frac{1}{1-\chi}} - (p^a A)^{\frac{1}{1-\chi}}\right\}}\right]^{1-\chi} \tag{4.13}$$

$$\hat{a}_j^h = \left[\frac{\phi\gamma_j^h}{(1-\chi)\left(\frac{\chi}{\lambda_j}\right)^{\frac{\chi}{1-\chi}}\left\{(p^h H+\phi\alpha)^{\frac{1}{1-\chi}} - (p^a A)^{\frac{1}{1-\chi}}\right\}}\right]^{1-\chi} \tag{4.14}$$

$$\tilde{a}_j^h = \left[\frac{\phi(\gamma_j^h - \gamma_j^m)}{(1-\chi)\left(\frac{\chi}{\lambda_j}\right)^{\frac{\chi}{1-\chi}}\left\{(p^h H+\phi\alpha)^{\frac{1}{1-\chi}} - (p^m M+\phi\alpha)^{\frac{1}{1-\chi}}\right\}}\right]^{1-\chi} \tag{4.15}$$

Equation 4.13 defines the threshold ability level $\hat{a}^m$ for which consumption from working in sector-a is the same as consumption from working in sector-m, i.e., $c_{ij}^a = c_{ij}^m$. Hence, an agent with ability $\hat{a}^m$ is indifferent between working in sector-a or sector-m. $\hat{a}^h$ and $\tilde{a}^h$ give the corresponding indifference between sectors-a and h, and between sectors m and h, respectively.

We now make the following assumption to provide greater structure to the cross-sectoral distribution of ability and skills that the model can generate:

Assumption 3: Parameter values guarantee $p^h H + \phi\alpha > p^m M + \phi\alpha > p^a A$

Assumption 3 is necessary (but not sufficient) for there to be a distribution of abilities across all three sectors. This will become clearer in the analysis below.

The thresholds along with Assumptions 1-3 allow a clear pairwise ranking of sectors for each ability type. This is summarized in the following Lemma:

Lemma 4.1. *All individuals $i \in$ caste $j = n, s$ with ability a_{ij} prefer employment in sector-m to employment in sector-a if $a_{ij} \geq \hat{a}_j^m$; employment in sector-h to sector-a if $a_{ij} \geq \hat{a}_j^h$; and employment in sector-h to sector-m if $a_{ij} \geq \tilde{a}_j^h$.*

Proof. See Appendix. ■

4.4.3 Mapping Abilities to Sectors

How do agents get distributed across sectors in this economy? This depends on the relative rank ordering of the three thresholds $\hat{a}_j^m, \hat{a}_j^h$, and $\tilde{a}^h$. The following lemma is useful for characterizing the different possibilities:

Lemma 4.2. *The rank order of the three ability thresholds are*

$$\tilde{a}_j^h < \hat{a}_j^h < \hat{a}_j^m \quad if \quad \hat{a}_j^h = min[\hat{a}_j^m, \hat{a}_j^h]$$
$$\tilde{a}_j^h > \hat{a}_j^h > \hat{a}_j^m \quad if \quad \hat{a}_j^h = max[\hat{a}_j^m, \hat{a}_j^h]$$

Proof. See Appendix. ■

Lemma 4.2 describes the relationship between the three thresholds in the model. Specifically, it says that $\tilde{a}_j^h$ cannot lie in between $\hat{a}_j^m$ and $\hat{a}_j^h$. Rather, it lies on the same side of $\hat{a}_j^m$ as $\hat{a}_j^h$.

Since the model structure can give rise to $\hat{e}^h \gtreqless \hat{e}^m$, the following Proposition characterizes the mapping of the abilities to sectoral employment under both these cases:

Proposition 4.1. *(a) When $\hat{a}_j^h > \hat{a}_j^m$, $j = n, s$, the sectoral distribution of abilities is*

$$a_i \in \begin{cases} [\underline{a}_j, \hat{a}_j^m) & : \ i \in A \\ [\hat{a}_j^m, \tilde{a}_j^h) & : \ i \in M \\ [\tilde{a}_j^h, \bar{a}_j] & : \ i \in H \end{cases}$$

b) When $\hat{a}_j^h < \hat{a}_j^m$, $j = n, s$, the sectoral distribution of abilities is

$$a_i \in \begin{cases} [\underline{a}_j, \hat{a}_j^h) & : \ i \in A \\ [\hat{a}_j^h, \tilde{a}_j^m) & : \ i \in H \\ [\tilde{a}_j^m, \bar{a}_j] & : \ i \in H \end{cases}$$

Proof. (a) When $\hat{a}_j^m < \hat{a}_j^h$, Lemma 4.2 says that we must have $\hat{a}_j^m < \hat{a}_j^h < \tilde{a}_j^h$. The distribution of ability types across the three sectors in this case follows directly from equations 4.13, 4.14, 4.15, and Lemma 4.1. Ability types below $\hat{a}_j^m$ work in sector-a while those in between $\hat{a}_j^m$ and $\hat{a}_j^h$ choose sector-m. For ability types between $\hat{a}_j^h$ and $\tilde{a}_j^h$, equation 4.15 implies that employment in sector-m is strictly preferred to sector-h. Those with ability above $\tilde{a}_j^h$ choose to work in sector-h, which follows directly from equation 4.15.

(b) When $\hat{a}_j^h < \hat{a}_j^m$, from Lemma 4.2 we have $\tilde{a}_j^h < \hat{a}_j^h < \hat{a}_j^m$. In this case, the distribution of ability types across sectors follows directly from equations 4.13-4.14 and Lemma 4.1. Ability types below $\hat{a}_j^h$ strictly prefer employment in sector-a to both sectors h and m. For all ability types in caste $j = n, s$ with $a \in [\hat{a}_j^h, \hat{a}_j^m)$, employment in sector-$h$ dominates both sectors a and m. For $a \geq \hat{a}_j^m > \tilde{a}_j^h$, equation 4.13 says that sector-m dominates sector-a while equation 4.15 says that working in sector-h is strictly preferred by these types over sector-m employment. ■

While the message of Proposition 4.1 is self-explanatory, a comment on part (b), which describes allocations when $\hat{a}_j^h < \hat{a}_j^m$, is useful. The ability distribution described in Proposition 4.1 for this case implies that labor from both castes choose employment in either sector-a or sector-h, thereby rendering sector-m empty. This is clearly counterfactual since our data analysis revealed that both castes were employed in all three sectors. In the remainder of the paper we ignore this case and focus exclusively on parameter configurations such that $\hat{a}_j^h > \hat{a}_j^m$ for $j = n, s$.[9]

4.5 Market clearing and Equilibrium

Markets for each good must clear individually. For the intermediate goods, this implies that total production must equal total demand for each good individually:

$$Y^a = L\left[s\int_{\underline{a}}^{\bar{a}} y_{is}^a dG(a) + n\int_{\underline{a}}^{\bar{a}} y_{in}^a dG(a)\right] \tag{4.16}$$

[9]The case $\hat{a}_j^h = \hat{a}_j^m = \tilde{a}_j^j$ is possible but clearly non-generic. Consequently, we ignore this pathological possibility.

$$Y^m = L\left[s\int_{\underline{a}}^{\bar{a}} y_{is}^m dG(a) + n\int_{\underline{a}}^{\bar{a}} y_{in}^m dG(a)\right] \tag{4.17}$$

$$Y^h = L\left[s\int_{\underline{a}}^{\bar{a}} y_{is}^h dG(a) + n\int_{\underline{a}}^{\bar{a}} y_{in}^h dG(a)\right] \tag{4.18}$$

where Y^k denotes total production of intermediate good $k = a, m, h$. Note that in equations 4.16-4.18, sectoral output of individual i belonging to caste $j = n, s$ whose ability is outside the relevant sectoral ability thresholds given in Proposition 4.1 will be zero.

Total production of the final good must equal the total demand for the final good:

$$C + Q + F = Y = L\left[s\int_{\underline{a}}^{\bar{a}} y_{is} dG(a) + n\int_{\underline{a}}^{\bar{a}} y_{in} dG(a)\right] \tag{4.19}$$

where Q denotes total costs of schooling by all workers, F denotes the total skill acquisition costs incurred by workers employed in sector m and sector h, while Y denotes total production of the final good by all agents.. The market clearing condition for the m good recognizes that part of the use of the good is for acquiring skills.

Definition: *The Walrasian equilibrium for this economy is a vector of prices $\{p_m, p_h\}$ and quantities $\left\{Y^a, Y^m, Y^h, C_s, C_n, Q_s, Q_n, F^m, F^h,\ \hat{a}_s^m, \hat{a}_s^h, \hat{a}_n^m, \hat{a}_n^h\right\}$ such that all worker-households satisfy their optimality conditions, budget constraints are satisfied and all markets clear.*

4.6 Sectoral Labor and Wage Gaps Between Castes

It is useful at this stage to describe the caste labor gaps and wage gaps in the three sectors since those are a key object of interest. The precise expressions for these gaps depend on the specifics of the underlying distribution from which individuals draw their ability endowment. Throughout the rest of the paper we shall maintain the assumption that the ability distribution is uniform:

Assumption 4: The ability distribution $G(a)$ is uniform on the support $[\underline{a}, \bar{a}]$.

The labor employment gap between caste n and caste s in sector $k = a, m, h$ is the ratio of the fraction of caste n workers employed in sector k to the fraction of caste s workers employed in sector k. Under Assumption 4, these gaps are given by:

$$\Delta s^a = \frac{\hat{a}_n^m - \underline{a}}{\hat{a}_s^m - \underline{a}} \tag{4.20}$$

$$\Delta s^m = \frac{\tilde{a}_n^h - \hat{a}_n^m}{\tilde{a}_s^h - \hat{a}_s^m} \tag{4.21}$$

$$\Delta s^h = \frac{\bar{a} - \tilde{a}_n^h}{\bar{a} - \tilde{a}_s^h} \tag{4.22}$$

To derive the sectoral caste wage gaps from the model, note that the ability thresholds and the sector-contingent schooling choices given by equations 4.7-4.9 imply that the mean sectoral wages of agents belonging to caste $j = n, s$ are

$$w_j^a = (p^a A)^{\frac{1}{1-\chi}} \left(\frac{\chi}{\lambda_j}\right)^{\frac{\chi}{1-\chi}} \int_{\underline{a}}^{\hat{a}_j^m} a^{\frac{1}{1-\chi}} \frac{dG(a)}{G(\hat{a}_j^m)}$$

$$w_j^m = p^m M \left(p^m M + \phi\alpha\right)^{\frac{\chi}{1-\chi}} \left(\frac{\chi}{\lambda_j}\right)^{\frac{\chi}{1-\chi}} \int_{\hat{a}_j^m}^{\tilde{a}_j^h} a^{\frac{1}{1-\chi}} \frac{dG(a)}{G(\tilde{a}_j^h) - G(\hat{a}_j^m)}$$

$$w_j^h = p^h H \left(p^h H + \phi\alpha\right)^{\frac{\chi}{1-\chi}} \left(\frac{\chi}{\lambda_j}\right)^{\frac{\chi}{1-\chi}} \int_{\tilde{a}_j^h}^{\bar{a}} a^{\frac{1}{1-\chi}} \frac{dG(a)}{1 - G(\tilde{a}_j^h)}$$

Since the caste wage gap in sector $k = a, m, h$ is the ratio of the mean wage of caste n relative to the mean wage of caste s in sector k, the sectoral caste wage gaps under Assumption 4 are given by:

$$\Delta w^a = \left(\frac{\lambda_s}{\lambda_n}\right)^{\frac{\chi}{1-\chi}} \left(\frac{(\hat{a}_n^m)^{\frac{1}{1-\chi}+1} - (\underline{a})^{\frac{1}{1-\chi}+1}}{(\hat{a}_s^m)^{\frac{1}{1-\chi}+1} - (\underline{a})^{\frac{1}{1-\chi}+1}}\right) \left(\frac{\hat{a}_s^m - \underline{a}}{\hat{a}_n^m - \underline{a}}\right) \tag{4.23}$$

$$\Delta w^m = \left(\frac{\lambda_s}{\lambda_n}\right)^{\frac{\chi}{1-\chi}} \left(\frac{(\tilde{a}_n^h)^{\frac{1}{1-\chi}+1} - (\hat{a}_n^m)^{\frac{1}{1-\chi}+1}}{(\tilde{a}_s^h)^{\frac{1}{1-\chi}+1} - (\hat{a}_s^m)^{\frac{1}{1-\chi}+1}}\right) \left(\frac{\tilde{a}_s^h - \hat{a}_s^m}{\tilde{a}_n^h - \hat{a}_n^m}\right) \tag{4.24}$$

$$\Delta w^h = \left(\frac{\lambda_s}{\lambda_n}\right)^{\frac{\chi}{1-\chi}} \left(\frac{\bar{a}^{\frac{1}{1-\chi}+1} - (\tilde{a}_n^h)^{\frac{1}{1-\chi}+1}}{\bar{a}^{\frac{1}{1-\chi}+1} - (\tilde{a}_s^h)^{\frac{1}{1-\chi}+1}}\right) \left(\frac{\bar{a} - \tilde{a}_s^h}{\bar{a} - \tilde{a}_n^h}\right) \tag{4.25}$$

where the thresholds $\hat{a}_j^m, \tilde{a}_j^h$ are given by equations 4.13 and 4.15, respectively.

The wage and labor expressions above make clear that the key variables that determine the sectoral caste gaps in the model are the ability thresholds $\hat{a}_j^m$ and $\tilde{a}_j^h$ for $j = n, s$. The differences in the ability thresholds across the castes, in turn, depend on differences in schooling costs and sectoral entry costs. This follows directly from equations 4.13 and 4.15 which can be used to get

$$\frac{\hat{a}_n^m}{\hat{a}_s^m} = \left(\frac{\lambda_n}{\lambda_s}\right)^{\chi} \left(\frac{\gamma_n^m}{\gamma_s^m}\right)^{1-\chi} \tag{4.26}$$

$$\frac{\tilde{a}_n^h}{\tilde{a}_s^h} = \left(\frac{\lambda_n}{\lambda_s}\right)^{\chi} \left(\frac{\gamma_n^h - \gamma_n^m}{\gamma_s^h - \gamma_s^m}\right)^{1-\chi} \tag{4.27}$$

These results show that the ability thresholds as well as the education and employment distributions differ across the castes in the model despite members of the two castes drawing from the same ability distribution. These caste gaps arise due to differences in the costs of schooling and the sectoral entry fixed costs which are the only sources of difference across castes in the model.

5 A Quantitative Evaluation

We now turn to a quantitative implementation of the full version of the three-sector model. Specifically, we examine whether a calibrated version of the three sector model can explain the observed caste gap dynamics through the observed macroeconomic growth; and whether the caste education subsidization in India through reservations were crucial for the observed convergence.

The quantitative strategy of this section is to calibrate the model to the mimic the 1983 distribution of education, sectoral employment and sectoral wage of the two castes. Next, we identify the sectoral productivity changes between 1983 and 2012 by matching the change in sectoral labor productivities in the model with the corresponding changes in the sectoral output per unit labor reported in the National Income and Product Accounts data. We then feed the estimated paths of sectoral productivity into the calibrated model. The resulting distributional implications of the model at each date are then compared to the data in order to evaluate the explanatory power of aggregate productivity shocks for the caste wage gap dynamics.

Our focus is on eight key data moments for 1983: the three sectoral caste employment gaps; the three sectoral caste wage gaps; and the two average education levels $\bar{q}_n$ and $\bar{q}_s$. Our calibration strategy is to match these eight data moments by choosing the following eight parameters: the sectoral entry cost parameters $\left(\gamma_s^m, \gamma_s^h, \frac{\gamma_n^m}{\gamma_s^m}, \frac{\gamma_n^h}{\gamma_s^h}\right)$, the two education cost parameters $\left(\frac{\lambda_n}{\lambda_s}, \lambda_s\right)$, the scaling parameter ϕ and the schooling elasticity of human capital χ.

Table 2 reports the key parameters. The upper panel of the table gives the parameters that were either normalizations or values that were taken from other studies. The numbers in the lower panel are the ones that were calibrated to match the moments of the 1983 caste distribution.

There are two features to note about the calibration parameters in Table 2. First, in order to match the sectoral caste gaps in 1983 the model demands that $\frac{\lambda_s}{\lambda_n} = 1.55$ so that the schooling costs for caste-s are 55 percent higher than that for caste-n. This feature allows the model to match the fact that SC/STs are over-represented in sector-a. The higher cost of schooling limits their access to the non-agricultural sectors. Second, matching the caste gaps in 1983 also requires the

Table 2: Calibration of Key Variables

Variable	Value	Variable	Value
$\underline{c}$	0.5	θ	0.46
η	0.15	α	1
$\underline{a}$	1	$\bar{a}$	50
$\frac{M}{A}_{1983}$	1.2	$\frac{H}{A}_{1983}$	1.1
L	1	S	0.25
Calibrated variables			
γ_s^m	20.1360	γ_s^h	299.1381
$\frac{\gamma_n^m}{\gamma_s^m}$	1.036	$\frac{\gamma_n^h-\gamma_n^m}{\gamma_s^h-\gamma_s^m}$	1.332
$\frac{\lambda_s}{\lambda_n}$	1.55	ϕ	0.53
λ_s	2.53	χ	0.61

Notes: The table gives the parameters used for calibrating the model. The top panel lists the parameter values that were taken from other studies. The parameters in the bottom panel of the table were picked to match data moments from 1983.

fixed costs of entry into sectors m and h to be lower for the disadvantaged caste-s. This feature is consistent with the presence of affirmative action programs that provide reservations for SC/STs in public sector jobs, which are mostly in the non-agricultural sectors.

Our quantification strategy is to freeze the calibrated parameters at the 1983 values and recompute the equilibrium by feeding in the identified change in the exogenous sectoral productivities A, M, H between 1983 and 2012. Note that since the model has no intrinsic dynamics, each new level for productivity generates a new equilibrium.

Given the specification of our model, one cannot compute the exogenous sectoral productivities from the sectoral labor productivities reported in the National Income accounts. In the model, agents endogenously acquire human capital through schooling which impacts their productivity. Consequently, sectoral output per unit of sectoral labor would reflect both the exogenous sectoral productivity and the endogenous human capital of the sectoral labor force. This is true both in the data and the model.

We approach the problem in a hybrid way. We first estimate sectoral productivities in 1983 by running sectoral Mincer wage regressions on five categories of education attainment of workers (primary, middle, secondary, college, diploma/technical) and a constant using the NSS employment/unemployment household survey for 1983. We use the constant in these sectoral wage regressions as our estimates of sectoral productivity in 1983. These numbers for relative sectoral productivities are reported in the top panel of Table 2.

Next, we identify the exogenous sectoral productivity growth between 1983 and 2012 in the data by using the model. Specifically, to get the growth rates between 1983 and 2012 of the exogenous sectoral productivities A, M, and H, we first fix the calibrated parameters at 1983 level. We then pick the exogenous sectoral productivity growth rates such that the implied growth rates of sectoral labor productivities between 1983 and 2012 in the model exactly match the corresponding growth rates in the data.[10] This procedure yields the following sectoral productivity growth rates:

$$g_A = 1.1436 \quad g_M = 2.1421 \quad g_H = 2.4068$$

Table 3 shows the match between the eight targeted variables and their corresponding data values in 1983. The model clearly matches the rank order and magnitudes of the targeted moments for the sectoral caste gaps in both labor shares and wages gaps. It also does well in matching the mean education levels of the two castes in 1983, though the fit is not quite as precise as that for the six sectoral caste gaps.[11]

How well does the model perform with respect to the non-targeted moments in 1983? The bottom panel of Table 3 shows the fit of the model with respect to nine non-targeted moments. The first is the one that is the main object of the paper: the overall caste wage gap. The model generates a relative wage premium for non-SC/STs of 34 percent. Relative to the 45 percent non-SC/ST wage premium in the data, we consider the fit to be quite good. The model also does well in matching the six aggregate macroeconomic moments for the sectoral output and labor shares, both in terms of the predicted rank order of the sectors as well as the quantitative magnitudes.[12]

The model allows for heterogeneity both within and across groups. To examine the fit of the

[10] In our data analysis the labor productivity is computed as average output for each sector in 1983 prices. It's model counter-part is then:

$$Ey^k = \frac{p^k_{83} Y^k}{L^k} \quad k = a, m, h$$

where Y^k is given by (4.16)-(4.18), p^k_{83} is price levels at 1983, and L^k is the measure for employment in sector k.

[11] Schooling in the model is a continuous variable whereas in the data it is in years of schooling. To compare the schooling statistics in the model with the data, we normalize both the model and the data education series by de-meaning them. The statistics reported in Table 3 are computed using these de-meaned series.

[12] The model also matches the sectoral ranking of average education and wages shown in Figure 5.

Table 3: Data and Model Moments

		1983		2012	
Variable	Formula	Data	Model	Data	Model
Targeted					
Wage Gap Agriculture NST/ST	Δw^a	1.04	1.04	1.08	1.05
Wage Gap Manufacture NST/ST	Δw^m	1.20	1.20	1.14	1.20
Wage Gap Service NST/ST	Δw^h	1.45	1.45	1.33	1.16
Labor Share Gap Agri NST/ST	Δs^a	0.80	0.85	0.79	0.85
Labor Share Gap Manuf NST/ST	Δs^m	1.43	1.43	1.57	2.15
Labor Share Gap Serv NST/ST	Δs^h	1.61	1.60	1.21	1.32
Mean educ ST	$\bar{q}_s$	1.81	1.75	4.73	3.78
Mean educ NST	$\bar{q}_n$	4.08	3.86	5.78	6.59
Non-Targeted Moments					
Total wage gap	Δw	1.45	1.34	1.30	1.24
Pareto shape para: Schooling ST	k_s	0.57	0.77	1.33	1.19
Pareto shape para: Schooling NST	k_n	1.12	1.16	1.52	1.58
Output Share Agri	y^a	0.56	0.46	0.14	0.37
Output Share Manuf	y^m	0.14	0.15	0.18	0.12
Output Share Serv	y^h	0.30	0.39	0.68	0.51
Labor Share A	S^a	0.69	0.68	0.49	0.71
Labor Share M	S^m	0.11	0.19	0.11	0.12
Labor Share H	S^h	0.20	0.13	0.40	0.17

Notes: The top panel of the table reports the sectoral caste gaps in employment and wages while the bottom panel reports the data and model generated of selected non-targeted moments.

model with regard to its predicted heterogeneity, we first fit a Pareto distribution to the years of schooling of agents separately for each caste in the NSS household survey data for 1983. We then do the same to the schooling outcomes in the model and compare the model with the data.

Table 3 reports the Pareto shape parameter estimated in the data and in the model for 1983. The model accurately generates thicker tails for the non-SC/ST education distribution relative to SC/STs. The quantitative fit of the shape parameter is very close for non-SC/STs but somewhat less so for SC/STs. We interpret this as evidence that the model performs well in matching the observed schooling heterogeneity in 1983. This is important since schooling heterogeneity is the key for the economic heterogeneity in the model.

Having described the fit of the model to the data moments in 1983, we now examine its dynamic predictions for caste gaps. Table 3 also gives the labor and wage gaps across castes in the model and the data in 2012. The main takeaway from the Table is in the last row. In the data, the wage gap between non-SC/STs and SC/STs declined by 0.15/1.45 or 10.3 percent between 1983 and 2012. The corresponding reduction generated by the model is 7.5 percent. Thus, the baseline model can explain 72 percent of the observed decline in the percentage wage gap.

Underneath the success in reproducing the overall caste wage gap dynamics, the model also has qualitative and quantitative success in generating the observed dynamics of the caste gaps in both sectoral wages and employment shares. Thus, the agricultural wage gap marginally increased during 1983-2012 while the services wage gap decreased, both in the data and in the model. Correspondingly, the model reproduces the relatively unchanged agricultural labor share gap as well as the very sharp decline in the services labor share gap in the data. This last feature is particularly important since, as we showed in the decomposition exercise, the size of the change in the caste labor share gap in services was the largest amongst all the sectoral gaps.

Where the model misses quantitatively is in matching the dynamics of the labor share and wage gaps in the manufacturing sector. In the data, the manufacturing labor gap widened by 10 percent while the model generates a 50 percent increase. The model also predicts an unchanged manufacturing wage gap while there was a marginal decrease in this gap in the data.

A key feature of the data is that there was a switch between the relative rank orders of the labor share gaps between manufacturing and services. While services had the largest caste gap in labor shares in 1983, by 2012 it was manufacturing that had the largest caste labor share gap. The model successfully reproduces this switch.

Table 3 also reports the change in the Pareto shape parameter for the schooling distribution of the two castes. Clearly, the model correctly matches the thickening tails of the schooling distribution for both castes, though with slightly more quantitative precision for non-SC/STs. We view this as evidence that sectoral productivity growth can account for a large part of the changes in the distribution of schooling outcomes in India since 1983.

5.1 Statistical wage decomposition: model versus data

In Table 1 above, we had conducted a statistical decomposition of the caste wage gap to show that decreases in the caste employment gap and caste wage gap in the services sector were the two largest contributors to the overall relative caste wage convergence between non-SC/STs and SC/STs during 1983-2012. Can the model generate the same patterns?

To answer this question, note that the calibrated model generates model counterparts of all the data components that were used to conduct the statistical decomposition of caste wage gap. Using these model moments, we can create a model counterpart of Table 1 which would allow us to examine whether the model reproduces the data decomposition results.

Table 4: Wage Gap Decomposition: Model versus Data

	$\frac{\Delta w_{2012}}{\Delta w_{1983}}$	
Caste Gap	Data	Model
Δs^A	0.98	1.00
Δs^M	1.00	1.08
Δs^H	0.88	0.93
Δw^A	1.00	1.00
Δw^M	0.98	1.00
Δw^H	0.95	0.92

Notes: 1. Each row of the table shows the change in the overall wage gap in response to a change only in the sectoral caste gap of that row while holding the other five sectoral caste gaps constant. These decompositions are based on equation 3.2.
2. All changes are computed for the period 1983-2012.
3. The "Data" column shows the the effects of changing the relevant caste gap as reported in Table 1 while the numbers in the "Model" column report the effects of changing the associated caste gap as in the model.

Table 4 shows the results of this exercise. The main point to note from the table is that just as in Table 1, the two caste gaps that are associated with the largest effects on the overall wage convergence in the model are the caste gaps in employment and wages in services. In addition, as in the data, the other caste gaps have relatively muted effects on the overall wage convergence. We interpret this evidence as independent support for the model.

5.2 Relative versus Absolute Convergence

The entire focus of the paper has been on the facts and explanations for the observed convergence in relative wages between non-SC/STs and SC/STs. Our focus on relative convergence is in keeping with the typical approach in inter-group inequalities like racial gaps which examines log wage differences between the groups of interest. Examining the evolution of relative gaps is also consistent with the approach in the cross-country growth literature which looks at the relative income gaps across countries. We believe that issues of income inequality are best examined through the lens of relative gaps.

There is however, a parallel concern amongst some social scientists and policymakers about absolute inequality. Indeed, this is the reason why researchers sometimes use measures like the absolute Gini coefficient. Our model clearly has predictions for absolute wage convergence between castes. How do these predictions compare with the evidence on the behavior of absolute wage gaps between non-SC/STs and SC/STs during the period 1983-2012? Table 5 shows the change in the relative and absolute caste wage gaps in the data and in the model. We measure the relative caste wage gap at date t as w_{nt}/w_{st} and absolute caste wage gaps as $w_{nt} - w_{st}$. The table reports the percentage change between 1983 and 2012 in these two measures.

Table 5: Absolute versus Relative Convergence

	Change: 1983-2012	
Variable	Data	Model
Relative wage gap	-10.5	-7.5
Absolute wage gap	71.3	96.0

Note: The table reports changes in the relative and absolute wage gaps between non-SC/STs and SC/STs during 1983-2012

As the table shows, the 10.5 percent decrease in the relative caste wage gap during 1983-2012 in the data was accompanied by a 71.3 percent increase in the absolute wage gap between the two groups during the period. Reassuringly, the model reproduces this feature of the data as well by predicting a 96 percent rise in the absolute wage gap.

We view the results in Table 5 as independent evidence in support of the model since it was not calibrated to target the absolute gaps either in 1983 or in 2012.

5.3 Mechanisms at Play

The model developed and quantified above has a few important features built into it. These include selection effects in sectoral choices by workers, non-homothetic preferences, education costs as well as differential sectoral productivity growth. While the education costs are more specific to our model, selection effects, non-homothetic preferences and unbalanced sectoral growth have been emphasized by a number of authors in models of structural transformation.

Which of these features is key for our baseline results? We try to uncover the answer by re-solving the quantitative model under combinations of four special cases: (a) random sorting of workers across sectors; (b) homothetic preferences with $\bar{y} = 0$; (c) balanced sectoral labor productivity growth;[13] and (d) education and sectoral entry costs that are scaled to the average growth rate of labor productivity in the economy.

Recall that not scaling schooling and sectoral entry costs implies that education costs decline in relative terms as productivity grows in the other sectors of the economy. This induces an endogenous expansion of output as people get more schooling and more people enter the higher skill sectors.

5.3.1 Random sorting: No selection effects

In the first special case of the model, we shut down all selection effects in the sectoral re-sorting of workers in 2012 in response to productivity shocks. Specifically, we feed the same sectoral productivity growth as in the baseline model but instead of allowing workers to endogenously make their schooling and sectoral employment choices in response, we assign random selections of workers from agriculture to manufacturing and from manufacturing to services. The random selections are done such that the overall shares of workers of each caste changing sectors in 2012 relative to 1983 matches the corresponding shares in the baseline model.

This experiment effectively keeps the number of workers changing sectors the same as in the baseline model but does not permit any selection effects to dictate the identity of those changing sectors. The results are shown in Table 6.

The main takeaway can be gleaned from the row corresponding to Δw in the top panel which gives the overall caste wage gaps in the different cases. While the caste wage gap falls by 7.5 percent (0.10/1.34) in the baseline model, the corresponding decline under random sorting is 6.7 percent (0.09/1.34). Effectively, selection effects account for at most around 10 percent of the wage convergence generated by the model.

The effects of selection are illustrated by the last two columns of the other panels of Table 6. When labor is reassigned across sectors randomly rather than through selection, the average human capital of both castes rises in agriculture and manufacturing while falling in services. This is intuitive. Under selection, only the most able types move from agriculture to manufacturing and from manufacturing to services. When the re-sorting is random, the average ability of the group that moves is lower. This raises the average ability of the pool that remains in the sectors that are

[13] The results presented below are not sensitive to choosing the rate of labor productivity of one of the other two sectors as the common growth rate.

Table 6: Wage Gaps with Random Resorting

Variable	Baseline 1983	Baseline 2012		Random Sorting 2012
Wage Gaps				
Δw^a	1.04	1.05	$<$	1.07
Δw^m	1.20	1.20	$>$	1.197
Δw^h	1.45	1.16	$>$	1.14
Δw	1.34	1.24	$<$	1.25
Sectoral average ability				
Ee^a_{nst}	17.06	17.68	$<$	17.85
Ee^m_{nst}	38.00	37.68	$<$	38.01
Ee^h_{nst}	46.49	45.54	$>$	44.67
Ee^a_{st}	19.86	20.57	$<$	20.67
Ee^m_{st}	42.19	41.72	$<$	42.18
Ee^h_{st}	47.81	46.64	$>$	45.84
Output and Price				
Y^a	134.0	289.2	$<$	293.4
Y^m	220.7	479.7	$<$	487.5
Y^h	294.0	104.5	$>$	101.6
Y_f	195.9	514.5	$>$	513.6
p_a	0.676	0.819	$>$	0.806
p_m	0.133	0.161	$>$	0.158
p_h	0.259	0.192	$<$	0.197

net releasers of labor while simultaneously reducing the average ability of the new pool of workers in the expanding sector.

The altered sectoral composition of workers under random sorting has macroeconomic implications. The higher average ability of agricultural and manufacturing workers raises output of those two sectors in 2012 relative to the baseline. The output level of services declines due to the declining average ability of workers in that sector. This raises the sectoral relative prices of services relative to the baseline case.

Note that in this experiment we allow all workers to acquire education as in the baseline case. Thus, all workers continue to make education choices based on their expectations regarding their sector of employment. The difference relative to the baseline case is that instead of letting sectoral employment be actually chosen by the optimality conditions, we allot workers to sectors randomly. As a result, the sectoral outputs reflect the higher education levels of workers that is induced in the baseline case by the higher sectoral productivities.

These results show that labor flows across sectors along with higher education are the key driver of the wage convergence in the model. Selection effects, while present, have relatively smaller effects. This is consistent with our statistical decomposition exercise on the data where we had found that sectoral caste labor convergence was the main contributor to the overall wage convergence.

5.3.2 Non-homothetic Preferences

Next, we examine the importance of non-homothetic preferences. The last column of Table 7 gives the changes in the caste labor and wage gaps between 1983 and 2012 predicted by the model under our baseline calibration where we have non-homothetic preferences ($\bar{y} = 0.5$), differential sectoral productivity growth and no scaling of the skilling costs.

The main result to note is that non-homotheticity is quantitatively not important in generating the caste wage convergence. Comparing the changes in the overall caste wage gap for $\bar{y} = 0$ and $\bar{y} = 0.5$ for differential sectoral growth under unscaled skilling costs shows that the predicted changes in the wage gaps are quite similar (-7.62 percent and -7.53 percent, respectively). Similarly, the predicted changes under $\bar{y} = 0$ and $\bar{y} = 0.5$ for common sectoral growth when costs are not scaled are also very similar (-7.62 percent and -7.52 percent).

Table 7: Assessment of Different Mechanisms

		Percentage Growth Rate 1983-2012							
		Common Growth				Differential Growth			
		Scaled costs		Unscaled costs		Scaled costs		Unscaled costs	
Variable	Data	$\bar{y}=0$	$\bar{y}=0.5$	$\bar{y}=0$	$\bar{y}=0.5$	$\bar{y}=0$	$\bar{y}=0.5$	$\bar{y}=0$	$\bar{y}=0.5$
Δs^a	-1.52%	0.00%	0.01%	0.13%	0.14%	0.00%	0.01%	0.13%	0.15%
Δs^m	9.37%	0.00%	-0.20%	50.25%	49.99%	0.17%	-0.08%	50.35%	50.23%
Δs^h	-24.37%	0.00%	-0.16%	-17.26%	-17.39%	-0.11%	-0.02%	-17.28%	-17.41%
Δw^a	4.12%	0.00%	0.02%	0.20%	0.25%	-0.02%	0.03%	0.20%	0.26%
Δw^m	-5.00%	0.00%	0.02%	0.32%	0.35%	-0.01%	0.01%	0.32%	0.38%
Δw^h	-8.19%	0.00%	0.01%	-19.96%	-19.96%	0.00%	-0.00%	-19.96%	-19.96%
Δw	-10.51%	0.00%	0.09%	-7.62%	-7.52%	-0.03%	0.03%	-7.62%	-7.53%

Notes: The table reports the percent changes in sectoral caste gaps in employment and wages between 1983 and 2012. $\Delta s^j,\ j = a, m, h$ is the ratio of the fraction of all of all non-SC/STs working in sector j to the fraction of all SC/STs working in sector j. $\Delta w^j,\ j = a, m, h$ is the ratio of the mean non-SC/ST to mean SC/ST wage in sector j. Δw is the ratio of the mean non-SC/ST to mean SC/ST wage.

These results do not imply that homothetic preferences are irrelevant in the model. As can be seen from the column for $\bar{y} = 0$ in the common sectoral growth rate panel under scaled costs, both labor and wage caste gaps remain unaffected by growth when preferences are homothetic. Since all sectors expand proportionately under balanced growth and scaled costs, and demand grows proportionately as well due to homotheticity, relative sectoral prices remain unchanged in this case. This leaves the caste-specific ability cut-offs for switching sectors unaffected by growth.

Consequently, caste gaps are invariant to growth. Introducing non-homotheticity changes this as growth induces unbalanced demand increases across sectors.

The general takeaway from these results is that the quantitative effect of non-homotheticity in our baseline model is small.

5.3.3 Differential Sectoral Labor Productivity Growth

Table 7 also illustrates the role played by differential sectoral productivity growth in inducing the wage convergence. To examine its role, we first compute the growth rate of the final good in our baseline calibration. We then conduct a counterfactual exercise where all the sectoral productivities grow at this common rate. Comparing the columns in Table 7 under differential growth with the corresponding columns under common growth, the key feature to leap out is that the results for all the moments are very similar under the two characterizations.

We conclude from this exercise that differential sectoral productivity growth wasn't the key factor in driving the caste convergence during 1983-2012.

5.3.4 Scaling of Costs

In the quantitative implementation of the model, we did not scale up the costs of schooling and sectoral entry with productivity growth in the agriculture, manufacturing and services. The non-scaling effectively reduces relative skilling costs when productivity grows in the other three sectors. This mechanism acts as a form of endogenous propagation of exogenous productivity shocks.

To uncover the importance of scaling costs, we recompute the effects of the baseline sectoral productivity growth when both schooling and sectoral entry costs are scaled to the growth rate of final output.

Table 7 shows that unscaled skilling costs do have quantitatively strong effects on the overall caste convergence. Comparing the results for scaled and unscaled skilling costs for otherwise identical growth and homotheticity specifications of the model shows that there is a sharp increase in the wage convergence when skilling costs remain unscaled. Clearly, this endogenous propagation mechanism is quantitatively very strong.

6 Counterfactual experiments

Having described the fit of the model to the 1983 sectoral labor and wage gaps across castes, we now turn to the issue of identifying the key drivers of the observed dynamics in these gaps. Two questions are of particular interest to us. We examine them below.

6.1 Re-sorting of workers

A key narrative surrounding the issue of castes in India is that it often acts as a barrier to schooling and entry into different occupations and sectors. In our model, productivity changes induce a re-sorting of workers by education and sector of employment. This re-sorting of workers is based on their costs of schooling and sectoral entry. How important was this re-sorting for the declining caste gaps?[14]

We assess the importance of re-sorting by workers by conducting three counterfactual experiments. The first freezes the workers' sectoral employment choices at the 1983 levels by keeping the ability thresholds unchanged but allows them to change their schooling choices. The second experiment freezes worker education choices at the 1983 levels but allows them to switch their sector of employment. The third experiment freezes both the education and sector of employment of workers at the 1983 levels. In all thee experiments we hit the model with the same observed sectoral productivity changes as in the baseline model.

Comparing the baseline case with the first counterfactual experiment gives the importance of educational re-sorting of workers while the second experiment isolates the importance of sectoral re-sorting of workers by itself. The third experiment measures their joint importance of these two forms of re-sorting for the overall results. Table 8 gives the results. The column "No Entry" gives the results of the first experiment, the column labelled "No Educ" gives the results of the second experiment, while the last column gives the outcome of the third experiment.

The first result of interest from this counterfactual exercise is the importance of education and selection effects in worker sorting in driving sectoral labor productivity. This can be seen from the last column of the top panel of Table 8. All the sectoral labor productivity growth rates are lower than in the baseline case. Sectoral labor productivity reflects the exogenous sectoral productivity, the worker quality and the human capital of workers. In this experiment we are holding the

[14] Note that the issue of the importance of sectoral reallocation being addressed here is different from the random reallocation versus selected reallocation issue that was addressed in subsection 5.3.1 above. There our focus was on who was moving across sectors. The question here is about the importance of the ability to relocate itself.

Table 8: Worker Re-sorting

		2012				
Name	Variable	Data	Baseline	No Entry	No Educ	Neither
	$\frac{Ey_{11}^a}{Ey_{83}^a}$	2.07	2.07	1.93	1.42	1.14
Labor Prod	$\frac{Ey_{11}^m}{Ey_{83}^m}$	3.40	3.40	2.79	2.36	2.14
	$\frac{Ey_{11}^h}{Ey_{83}^h}$	2.70	2.70	2.83	2.41	2.41
	Δw^a	1.08	1.05	1.04	1.05	1.04
	Δw^m	1.14	1.20	1.20	1.19	1.20
	Δw^h	1.33	1.16	1.01	1.44	1.44
Gaps	Δs^a	0.79	0.85	0.85	0.85	0.85
	Δs^m	1.57	2.15	1.43	1.96	1.43
	Δs^h	1.21	1.32	1.60	1.60	1.60
	Δw	1.30	1.24	1.21	1.39	1.34

exogenous sectoral productivities at their baseline values. Hence, the lower measured sectoral labor productivity relative to the baseline case is due to the absence of the worker selection and human capital effects. Clearly, these effects are quantitatively large.

Second, the last column and row of Table 8 reveals that without any worker re-sorting through changes in schooling and reallocation across sectors, sectoral productivity growth alone would have induced a *widening* of the relative caste wage gap from 1.30 to 1.34. The reason for this is that productivity growth was faster in the non-agricultural sectors where SC/STs were under-represented in 1983. Without the possibility of reallocation of SC/ST labor towards the faster growing sectors, the overall wage gap increases even though each sectoral wage gap remains unchanged in this case since the relative worker abilities of the two types in each sector remains constant.

Third, comparing the results for the overall wage gap in the column "No Entry" with the baseline case illustrates the importance of educational re-sorting. Specifically, educational re-sorting in response to the observed sectoral productivity growths was enough to create an even larger wage convergence. Intuitively, higher ability SC/STs in the service sector respond to the higher rewards for talent by increasing their schooling which raises their wages. Non-SC/STs do not respond by raising their schooling levels in the same way since the typical high ability non-SC/ST worker in the service sector is already close to the upper limit on schooling attainment. Hence, the caste wage gap in services falls, which drives the overall wage convergence in this case.

Fourth, the column "No Educ" shows that without education re-sorting, sectoral re-sorting of workers alone would widen the overall caste wage gap since the movement of SC/ST workers into the service sector without additional schooling would reduce the average productivity of SC/ST workers in services due to a deteriorating ability composition.

These results shows the salience of re-sorting of workers across sectors for the caste wage convergence. The importance of growth for narrowing inter-group inequality arises due to the fact that it encourages workers to re-optimize their schooling and sector of employment in accordance with comparative advantage based on their ability. Schooling, in particular, was the key driver of the overall wage convergence.

6.2 Importance of Affirmative Action Policies

As we noted earlier, India has had affirmative action protection enshrined in the constitution with reservations extended to SC/STs in seats in public institutions of tertiary education, in public sector employment and in political representation. How important were these reservation policies for the observed caste convergence between 1983 and 2012?

The proxy for reservations in the model are the lower fixed costs of accessing manufacturing and service sector employment for SC/STs. We examine the importance of reservations by conducting three counterfactual simulations: (a) $\frac{\gamma_n^m}{\gamma_s^m} = 1$; (b) $\frac{\gamma_n^h}{\gamma_s^h} = 1$; and (c) $\frac{\gamma_n^m}{\gamma_s^m} = \frac{\gamma_n^h}{\gamma_s^h} = 1$. In all these experiments we leave γ_n^m and γ_n^h at their baseline levels. In other words, we raise the fixed cost component of sectoral entry costs for SC/STs to non-SC/STs levels in each sector thereby eliminating the advantage of reservations for SC/STs. All the other baseline calibration parameters are left unchanged. Table 9 shows the effect of this re-calibration.

The left panel of Table 9 shows the effects of equalizing the sectoral entry costs in 1983 while the right panel shows the corresponding effects in 2012. Comparing the column "both" with the "Baseline" column in the Table, one can see that when both sectoral entry costs are equalized, the overall wage gap in 1983 rises to 1.58 from the baseline level of 1.34. For 2012, the model generates an overall wage gap of 1.31 when both entry costs are equalized relative to the baseline level of 1.24.

The sharpest effect of equalizing both entry costs is on the caste employment gap in services. For

Table 9: Role of Affirmative Action

	1983					2012				
Variable	Data	Baseline	γ^m	γ^h	both	Data	Baseline	γ^m	γ^h	both
Δs^a	0.80	0.85	0.84	0.85	0.84	0.79	0.85	0.84	0.85	0.84
Δs^m	1.43	1.43	1.54	0.79	0.84	1.57	2.15	2.54	0.77	0.84
Δs^h	1.61	1.60	1.58	93.37	82.78	1.21	1.33	1.31	3.90	3.84
Δw^a	1.04	1.04	1.01	1.04	1.01	1.08	1.05	1.01	1.05	1.01
Δw^m	1.20	1.20	1.18	1.01	1.00	1.14	1.20	1.18	1.02	1.00
Δw^h	1.45	1.44	1.45	1.26	1.26	1.33	1.16	1.16	1.02	1.02
Δw	1.45	1.34	1.31	1.62	1.58	1.30	1.24	1.22	1.33	1.31

Notes: The table reports the sectoral caste gaps in employment and wages in 1983 and 2012 in the data and under different special cases of the model. Δs^j, $j = a, m, h$, is the ratio of the fraction of all of all non-SC/STs working in sector j to the fraction of all SC/STs working in sector j. Δw^j, $j = a, m, h$ is the ratio of the mean non-SC/ST to mean SC/ST wage in sector j. Δw is the ratio of the mean non-SC/ST to mean SC/ST wage.

1983 this gap jumps to 82.78 from the baseline number of 1.60 when both entry costs are equalized. Intuitively, the removal of the lower sectoral entry cost advantage provided by affirmative action along with the continued higher education costs for SC/STs drastically reduces the the fraction of SC/STs getting educated and moving to services. This has a spillover effect in that the share of SC/STs in manufacturing rises as some who would have moved under a lower γ_s^h now choose to remain in manufacturing. Similarly, the 2012 caste employment gap in services jumps to 3.84 when both entry costs are equalized relative to the baseline number of 1.33. This change relative to the baseline is somewhat muted because the large sectoral productivity changes during 1983-2012 continue to provide an independent impetus for individuals to switch sectors.

These results indicate the importance of affirmative action programs in reducing the caste gaps in employment and wages at any point in time. The policy likely worked by inducing some relatively higher ability SC/STs to take advantage of the lower education costs and move out of agriculture to take up employment in the non-agricultural sectors with higher wages. Without these reservations in higher education, the caste wage gaps would have been higher at all points.

There are two other ways of evaluating the effects of affirmative action programs on the caste gaps. First, one can compare caste wage gaps in 1983 under equal entry costs in both sectors ($\Delta w = 1.58$) with the corresponding gap in 2012 ($\Delta w = 1.31$) under equal entry costs. This experiment estimates the dynamic changes in caste gaps during the period 1983-2012 with no affirmative action in jobs at any time. The implied reduction in the caste wage gap between 1983 and 2012 is 17.1 percent. This is more than double the 7.5 percent caste wage convergence in the baseline. Clearly, the magnitude of the wage convergence would be even greater without affirmative action protection.

Second, we can compare the caste wage gap in 1983 in the baseline case under reservations ($\Delta w = 1.34$) with the caste gap in 2012 under equal entry costs in both sectors ($\Delta w = 1.31$). This experiment corresponds to a counterfactual where 2012 differs from 1983 along two dimensions: sectoral labor productivity and sectoral entry costs. The implied reduction in the caste wage gap in this case during 1983-2012 is 2.3 percent. Thus, there would still be convergence in this case though less than than the 7.5 percent caste wage gap decline in the baseline case.

The main takeaway from these "equal costs" counterfactual experiments is that for given productivity levels, removal of reservations for SC/STs induce an increase in the caste wage gap at all dates. However, the dynamic effects of productivity growth remain qualitatively unchanged even without affirmative action.

6.3 Caste Gaps and Structural Transformation

An important feature of the model that we have presented is the joint evolution of structural transformation at the aggregate macroeconomic level and changes in caste gaps at the microeconomic level. The natural question that arises here is with regard to the role of structural transformation in inducing the microeconomic changes.

The baseline model has three mechanisms that induce structural transformation: (a) non-homothetic production technology; (b) differential sectoral productivity growth; and (c) unscaled schooling and sectoral entry costs. The first two are standard in many models of structural transformation. The last one is more specific to our model. During productivity growth, if the costs of schooling and sectoral entry do not change, then the relative costs in terms of output declines. This, by itself, would potentially induce changes in the sectoral composition of labor and output since the entry costs are different for the three sectors.

We examine the importance of macroeconomic structural transformation for the changes in the caste gaps by conducting a quantitative experiment where we remove all the ingredients in the model that induce structural transformation in response to productivity shocks. Thus, we compare the baseline model with one where we impose a common productivity growth on all three sectors (set at the rate of aggregate output growth), set $\bar{y} = 0$, and scale all the costs by making both $\lambda_j,\ j = n, s$ and $\gamma_j^k,\ k = m, h;\ j = n, s$ proportional to the growth rate of aggregate output.

Table 10: Role of Structural Transformation

Changes under common growth and scaled costs 1983-2012					
Caste Gaps			Aggregate Sectoral Shares		
Variable	Baseline	$\bar{y}=0$	Variable	Baseline	$\bar{y}=0$
Δs^a	0.15%	0.00%	SL^a	$0.68-0.71$	$0.68-0.68$
Δs^m	50.23%	0.00%	SL^m	$0.19-0.12$	$0.19-0.19$
Δs^h	−17.41%	0.00%	SL^h	$0.13-0.17$	$0.13-0.13$
Δw^a	0.26%	0.00%	SY^a	$0.46-0.37$	$0.46-0.46$
Δw^m	0.38%	0.00%	SY^m	$0.15-0.12$	$0.15-0.15$
Δw^h	−19.96%	0.00%	SY^h	$0.39-0.51$	$0.39-0.39$
Δw	−7.53%	0.00%			

Notes: The left panel of the table gives changes in the caste gaps in sectoral employment and wages between 1983 and 2012 in the baseline case and in the case when $\bar{y}=0$, common sectoral growth rate, and scaled schooling and sectoral entry costs. The right panel gives the corresponding changes in the sectoral employment and output shares under the baseline case and in the case with $\bar{y}=0$, common sectoral growth rates and scaled costs. SL^k denotes the employment share of sector $k=a,m,h$. SY^k denotes the output share of sector $k=a,m,h$.

Table 10 shows the results both for the baseline case and when we shut down all three forces driving structural transformation. The main takeaway from the Table is that without the conditions that generate structural transformation in the model, productivity changes have no impact on the caste employment and wage gaps. Intuitively, when all the sectors become proportional to aggregate growth, the ability thresholds for the two castes do not respond to changes in productivity since the rewards from switching sectors change at the same rate as the costs schooling and the cost of accessing those sectors.

We interpret this result as indicative of the importance of the aggregate structural transformation in the Indian economy during 1983-2012 for understanding the dynamic evolution of the caste gaps during this period.

7 Welfare Costs of Caste Distortions

The model that we have outlined has two sources of differences across castes: the costs of schooling and the costs of entry into sectoral labor markets. How expensive are these distortions? How much would SC/ST welfare rise if these distortions were removed? Would non-SC/STs gain as well?

What would be the aggregate welfare gains?

In order to interpret the differences across castes in schooling and sectoral entry costs as distortions, we now provide a tax representation of these costs. Specifically, we define:

$$\lambda_s = \lambda_n + \tau_\lambda$$
$$\gamma_s^k = \gamma_n^k + \tau_\gamma^k, \quad k = m, h$$

where τ_λ is the tax on schooling and $\tau_\gamma^k, k = m, h$ is the tax on sectoral entry costs borne by SC/ST agents. Note that since $\gamma_s^k < \gamma_n^k,\ k = m, h$ under our calibration in in Table 2, $\tau_\gamma^k < 0,\ k = m, h$, i.e., affirmative action will act as a subsidy for SC/STs in accessing sectoral labor markets.

Using T_i to denote per capita public expenditure, the government's budget constraint is

$$L\left[s\int_{\underline{a}}^{\bar{a}} T_i dG(a_i) + n\int_{\underline{a}}^{\bar{a}} T_i dG(a_i)\right] = L\left[s\int_{\underline{a}}^{\bar{a}} \tau_\lambda q_{i,s}^* dG(a_i)\right] + L\left[s\int_{\hat{a}_s^m}^{\tilde{a}_s^h} \tau_\gamma^m \phi dG(a_i) + s\int_{\tilde{a}_s^h}^{\bar{a}} \tau_\gamma^h \phi dG(a_i)\right] \tag{7.28}$$

where $q_{i,s}^*$ stands for the optimal choices of schooling given by equations 4.7-4.9.

This formulation of the cost differences as tax distortions leaves unchanged the production details of the economy since we retain the same calibrated $\lambda_n, \lambda_n, \gamma_n^k, \gamma_s^k$ as in Table 2. The consumption side of the model however does get affected by this reformulation. To see this, note that government expenditure could either be direct consumption by the government or they could be transfers from the government to private citizens. If government expenditures are lump-sum transfers to private agents then consumption of individual i becomes

$$\hat{c}_i = P(w_i - p^a \bar{y}) - \lambda_j q_i^* - E_i^* + T_i \tag{7.29}$$

where T_i is a lump-sum rebate made to each individual i. E_i^* is the optimal expenditure by agent i on sectoral entry.

When the taxes are consumed by the government instead of being rebated then private consumption is given by

$$\hat{c}_i = P(w_i - p^a \bar{y}) - \lambda_j q_i^* - E_i^* \tag{7.30}$$

To assess the welfare costs of caste distortions, we compare aggregate outcomes under the baseline case with two sets of counterfactual experiments: (a) equal sectoral entry costs for the two castes; and (b) equal schooling and sectoral entry costs. We conduct this comparison both with and without tax rebates. Note that since the two castes draw their ability endowments from the same distribution, equalizing both caste distortions (as in experiment (b) here) would eliminate all caste gaps.

Table 11: Welfare Costs of Caste Distortions Under No Rebate

	1983			2012		
Variable	Baseline	γ's equal	all equal	Baseline	γ's equal	all equal
C_s	101.29	98.22	160.1	226.78	223.29	349.0
C_n	160.00	160.27	160.1	346.45	349.02	349.0
C	145.32	144.76	160.1	316.53	317.59	349.0
Y_a	134.04	133.72	146.3	287.97	288.91	310.6
Y_m	220.68	224.42	241.1	485.35	479.88	515.3
Y_h	293.97	288.55	325.6	1025.8	1035.57	1127.0
Y_f	195.87	194.73	218.13	510.71	512.50	553.6

Notes: The table reports average consumption of each caste as well as per capita outputs of the sectoral and final goods under various parameter configurations for schooling and sectoral entry costs when taxes are not rebated to the public.

Table 11 reports the results for the case when taxes are not rebated. The last column of the Table ("all equal") in the left panel (1983) shows the effect of removing all caste distortions. As expected, equalizing all costs equalizes average consumption for both castes since they both draw from the same ability distribution. This translates into an increase in average consumption for SC/STs by 58.8 percent in 1983 and 53.9 percent in 2012. Interestingly, it also marginally raises the average consumption of non-SC/STs in both years. This occurs due to the rise in aggregate output that is induced by the removal of caste distortions. The resultant fall in the relative prices of the intermediate goods benefits non-SC/STs as well.

Aggregate output, Y_f, rises by 11.4 percent in 1983. This is the static gain from removing caste distortions. The corresponding output gain in 2012 is 8.4 percent. The increase in average per capita consumption, C, from removing all caste distortions in this economy is 10.2 percent in 1983 and 10.3 percent in 2012.

How do these estimates change when the caste taxes are rebated back to the public in the form of lump-sum transfers? Table 12 reports the results for average consumption in this case. Since the production side of the economy is unaffected by whether taxes are rebated or not, the output numbers in this case are identical to those in Table 11 above.

Table 12: Welfare Costs of Caste Distortions Under Lump-Sum Rebates

	1983			2012		
Variable	Baseline	γ's equal	all equal	Baseline	γ's equal	all equal
C_s	110.94	107.48	160.1	250.33	245.39	349.0
C_n	169.65	169.53	160.1	370.67	371.12	349.0
C	154.97	154.01	160.1	340.58	339.69	349.0

Notes: The table reports average consumption of each caste as well as per capita outputs of the sectoral and final goods under various parameter configurations for schooling and sectoral entry costs when taxes are fully rebated to the public.

As one might expect, the tax rebate raises the average consumption of both castes in the distorted baseline economy relative to the no-rebate case. Outcomes when all distortions are removed however remain identical to those in Table 11. Consequently, the welfare gains for SC/STs from removing all distortions are now smaller in both years. The average per capita consumption gains for SC/STs is 44.3 percent in 1983 and 39.4 percent in 2012.

The interesting feature of the full rebate case is that removal of all distortions now does hurt non-SC/STs. Since non-SC/STs receive net positive transfers from SC/STs through the tax rebates under the distorted economy, the removal of all taxes reduces their net income. This effect is strong enough for removal of distortions to cause a reduction in the average consumption of non-SC/STs.

The main takeaway from these results is that there are significant welfare gains from removing caste distortions. These gains are very high for SC/STs who face the burden of the cost distortions in schooling and sectoral entry. Strikingly, in the realistic case of no tax rebates, reforms that remove all caste distortions also raise the welfare of non-SC/STs indicating that the reforms are Pareto improvements.

8 Conclusion

The past three decades have seen a significant convergence in the education attainments, occupation choices and wages of scheduled castes and tribes (SC/STs) in India toward the corresponding levels of non-SC/STs. In this paper we have examined the possibility that the large aggregate changes that were occurring in the Indian economy at this time may have jointly contributed to both the observed caste convergence and the structural transformation of the economy during 1983-2012.

We formalized a multi-sector, heterogenous agent model where all individuals draw their innate ability from the same ability distribution. However, the cost of acquiring schooling and the cost of accessing sectoral labor markets are different for individuals belonging to different castes. We examined the aggregate implications of the talent misallocations induced by these two caste based distortions in an environment of aggregate sectoral productivity growth.

Based on quantitative experiments on the model, we estimate that sectoral labor productivity growth can account for 72 percent of the observed wage convergence between SC/STs and non-SC/STs during the period 1983-2012. Decreasing caste gaps in service sector employment and wages are key for the overall convergence, both in the data and in the model. Importantly, our quantitative model matches the data dynamics of both the relative wage gap, whose narrowing is the focus of the paper, and the absolute caste wage gap, which widened during this period.

The model allows a quantification of the costs of caste distortions. We estimate the output costs of caste distortions to be 11.4 percent in 1983 and 8.5 percent in 2012. The corresponding per capita consumption costs of caste distortions are 10.2 percent and 10.3 percent. In the realistic case where distortionary caste taxes are deadweight losses, we find that eliminating caste distortions are Pareto improving: average consumption of both SC/STs and non-SC/STs increase.

Using counterfactual experiments on the model, we find that the main mechanism driving the caste convergence was SC/ST workers increasing their education levels and switching employment into the higher paying service sector. Absent this re-sorting, the caste wage gap would have actually widened despite the productivity growth.

We also find that affirmative action policies that lowered the sectoral entry costs for SC/STs may have played an important role in raising the levels of SC/ST wages. However, we also find that even without any affirmative action protection, sectoral productivity growth would have induced a large reduction in the caste wage gap during 1983-2012. In other words, growth appears to lift all boats, with or without reservations.

In summary, our results suggest that the key for the caste convergence was the response of SC/ST education attainment to the productivity growth. Indeed, a more general takeaway of our results is that the benefits to SC/STs of easier access to education far outweigh the potential costs of losing affirmative action protection.

An important mechanism that we have ignored here is changes in discrimination against SC/STs. As is well known from the work of Becker (1957), rising competition can make discrimination more expensive for business owners. This could reduce barriers for SC/STs and the caste gaps. To examine this hypothesis we would need to conduct a detailed analysis of more disaggregated sectoral data to both document changes in the degree of competition and changes in employment patterns. We hope to examine this in future work.

References

Acemoglu, D. and V. Guerrieri (2008, 06). Capital deepening and nonbalanced economic growth. *Journal of Political Economy 116*(3), 467–498.

Banerjee, A. and K. Munshi (2004). How efficiently is capital allocated? evidence from the knitted garment industry in tirupur. *Review of Economic Studies 71*(1), 19–42.

Banerjee, B. and J. Knight (1985). Caste discrimination in the indian urban labour market. *Journal of Development Economics 17*(3), 277–307.

Becker, G. (1957). *The Economics of Discrimination*. University of Chicago Press, Chicago.

Borooah, V. K. (2005, 08). Caste, inequality, and poverty in india. *Review of Development Economics 9*(3), 399–414.

Herrendorf, B., R. Rogerson, and A. Valentinyi (2014). Growth and Structural Transformation. In P. Aghion and S. Durlauf (Eds.), *Handbook of Economic Growth*, Volume 2 of *Handbook of Economic Growth*, Chapter 6, pp. 855–941. Elsevier.

Hnatkovska, V., A. Lahiri, and S. Paul (2012, April). Castes and labor mobility. *American Economic Journal: Applied Economics 4*(2), 274–307.

Hnatkovska, V., A. Lahiri, and S. Paul (2013, Spring). Breaking the caste barrier: Intergenerational mobility in india. *Journal of Human Resources 48*(2), 435–473.

Hsieh, C., E. Hurst, C. I. Jones, and P. J. Klenow (2019, September). The Allocation of Talent and U.S. Economic Growth. *Econometrica 87*(5), 1439–1474.

Ito, T. (2009). Caste discrimination and transaction costs in the labor market: Evidence from rural north india. *Journal of Development Economics 88*(2), 292–300.

Kongsamut, P., S. Rebelo, and D. Xie (2001). Beyond balanced growth. *Review of Economic Studies 68*(4), 869–882.

Lagakos, D. and M. E. Waugh (2013, April). Selection, agriculture, and cross-country productivity differences. *American Economic Review 103*(2), 948–80.

Madheswaran, S. and P. Attewell (2007). Caste discrimination in the indian urban labour market: Evidence from the national sample survey. *Economic and Political Weekly 42*(41), 4146.

Matsuyama, K. (1992, December). Agricultural productivity, comparative advantage, and economic growth. *Journal of Economic Theory 58*(2), 317–334.

Munshi, K. and M. Rosenzweig (2006). Traditional institutions meet the modern world: Caste, gender, and schooling choice in a globalizing economy. *American Economic Review 96*(4), 1225–1252.

Munshi, K. and M. Rosenzweig (2016, January). Networks and Misallocation: Insurance, Migration, and the Rural-Urban Wage Gap. *American Economic Review 106*(1), 46–98.

Ngai, L. R. and C. A. Pissarides (2007, March). Structural change in a multisector model of growth. *American Economic Review 97*(1), 429–443.

Young, A. (2013, November). Inequality, the urban-rural gap and migration. *The Quarterly Journal of Economics 128*(4), 1727–1785.

9 Appendix

9.1 Data

Table 13 summarizes one-digit industry codes in our dataset. In the presentation in the text we group these codes further into three broad industry categories: Ind 1 refers to Agriculture, Hunting, Forestry and Fishing; Ind 2 collects Manufacturing and Mining and Quarrying; while Ind 3 refers to all Service industries. These groupings are detailed in Table 13.

Table 13: Industry categories

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

9.2 Model

9.2.1 Household's Problem

Given the final production function, an agent i belonging to caste j chooses optimal intermediate good to maximize:

$$\max_{y_{ij}^a, y_{ij}^m, y_{ij}^h} (y_{ij}^a - \bar{y})^{\theta} (y_{ij}^m)^{\eta} (y_{ij}^h)^{1-\theta-\eta} \quad s.t. \quad w_{ij} \geq p^a y_{ij}^a + p^m y_{ij}^m + p^h y_{ij}^h \tag{9.31}$$

Taking w_{ij} as given, solve for the FOCs:

$$p^a \eta (y_{ij}^a - \bar{y}) = \theta p^m y_{ij}^m \tag{9.32}$$

$$p^a (1-\theta-\eta)(y_{ij}^a - \bar{y}) = \theta p^h y_{ij}^h \tag{9.33}$$

Using the above FOCs and the constraint we get the demand functions in main text:

$$p^a y_{ij}^a = p^a \bar{y} + \theta(w_{ij} - p^a \bar{y}) \tag{9.34}$$

$$p^m y_{ij}^m = \eta(w_{ij} - p_a \bar{y}) \tag{9.35}$$

$$p^h y_{ij}^h = (1 - \eta - \theta)(w_{ij} - p^a \bar{y}) \tag{9.36}$$

9.2.2 Education and Sectoral Choices

In the main text, the final good consumption contingent to sectoral choice $k = a, m, h$ is defined as:

$$c_{ij}^k = y_{ij}^k - \lambda_j q_{ij}^k - f_{ij}^k \tag{9.37}$$

where y_{ij}^k is the final good production of agent i when employed in sector k:

$$y_{ij}^k = w_{ij}^k - p^a \bar{y}$$

The wage w_{ij}^k will depend on the sector k:

$$w_{ij}^k = \begin{cases} p^a A e_{ij} = p^a A q_{ij}^{\chi} a_{ij} & k = a \\ p^m M e_{ij} = p^m M q_{ij}^{\chi} a_{ij} & k = m \\ p^h H e_{ij} = p^h H q_{ij}^{\chi} a_{ij} & k = h \end{cases} \tag{9.38}$$

Education Choice: Given the formulation above and the form of f_{ij}^k defined in Assumption 1, take F.O.C with respect to q_{ij} to get sectoral specific schooling:

$$q_{ij}^a = \left[\frac{\chi a_{ij} p^a A}{\lambda_j}\right]^{1/(1-\chi)} \tag{9.39}$$

$$q_{ij}^m = \left[\frac{\chi a_{ij}(p^m M + \phi\alpha)}{\lambda_j}\right]^{1/(1-\chi)} \tag{9.40}$$

$$q_{ij}^h = \left[\frac{\chi a_{ij}(p^h H + \phi\alpha)}{\lambda_j}\right]^{1/(1-\chi)} \tag{9.41}$$

Sectoral Choice: Plug (9.39)-(9.41) into (9.37) and get:

$$c_{ij}^{a} = (1-\chi)\left(\frac{\chi}{\lambda_j}\right)^{\frac{\chi}{1-\chi}} (a_{ij}p^{a}A)^{\frac{1}{1-\chi}} - p^{a}\bar{y} \tag{9.42}$$

$$c_{ij}^{m} = (1-\chi)\left(\frac{\chi}{\lambda_j}\right)^{\frac{\chi}{1-\chi}} \{a_{ij}\,(p^{m}M+\phi\alpha)\}^{\frac{1}{1-\chi}} - \phi\gamma_j^{m} - p^{a}\bar{y} \tag{9.43}$$

$$c_{ij}^{h} = (1-\chi)\left(\frac{\chi}{\lambda_j}\right)^{\frac{\chi}{1-\chi}} \left\{a_{ij}\left(p^{h}H+\phi\alpha\right)\right\}^{\frac{1}{1-\chi}} - \phi\gamma_j^{h} - p^{a}\bar{y} \tag{9.44}$$

The agent will choose the sector that gives the highest c_{ij}^{k}. To ease some notations, we define:

$$\Psi_j = (1-\chi)\left(\frac{\chi}{\lambda_j}\right)^{\frac{\chi}{1-\chi}}$$

First it is easy to see that agent prefers sector a to m if and only if:

$$c_{ij}^{a} = \Psi_j(p^{a}A)^{\frac{1}{1-\chi}} a_{ij}^{\frac{1}{1-\chi}} - p^{a}\bar{y} \geq c_{ij}^{m} = \Psi_j(p^{m}M+\phi\alpha)^{\frac{1}{1-\chi}} a_{ij}^{\frac{1}{1-\chi}} - \phi\gamma_j^{m} - p^{a}\bar{y} \tag{9.45}$$

Similarly, she prefers a to h iff $c_{ij}^{a} \geq c_{ij}^{h}$ and m to h iff $c_{ij}^{m} \geq c_{ij}^{h}$. We can rewrite these three conditions and define:

$$z_j^{m}(a_{ij}) \equiv \frac{\phi\gamma_j^{m}}{a_{ij}^{\frac{1}{1-\chi}}} \geq \Psi_j(p^{m}M+\phi\alpha)^{\frac{1}{1-\chi}} - \Psi_j(p^{a}A)^{\frac{1}{1-\chi}} \tag{9.46}$$

$$z_j^{h}(a_{ij}) \equiv \frac{\phi\gamma_j^{h}}{a_{ij}^{\frac{1}{1-\chi}}} \geq \Psi_j(p^{h}H+\phi\alpha)^{\frac{1}{1-\chi}} - \Psi_j(p^{a}A)^{\frac{1}{1-\chi}} \tag{9.47}$$

$$z_j^{h}(a_{ij}) - z_j^{m}(a_{ij}) \equiv \frac{\phi(\gamma_j^{h}-\gamma_j^{m})}{a_{ij}^{\frac{1}{1-\chi}}} \geq \Psi_j(p^{h}H+\phi\alpha)^{\frac{1}{1-\chi}} - \Psi_j(p^{m}M+\phi\alpha)^{\frac{1}{1-\chi}} \tag{9.48}$$

We then define the cut-off ability levels when equalities bind:

$$\hat{a}_j^{m} = \left[\frac{\phi\gamma_j^{m}}{\Psi_j(p^{m}M+\phi\alpha)^{\frac{1}{1-\chi}} - \Psi_j(p^{a}A)^{\frac{1}{1-\chi}}}\right]^{1-\chi} \tag{9.49}$$

$$\hat{a}_j^{h} = \left[\frac{\phi\gamma_j^{h}}{\Psi_j(p^{h}H+\phi\alpha)^{\frac{1}{1-\chi}} - \Psi_j(p^{a}A)^{\frac{1}{1-\chi}}}\right]^{1-\chi} \tag{9.50}$$

$$\tilde{a}_j^{h} = \left[\frac{\phi(\gamma_j^{h}-\gamma_j^{m})}{\Psi_j(p^{h}H+\phi\alpha)^{\frac{1}{1-\chi}} - \Psi_j(p^{m}M+\phi\alpha)^{\frac{1}{1-\chi}}}\right]^{1-\chi} \tag{9.51}$$

The sectoral choices are then given by Proposition 4.1 in the main text.

9.2.3 Proofs

In this section we sketch the proofs of **Lemma 4.1** and **Lemma 4.2** in the main text.

Lemma 4.1 *All individuals $i \in$ caste $j = n, s$ with ability a_{ij} prefer employment in sector-m to employment in sector-a if $a_{ij} \geq \hat{a}^m_j$; employment in sector-h to sector-a if $a_{ij} \geq \hat{a}^h_j$; and employment in sector-h to sector-m if $a_{ij} \geq \tilde{a}^h_j$.*

Proof. With $0 < \chi < 1$, $\phi, \gamma^k_j > 0$ and Assumption 2, it is obvious that $z^m_j(a_{ij})$, $z^h_j(a_{ij})$ and $z^h_j(a_{ij}) - z^m_j(a_{ij})$ defined by (9.46)-(9.48) are strictly decreasing in a_{ij}. From Assumption 3 that $p^h H + \phi\alpha > p^m M + \phi\alpha > p^a A$, we know that:

$$\begin{cases} c^a_{ij} \leq c^m_{ij} & \text{iff } a_{ij} \geq \hat{a}^m_j \\ c^a_{ij} \leq c^h_{ij} & \text{iff } a_{ij} \geq \hat{a}^h_j \\ c^m_{ij} \leq c^h_{ij} & \text{iff } a_{ij} \geq \tilde{a}^h_j \end{cases}$$

■

Lemma 4.2: *The rank order of the three ability thresholds are*

$$\tilde{a}^h_j < \hat{a}^h_j < \hat{a}^m_j \quad \text{if} \quad \hat{a}^h_j = min[\hat{a}^m_j, \hat{a}^h_j]$$
$$\tilde{a}^h_j > \hat{a}^h_j > \hat{a}^m_j \quad \text{if} \quad \hat{a}^h_j = max[\hat{a}^m_j, \hat{a}^h_j]$$

Proof. Consider first the case $\hat{a}^h_j < \hat{a}^m_j$. In this case, suppose $\tilde{a}^h_j > \hat{a}^h_j$. Using the definitions of $\hat{a}^h_j$ and $\tilde{a}^h_j$ from equations 9.50 and 9.51 above, $\tilde{a}^h_j > \hat{a}^h_j$ can be rewritten as

$$\left[\frac{\phi\gamma^h}{(1-\chi)\left(\frac{\chi}{\lambda_j}\right)^{\frac{\chi}{1-\chi}}\left\{(p^h H + \phi\alpha)^{\frac{1}{1-\chi}} - (p^a A)^{\frac{1}{1-\chi}}\right\}}\right]^{1-\chi} > \left[\frac{\phi\gamma^m}{(1-\chi)\left(\frac{\chi}{\lambda_j}\right)^{\frac{\chi}{1-\chi}}\left\{(p^m M + \phi\alpha)^{\frac{1}{1-\chi}} - (p^a A)^{\frac{1}{1-\chi}}\right\}}\right]^{1-\chi}$$

But this implies that $\hat{a}^h_j > \hat{a}^m_j$ which is a contradiction. Hence, if $\hat{a}^h_j < \hat{a}^m_j$ then $\tilde{a}^h_j < \hat{a}^h_j < \hat{a}^m_j$.

The other case $\hat{a}^h_j > \hat{e}^m_j$ but $\hat{a}^h_j > \tilde{a}^h_j$ leads to a contradiction by a similar logic. Hence, if $\hat{a}^h_j > \hat{a}^m_j$ then $\tilde{a}^h_j > \hat{a}^h_j > \hat{a}^m_j$. ■