Convergence Across Castes*

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(Incomplete)

Abstract

Over the past 25 years there has been a remarkable economic catch-up by the historically discriminated against scheduled castes and tribes (SC/STs) towards non-SC/ST levels in the terms of their education attainment levels, their occupation choices as well as their wage and consumption levels. This period of convergence has coincided with a sharp rise in aggregate economic growth as well as a significant structural transformation of the economy. In this paper we first document these aggregate data patterns as well as the evolution of the sectoral caste gaps in education and wages. We then develop a multi-sector model with two types of agents to show that aggregate TFP shocks along with a process of structural transformation can induce a convergence between the two groups without any other concurrent redistributive policy changes as long as there exists an *initial* affirmative action policy in education and/or jobs for the relatively disadvantaged group. We show some indirect evidence in support of this channel by examining the convergence patterns of Muslims who were not covered by such affirmative action policies.

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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 25 years. This period has witnessed a rapid takeoff of the Indian economy with average annual growth rates doubling relative to the pre-reform phase. However, this takeoff has also been accompanied by a vigorous debate regarding the effects of economic reforms on poverty and economic inequality. A big part of the development challenge is to devise policy initiatives in order to manage these often clashing goals. This paper aims to contribute to this challenge. In particular, the paper aims to uncover the channels through which the large macroeconomic changes in India have affected the economic fortunes of different social groups, i.e., uncover the black-box of the linkages between the macro and micro developments.

We approach the issue by focussing on the experience of Scheduled Castes and Scheduled Tribes (SC/STs) – an historically underprivileged section of Indian society. In recent work, we have shown that these groups have experienced a rapid catch-up towards non-SC/ST levels in their education attainment levels, their occupation choices, as well as in their wages and consumption levels (see Hnatkovska, Lahiri, and Paul (2012)). Accompanying this catch-up has been a sharp convergence in the intergenerational mobility rates in these three indicators as well (see Hnatkovska, Lahiri, and Paul (2013)). These developments immediately raise the key question: what are the forces that have driven these convergent trends? Have they been sparked by the large aggregate changes in the Indian economy during this period which affected all sectors symmetrically? Or, is the convergence primarily due to changes in the caste gap in specific sectors of the economy? This paper is an attempt at decoupling these two forces of change and assessing the relative importance of the two.

We develop a simple model with endogenous skill formation and multiple sectors. The goal of the exercise is two-fold. First, we want to isolate the various margins that affect the skill and industry distribution. A particular focus here is on the role played by productivity increases as well as changes in the costs of skill acquisition. We show that the model can explain the education and wage convergence between the groups as an endogenous response to a process of structural transformation of the economy induced by aggregate productivity shocks as long as there are some pre-existing education subsidies in place for SC/STs. We interpret the reservations in education and jobs provided to SC/STs in India since 1951 as the policy counterparts to the conditions identified by the model. Moreover, we provide independent corroborating evidence in support of this channel by documenting the widening gaps experienced by Muslims in India – another relatively disadvantaged minority group but without affirmative action protection.

Lastly, we use the model to first fit the skill and industry distribution in 1983 and then, keeping parameters unchanged, assess the contribution of measurable factors such as changes in TFP and/or education costs toward explaining the skill and industry distribution in 2004-05. The residual changes in these distributions would then be potentially attributable to changes in discrimination during this period.

2 Empirical regularities

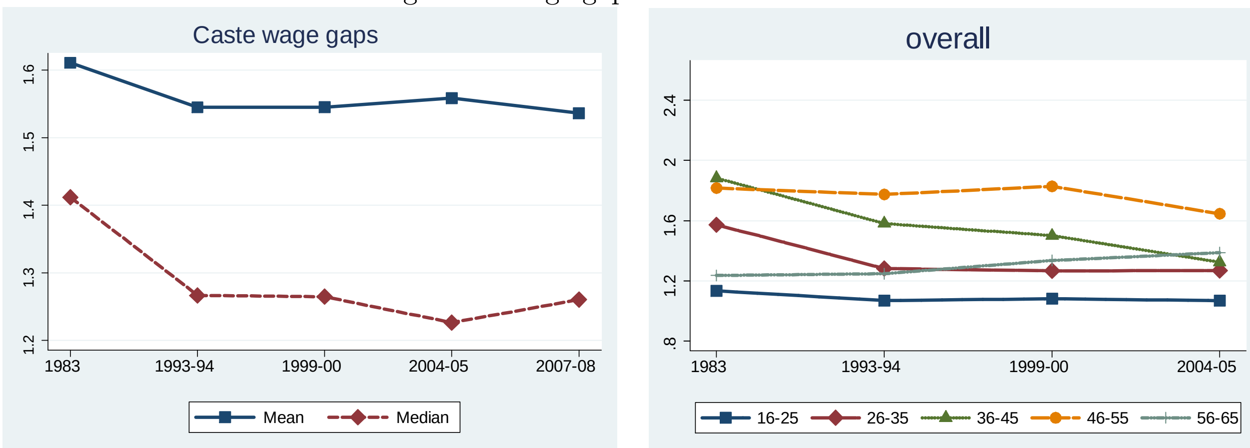
Our data comes from different sources. The primary data source is the National Sample Survey (NSS) rounds 38 (1983), 43 (1987-88), 50 (1993-94), 55 (1999-2000), 61 (2003-04) and 64 (2007-08). The NSS provides household-level data on approximately 600,000 individuals on education, employment, consumption, 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 code information as well as their education information.[1] Our focus is on full-time working individuals who are defined as those that worked at least 2.5 days per week, and who are not currently enrolled in any education institution. 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 mostly borrowed from the results reported in Hnatkovska, Lahiri, and Paul (2012). Figure 1 reports the wage gaps between the castes. Panel (a) shows the mean and median wage gaps between the groups across the NSS rounds. The picture shows that the gap between the groups declined by both measures. Panel (b) breaks down the groups by age and plots the median wage gaps by age cohort. For all except the oldest age-group, the median wage gaps declined secularly during this period. Hence, both plots reveal an unambiguous pattern of wage convergence between the two groups

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 Figure

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

Figure 1: Wage gaps between castes

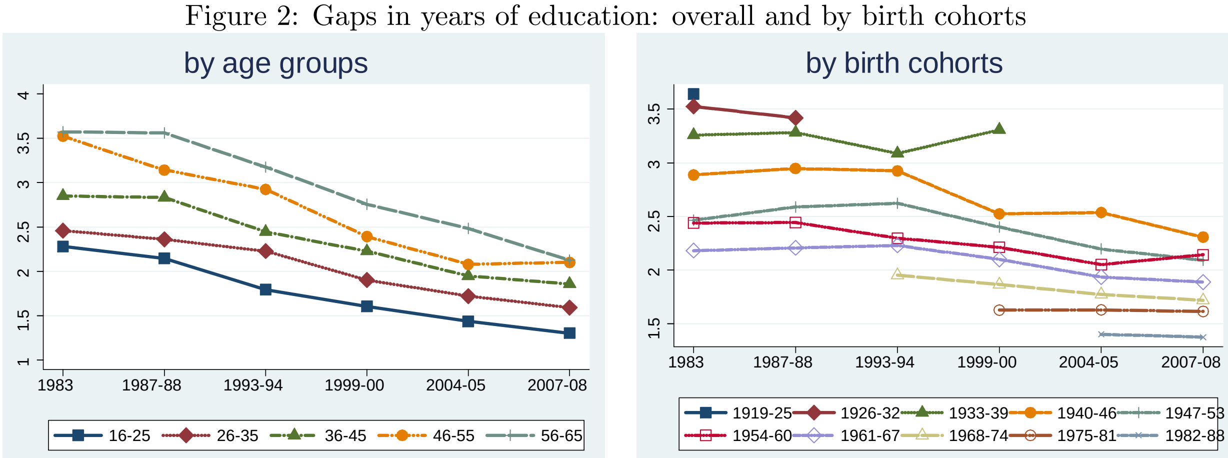


(a) (b)

Notes: Panel (a) of this Figure presents the mean and median wage gaps between SC/STs and non-SC/STs (expressed as non-SCST/SCST) for the 1983 and 2004-05 NSS rounds. Panel (b) shows the median wage gaps (non-SCST/SCST) by age cohort across all the NSS rounds.

shows the gaps for different age cohorts while panel (b) shows the corresponding gaps in the average years of schooling by birth cohorts. Again, both panels reveal the same pattern of convergence in education attainment rates between the two groups. In fact, the education convergence trends are even sharper than the trends in wage convergence.

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



(a) (b)

Notes: Panel (a) of this Figure shows the 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. In Hnatkovska, Lahiri, and Paul (2012) we examine precisely this question and find that most of the wage convergence is, in fact, due to education convergence.

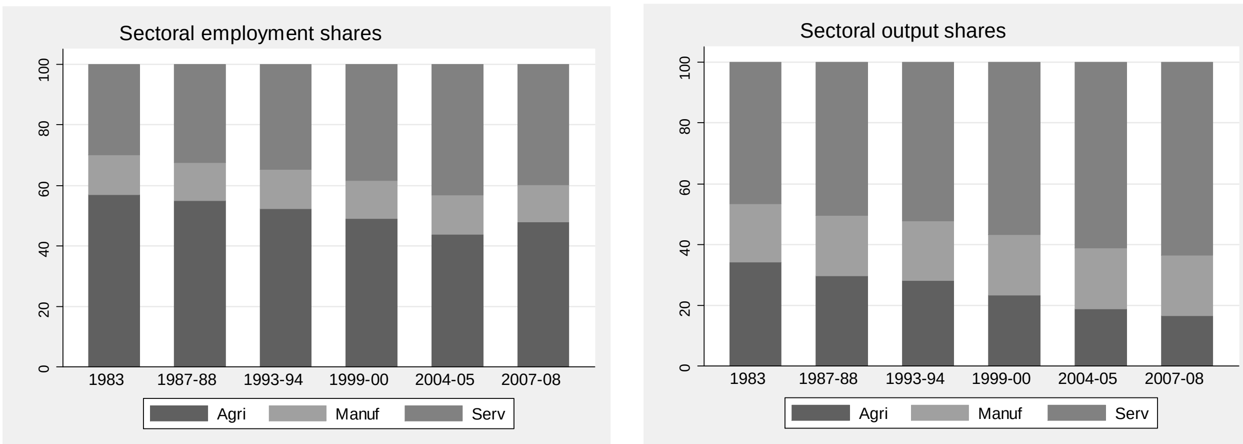
These trends, while interesting by themselves, raise the logical question about the deeper reasons behind the observed convergence between the groups during this period. While there may have been multiple factors operating simultaneously, in this paper we focus on the two biggest changes that occurred in the Indian economy during this period. As is well known, this period – 1983 to 2004-05 – has also been a period of major changes in economic policy 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. The primary question we address is whether the aggregate productivity improvement could have induced a wage and education convergence across the castes through the structural transformation that it sparked?

Before proceeding, it is useful to document some of the key data facts related to the structural transformation of the economy since the early 1980s as well as a breakdown by caste of these structural changes. In order to present the structural transformation facts, we combine one-digit industry categories into three broad industry categories: Ind 1, Ind 2 and Ind 3. Ind 1 comprises the Agricultural sector, Ind 2 collects Manufacturing and Mining and Quarrying, while Ind 3 comprises all Service industries. Our grouping reflects the traditional industrial classification according to the United Nations classification system. For the industry of employment of households, we aggregate the 4-digit industry code that individuals report into a one-digit code. This gives us seventeen categories. We then group these seventeen categories into the three broader industry categories: Ind 1 (Agriculture), Ind 2 (Manufacturing) and Ind 3 (Services). See Appendix 8 for more details on the industry grouping.

As Figure 3 shows, the period 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 both labor productivity and total factor productivity (TFP) at the aggregate and sectoral levels. Figure 4 reports labor productivity in each sector. Panel (a) is measured as output per worker, while panel (b) reports the sectoral total factor productivity numbers that we estimated assuming a Cobb-Douglas production

Figure 3: Industry distribution

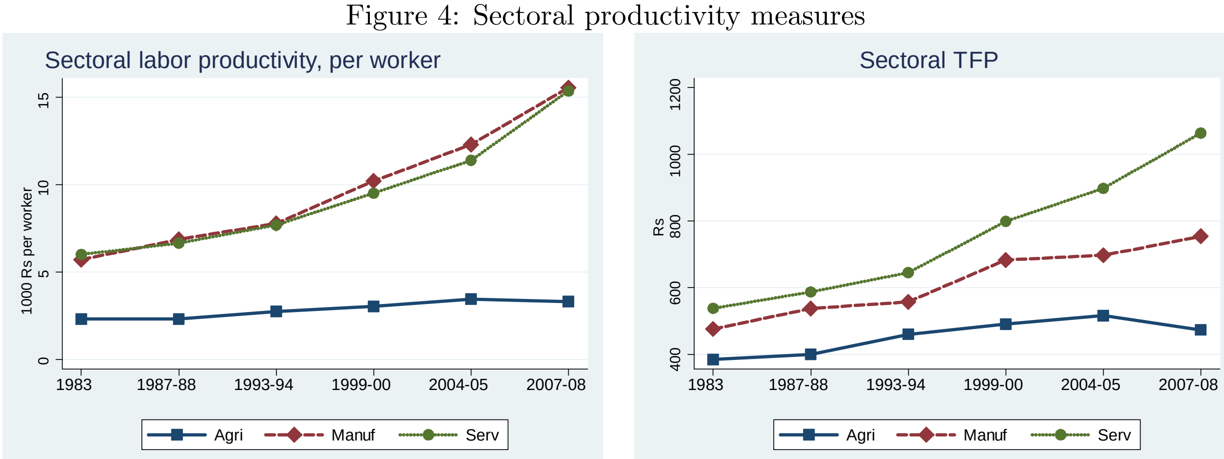


(a) (b)

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.

function including capital, human capital and employment.[2] The figures show a common feature of productivity growth across the three sectors, especially in TFP.

Figure 4: Sectoral productivity measures



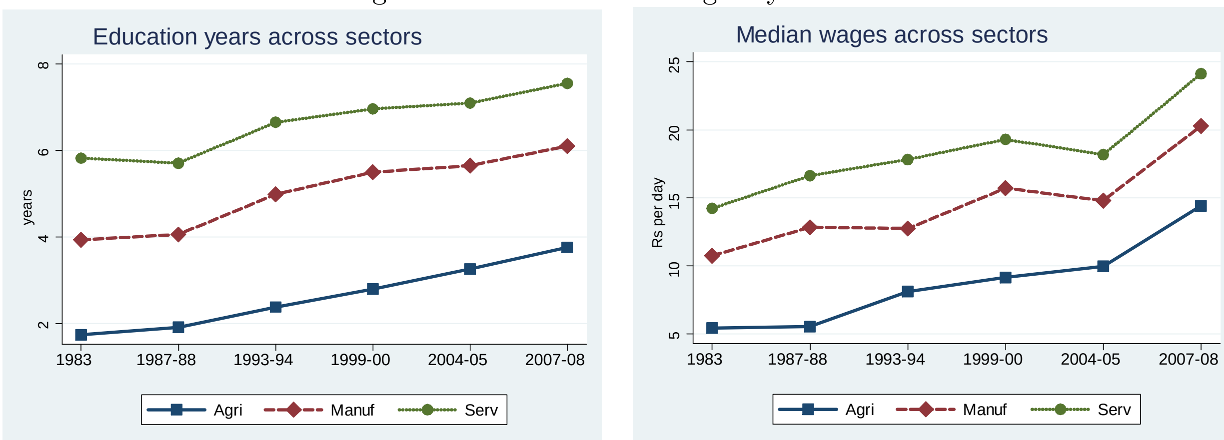
(a) (b)

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 total factor productivity by using a Cobb-Douglas production function for each sector using sectoral capital and labor.

Figure 5 reports mean years of education and median wages in the three sectors for various survey rounds. The figures reveal a dramatic increase in both education attainments and median wages in India during 1983-2008 period.

[2]The sectoral human capital stocks were constructed using standard Mincer regressions by using the education attainment rates of the sectoral workforce.

Figure 5: Education and wages by sector



(a) (b)

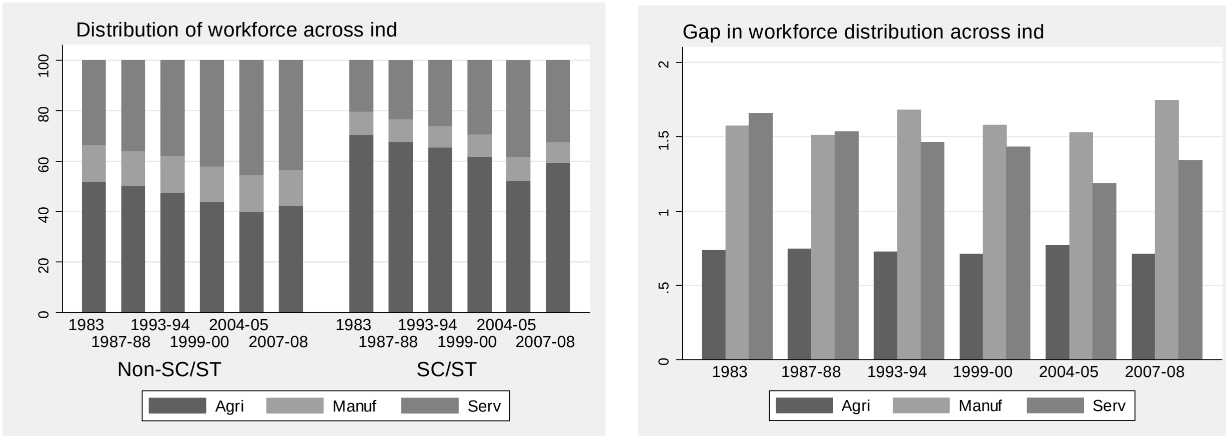
Notes: Panel (a) of this Figure presents average years of education of workers employed in each of the three sectors. Panel (b) reports median wages in the three sectors.

So, how did this overall transformation of the economy affect the two groups? Figure 6 reports the industry distribution of working individuals among SC/STs and non-SC/STs, and the relative gaps in this distribution. Clearly, SC/STs were and remain more likely to be employed in agriculture and other farming activities (Ind 1) than non-SC/STs. However the gap has somewhat narrowed in the last ten years of our sample. The second largest industry of employment for both social group is services, whose share has also been rising steadily over time. Interestingly, services also exhibit the sharpest convergence pattern between non-SC/STs and SC/STs followed by agriculture. In particular, the relative gap between non-SC/STs and SC/STs in employment shares in services has shrunk from more than 50 percent in 1983 to below 25 percent in 2007-08. Manufacturing shows little changes in the employment shares of the two groups over time.

Figures 7 report 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. Median wage gaps on the other hand declined in Services, stayed unchanged in Manufacturing, but widened somewhat in Agriculture.

To summarize the data features documented above, the period 1983-2008 was characterized by high aggregate growth in the economy, rising output per worker in all three sectors and similar productivity growth across the sectors. Concurrently, there was a gradual transformation of the economy that was underway as well with services becoming a larger share of the economy both in terms of output and employment while the corresponding agriculture shares were shrinking. In terms of the caste distributions, both SC/STs and non-SC/STs appeared to be exiting from

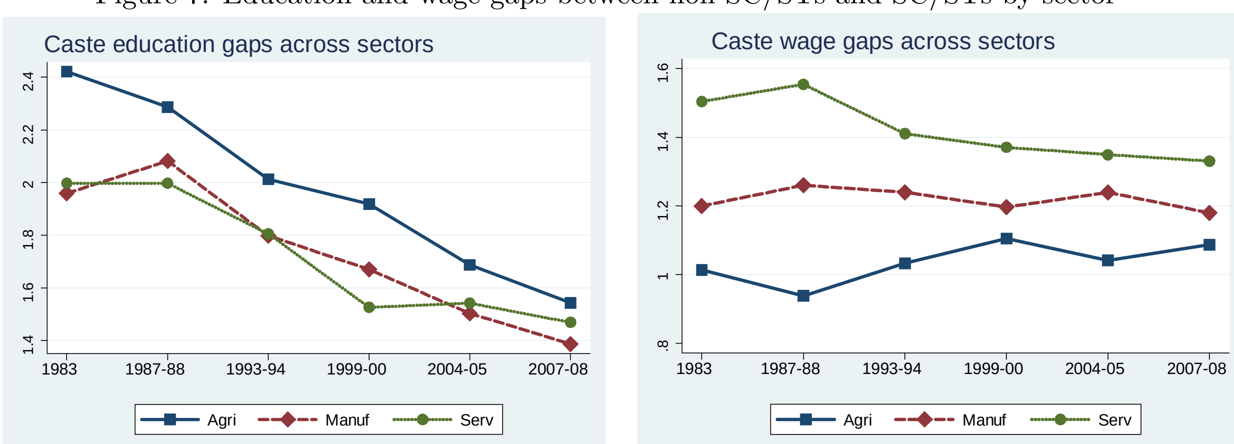
Figure 6: Industry employment distribution across castes



(a) (b)

Notes: Panel (a) of this Figure 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.

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



(a) (b)

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

agriculture and moving into service sector 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 median wage gaps in the manufacturing sector stayed relatively unchanged over this period.

The question that we turn to next is whether an aggregate productivity shock 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?

3 Model

We start by formalizing a model with heterogenous ability of the workforce. 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. Each agent i maximizes utility from

$$u(c_i) = \frac{c_i^{1-\rho}}{1-\rho}$$

where

$$c_i = (c_i^a - \bar{c})^{\theta} (c_i^m)^{\eta} \left(c_i^h\right)^{1-\theta-\eta}$$

$\bar{c}$ is the minimum level of consumption of the a good (which we think of as the agricultural good). 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.

Each agent i is born with one unit of labor time that is supplied inelastically to the market and an endowment of ability e_i. The ability distribution is caste specific. So, for agents belonging to caste s the ability e_i is drawn from an i.i.d. process that follows the cumulative distribution function $G_s(e), \quad e \in [\underline{e}_s, \bar{e}^s]$. Similarly, for agents belonging to caste n the ability type is drawn from an i.i.d. process summarized by the distribution function $G_n(e), \quad e \in [\underline{e}_n, \bar{e}^n]$. In the following we shall retain the assumptions

Assumption 1: $\underline{e}_s \leq \underline{e}_n$

Assumption 2: $\bar{e}^s \leq \bar{e}^n$

Assumptions 1 and 2 imply that caste s members draw their ability types from a distribution with lower levels of both the lower and upper supports relative to caste n members. This is intended to be a stand-in for the fact that centuries of discrimination against the lower castes left them with little to no education which, in turn, was perpetuated through the generations. In as much as education affects ability and some of that can be passed across generations, this may have left current generation of SC/STs with lower inherited ability levels, or shifted the ability distribution to the left.[3]

Ability is a productive input in both production and in skill acquisition. An agent can work in either of the three sectors. Sector a does not require any training or special skills, hence agents who choose to work in this sector can supply their labor endowment to this sector as is. Working in sector m requires some special, sector-specific skill. Agent i can acquire this skill by spending f_{ji}^{m} units of the sector m good where $j = s, n$ denotes the caste to which agent i belongs. This specification allows the skill acquisition costs to be caste specific. Similarly, to work in sector h the worker i needs to acquire a different skill level which can be acquired by expending f_{ji}^{h} units of the m good. In the following we shall assume that the costs of acquiring skills are decreasing in the ability level of the individual:

Assumption 3: $f_{ji}^{k} = f_{j}^{k}(e_i), \quad f_{j}^{k\prime} \leq 0, \quad j = s, n, \quad k = m, h$

The technologies for producing the three goods are all linear in the labor input. In particular, an unskilled 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 he/she works in.

The budget constraints of worker i is given by

$$c_i^a + p_m c_i^m + p_h c_i^h = \hat{y}_i$$

[3] The evolution of these supports of the distributions is clearly a dynamic issue and endogenous to time and investment decisions regarding education that are made by families. We intend to address these issues more fully in future work.

where

$$\hat{y}_i = \max\left\{y_i^a, p_m\left(y_i^m - f^m\left(e_i\right)\right), p_h y_i^h - p_m f^h\left(e_i\right)\right\}$$

The subscript i refers to household i with ability e_i. Recall that each worker will be working in only one sector.

The optimality conditions governing consumption of the three goods for household i are

$$\frac{\eta}{\theta}\left(\frac{c_i^a - \bar{c}}{c_i^m}\right) = p_m$$
$$\frac{(1-\eta-\theta)}{\theta}\left(\frac{c_i^a - \bar{c}}{c_i^h}\right) = p_h$$

Using these solutions along with the household's budget constraint gives

$$c_i^a = \bar{c} + \theta\left(\hat{y}_i - \bar{c}\right)$$
$$p_m c_i^m = \eta\left(\hat{y}_i - \bar{c}\right)$$
$$p_h c_i^h = (1-\eta-\theta)\left(\hat{y}_i - \bar{c}\right)$$

3.1 Occupation and Skill Choice

The decisions about which occupation to choose and what skill level to acquire are joint in this model since skills are matched uniquely to sectors. Thus, an agent of caste j with ability e_i will choose to remain unskilled and work in sector a if and only if

$$Ae_i \geq p_m\left(Me_i - f_j^m\left(e_i\right)\right)$$

and

$$Ae_i \geq p_h He_i - p_m f_j^h\left(e_i\right)$$

where p_m is the relative price of good m and p_h is the relative price of good h. Throughout we shall use good a as the numeraire. The two conditions can be rewritten as

$$\frac{f_j^m\left(e_i\right)}{e_i} \geq M - \frac{A}{p_m}$$
$$\frac{f_j^h\left(e_i\right)}{e_i} \geq \frac{p_h}{p_m}H - \frac{A}{p_m}$$

The right hand sides of these two conditions are the relative gains from working in sector m or h while the left hand sides are the relative costs. Crucially, the right hand side variables are aggregate variables that private agents take as given. The left hand sides, on the other hand, are individual specific and are clearly decreasing functions of e_i. Hence, these two conditions define two cutoff thresholds:

$$z_j^m\left(\hat{e}_j^m\right) = M - \frac{A}{p_m}, \quad j = s, n \tag{3.1}$$

$$z_j^h\left(\hat{e}_j^h\right) = \frac{p_h}{p_m}H - \frac{A}{p_m}, \quad j = s, n \tag{3.2}$$

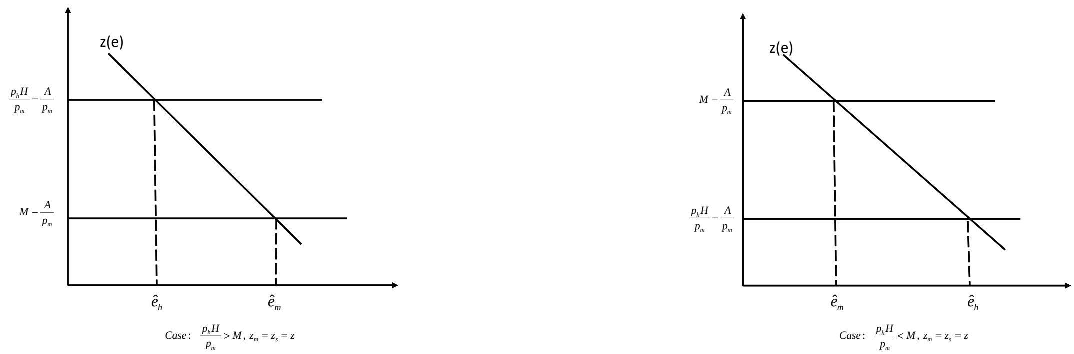
where we have used the definitions $z_j^m(e) \equiv \frac{f_j^m(e)}{e}$ and $z_j^h(e) \equiv \frac{f_j^h(e)}{e}$. Since z_j^k is decreasing in e for $j = m, h$ and $k = s, n$, all ability types above $\hat{e}_m^j$ will choose to acquire skill m and work in sector m while all types i with e_i above $\hat{e}_h^j$ will choose to work in sector h by acquiring skill h instead of staying unskilled and working in sector a. The rest will remain unskilled and work in sector a. Note that since the right hand sides of the threshold conditions given by equations (3.1) an d(3.2) are not caste specific (they are aggregate variables), the threshold conditions also imply that

$$z_s^m\left(\hat{e}_s^m\right) = z_n^m\left(\hat{e}_n^m\right)$$
$$z_s^h\left(\hat{e}_s^h\right) = z_n^h\left(\hat{e}_n^h\right)$$

In order to characterize the distribution of the different ability types in the three sectors, it is important to note that there are four possible configurations of cases: (i) $\frac{p_h H}{p_m} \geq M$ and $z_j^h(e) \geq z_j^m(e)$; (ii) $\frac{p_h H}{p_m} \geq M$ and $z_j^h(e) < z_j^m(e)$; (iii) $\frac{p_h H}{p_m} < M$ and $z_j^h(e) \geq z_j^m(e)$; and (iv) $\frac{p_h H}{p_m} < M$ and $z_j^h(e) < z_j^m(e)$. Figure 8 depicts the ability thresholds to get skilled and work in a non-agricultural sector in the special case of $f_j^h = f_j^m = f_j$. This collapses cases (i) and (ii) into one category and (iii) and (iv) into another leaving us with two cases for each caste. The two cases are shown in the two panels of Figure 8.

Panel (a) of the Figure shows the case in which $\hat{e}_j^m > \hat{e}_j^h$. Intuitively, when the $h-$sector is more productive than the $m-$sector, relatively low ability types find it profitable to pay the higher cost of skill acquisition in order to work in the $h-$sector even though they do not find it profitable to get skilled to work in the $m-$sector where productivity is lower. As a result, the cutoff threshold for the $h-$sector is lower than the $m-$sector where only the very high ability types find it profitable to invest and work. Panel (b) shows the opposite configuration.

Figure 8: Ability Cutoffs for Sectoral Allocation



(a) (b)

3.2 Market clearing and Equilibrium

Markets for each good must clear individually. Hence, we must have

$$c^a = y^a \tag{3.3}$$

$$c^m = y^m - F \tag{3.4}$$

$$c^h = y^h \tag{3.5}$$

where F denotes the total skill acquisition costs incurred by workers employed in sector m and sector h respectively. The market clearing condition for the m good recognizes that part of the use of the good is for acquiring skills. We shall derive the exact expression for F below.

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

3.3 Aggregation

There are six variables to aggregate – aggregate consumption of the three types of goods as well as their aggregate productions. We start with the consumption side. Aggregate consumption of each good is the sum of the consumptions of the good by each type of household. Recall that there are three types of households in this economy and that each household opts into only one of the three available occupations. The solution for c_i^a derived above says that

$$c_i^a = (1-\theta)\,\bar{c} + \theta \hat{y}_i$$

Using the net income of each type of worker, $\hat{y}_i$, aggregate consumption of sector a goods are given by

$$c_a = \theta \left[\sum_{j=s,n} s_j \left[\int_{\underline{e}_j}^{\hat{e}_j^m} Ae_i dG_j(e) + p_m \int_{\hat{e}_j^m}^{\hat{e}_j^h} \{Me_i - f_j^m(e_i)\} dG(e) + \int_{\hat{e}_j^h}^{\bar{e}_j} \left\{ p_h He_i - p_m f_j^h(e_i) \right\} dG_j(e) \right] \right] \tag{3.6}$$

$$+ L(1-\theta)\,\bar{c}$$

where $s_s = S$, and $s_n = N$ represent the population sizes of the two two castes. Similarly, we have $p_m c_{mi} = \eta(\hat{y}_i - \bar{c})$ which when aggregated across all households gives

$$p_m c_m = \eta \left[\sum_{j=s,n} s_j \left[\int_{\underline{e}_j}^{\hat{e}_j^m} Ae_i dG_j(e) + p_m \int_{\hat{e}_j^m}^{\hat{e}_j^h} \{Me_i - f_j^m(e_i)\} dG(e) + \int_{\hat{e}_j^h}^{\bar{e}_j} \left\{ p_h He_i - p_m f_j^h(e_i) \right\} dG_j(e) \right] \right] \tag{3.7}$$

$$- L\eta\bar{c}$$

Lastly, since $p_h c_{hi} = (1-\eta-\theta)(\hat{y}_i - \bar{c})$, aggregate consumption of the h good is

$$p_h c_h = (1-\eta-\theta) \left[\sum_{j=s,n} s_j \left[\int_{\underline{e}_j}^{\hat{e}_j^m} Ae_i dG_j(e) + p_m \int_{\hat{e}_j^m}^{\hat{e}_j^h} \{Me_i - f_j^m(e_i)\} dG(e) + \int_{\hat{e}_j^h}^{\bar{e}_j} \left\{ p_h He_i - p_m f_j^h(e_i) \right\} dG_j(e \right.\right.$$

$$- L(1-\eta-\theta)\,\bar{c} \tag{3.8}$$

Next, the expected output of a worker i of caste j in each sector is given by

$$\bar{w}_j^a = Ey_{ji}^a = \int_{\underline{e_j}}^{\hat{e}_m^j} Ae_i \frac{dG_j(e)}{G_j\left(\hat{e}_j^m\right)} \tag{3.9}$$

$$\bar{w}_j^m = Ey_{ji}^m = \int_{\hat{e}_m^j}^{\hat{e}_h^j} Me_i \frac{dG_j(e)}{G_j\left(\hat{e}_j^h\right) - G_j\left(\hat{e}_j^m\right)} \tag{3.10}$$

$$\bar{w}_j^h = Ey_{ji}^h = \int_{\hat{e}_h^j}^{\bar{e}_j} He_i \frac{dG_j(e)}{1 - G_j\left(\hat{e}_j^h\right)} \tag{3.11}$$

Given the linearity of the production technologies in ability, these are just the conditional means of the relevant distributions of ability in each sector.

Using these expected outputs, the aggregate output of each sector is

$$y^k = \sum_{j=s,n} y_j^k \quad , \quad k = a, m, h$$

where k indexes the sector. Clearly, $y_j^a = s_j G_j\left(\hat{e}_j^m\right) \bar{w}_j^a$, $y_j^m = s_j \left[G_j\left(\hat{e}_j^h\right) - G_j\left(\hat{e}_j^m\right)\right] \bar{w}_j^m$ and $y_j^h = s_j \left[1 - G_j\left(\hat{e}_j^h\right)\right] \bar{w}_j^h$, where $j = s, n$ and $s_j = S, N$. Substituting in the relevant expressions gives

$$y^a = S \int_{\underline{e}_s}^{\hat{e}_s^m} Ae_i dG_s(e) + N \int_{\underline{e}_n}^{\hat{e}_n^m} Ae_i dG_n(e) \tag{3.12}$$

$$y^m = S \int_{\hat{e}_s^m}^{\hat{e}_s^h} Me_i dG_s(e) + N \int_{\hat{e}_n^m}^{\hat{e}_n^h} Me_i dG_n(e) \tag{3.13}$$

$$y^h = S \int_{\hat{e}_s^h}^{\bar{e}_s} He_i dG_s(e) + N \int_{\hat{e}_n^h}^{\bar{e}_n} He_i dG_n(e) \tag{3.14}$$

Note that the aggregation above represents case (b) of Figure 1 above where $\hat{e}_j^h > \hat{e}_j^m$. The limits of integration would have to be altered appropriately for the opposite configuration.

To derive the skill acquisition costs, note that the average costs of skill acquisition by caste j conditional on the sector of employment is

$$F_j^m = \int_{\hat{e}_j^m}^{\hat{e}_j^h} f_j^m(e_i) \frac{dG_j(e)}{G_j\left(\hat{e}_j^h\right) - G_j\left(\hat{e}_j^m\right)}$$

$$F_j^h = \int_{\hat{e}_j^h}^{\bar{e}_s} f_j^h(e_i) \frac{dG_j(e)}{1 - G_j\left(\hat{e}_j^h\right)}$$

Hence, total skill acquisition cost of caste j is

$$F_j = s_j \left[\left\{G_j\left(\hat{e}_j^h\right) - G_j\left(\hat{e}_j^m\right)\right\} F_j^m + \left\{1 - G_j\left(\hat{e}_j^h\right)\right\} F_j^h\right], \quad j = s, n$$

where $s_s = S$ and $s_n = N$. Summing the costs across the castes then gives the total cost of acquiring skills by the different groups as

$$F = S\left[\int_{\hat{e}_s^m}^{\hat{e}_s^h} f_s^m(e_i)\, dG_s(e) + \int_{\hat{e}_s^h}^{\bar{e}_s} f_s^h(e_i)\, dG_s(e)\right] + N\left[\int_{\hat{e}_n^m}^{\hat{e}_n^h} f_n(e_i)\, dG_n(e) + \int_{\hat{e}_n^h}^{\bar{e}_n} f_n^h(e_i)\, dG_s(e)\right] \tag{3.15}$$

These relationships can then be used in equations (3.3-3.5) to derive the specific market clearing conditions for the a, m, and h goods. Note that only two of the three market clearing conditions are free - if two markets clear then the third must clear as well.

The equilibrium for the economy can be reduced to a system of four equations in four unknowns, $\hat{e}_s^m, \hat{e}_s^h, \hat{e}_n^m, \hat{e}_n^h$. The four equations that jointly determine these variables are two out of the three market clearing conditions along with the conditions $z_s^m(\hat{e}_s^m) = z_n^m(\hat{e}_n^m)$ and $z_s^h(\hat{e}_s^h) = z_n^h(\hat{e}_n^h)$. Note that the prices p_m and p_h can be eliminated from this system of equations by using any two of the four threshold conditions $z_j^m\left(\hat{e}_j^m\right) = M - \frac{A}{p_m}$ and $z_j^h\left(\hat{e}_j^h\right) = \frac{p_h}{p_m}H - \frac{A}{p_m}, \quad j = s, n.$

3.4 Thresholds and Wage Gaps

The key endogenous variables in this model are the four threshold ability levels $\hat{e}_j^m$ and $\hat{e}_j^h$ for $j = s, n$. The sectoral and overall wage gaps are all functions of these four thresholds. We now illustrate the relationship between these thresholds and the sectoral wage gaps under a special case for the skill cost function and the ability distribution. Specifically, while we retain Assumptions 1 and 2 so that $\underline{e}_s \leq \underline{e}_n$ and $\bar{e}^s \leq \bar{e}^n$, we impose the additional assumptions:

Assumption 4: The skill acquisition cost is given by $f_j^k(e) = \phi\left(\gamma_j^k - \alpha e\right)$ for $j = s, n$ and $k = m, h$ with $\gamma_j^k > \alpha \bar{e}^j$.
Assumption 5: $\frac{\gamma_j^h}{\gamma_j^m} = \beta$ for $j = s, n,\ \ \beta > 0$
Assumption 6: $G_j(e)$ is uniform on the support $\left[\underline{e}_j, \bar{e}^j\right]$ for $j = s, n.$

Assumption 4 imposes linearity on the skill cost function with the marginal effect of ability on the cost assumed to be identical for both castes and sectors. Crucially though, the specification allows the intercept term on the cost function to vary by sector and caste. The condition $\gamma_j > \alpha \bar{e}^j$ ensures that getting skilled involves a positive cost for even the highest ability type. Assumption 5 says that the proportional difference in the fixed costs of training between the m and h sectors are identical for the two castes. Assumption 6 incorporates the uniform distribution for ability which just makes the analytics simple.

Under this formulation, it is easy to check that

$$\frac{\hat{e}_n^m}{\hat{e}_s^m} = \frac{\gamma_n^m}{\gamma_s^m}$$
$$\frac{\hat{e}_n^h}{\hat{e}_s^h} = \frac{\gamma_n^h}{\gamma_s^h}$$

In other words, the relative sectoral ability thresholds of the two groups are proportional to their relative fixed costs of acquiring skills to work in that sector. Crucially, the conditions say that the ability cutoff of caste n for working in sector $k = m, h$ will be greater than the corresponding cutoff for caste s if and only if their fixed skill costs exceed the corresponding cost for caste s.

Using this proportional relationship, we can determine the relationship between the thresholds and the sectoral wage gaps. We define the sectoral wage gaps as $\Delta w^a = \frac{\bar{w}_n^a}{\bar{w}_s^a}, \Delta w^m = \frac{\bar{w}_n^m}{\bar{w}_s^m}$ and $\Delta w^h = \frac{\bar{w}_n^h}{\bar{w}_s^h}$. Further, we assume that parameters are such $\hat{e}_j^m < \hat{e}_j^h$ for $j = s, n$. Hence, we are assuming that the $h-$sector cutoff is always greater for both groups. This reflects the fact (as we showed in the empirical section earlier) that average education levels in the service sector are always higher than in the manufacturing sector for both groups and in all the survey rounds.

A key point of interest for us is the relative wage gap between SC/STs and non-SC/STs. Using equations (3.9) and (3.10) and evaluating them under the assumption of our model gives the sectoral wage gaps:

$$\frac{\bar{w}_n^a}{\bar{w}_s^a} = \Delta w^a = \frac{\hat{e}_n^m + \underline{e}_n}{\hat{e}_s^m + \underline{e}_s} = \frac{\frac{\gamma_n^m}{\gamma_s^m}\hat{e}_s^m + \underline{e}_n}{\hat{e}_s^m + \underline{e}_s}$$
$$\frac{\bar{w}_n^m}{\bar{w}_s^m} = \Delta w^m = \frac{\hat{e}_n^h + \hat{e}_n^m}{\hat{e}_s^h + \hat{e}_s^m} = \frac{\frac{\gamma_n^h}{\gamma_s^h}\hat{e}_s^h + \frac{\gamma_n^m}{\gamma_s^m}\hat{e}_s^m}{\hat{e}_s^h + \hat{e}_s^m}$$
$$\frac{\bar{w}_n^h}{\bar{w}_s^h} = \Delta w^h = \frac{\bar{e}_n + \hat{e}_n^h}{\bar{e}_s + \hat{e}_s^h} = \frac{\bar{e}_n + \frac{\gamma_n^h}{\gamma_s^h}\hat{e}_s^h}{\bar{e}_s + \hat{e}_s^h}$$

Proposition 3.1 *Under Assumptions 4, 5 and 6, Δw^a is increasing (decreasing) in $\hat{e}_s^m$ as $\frac{\gamma_n^m}{\gamma_s^m} \geq (<) \frac{\underline{e}_n}{\underline{e}_s}$; Δw^h is increasing (decreasing) in $\hat{e}_s^h$ as $\frac{\gamma_n^h}{\gamma_s^h} \geq (<) \frac{\bar{e}_n}{\bar{e}_s}$; and Δw^m is independent of $\hat{e}_s^m$ and $\hat{e}_s^h$.*

The proof follows from the facts that

$$\frac{\partial \Delta w^a}{\partial \hat{e}_s^m} \gtrless 0 \text{ as } \frac{\gamma_n^m}{\gamma_s^m} \gtrless \frac{\underline{e}_n}{\underline{e}_s}$$
$$\frac{\partial \Delta w^m}{\partial \hat{e}_s^m} = \frac{\partial \Delta w^m}{\partial \hat{e}_s^h} = 0 \text{ as } \frac{\gamma_n^h}{\gamma_s^h} = \frac{\gamma_n^m}{\gamma_s^m}$$

$$\frac{\partial \Delta w^h}{\partial \hat{e}_s^m} \gtreqless 0 \text{ as } \frac{\gamma_n^h}{\gamma_s^h} \gtreqless \frac{\bar{e}_n}{\bar{e}_s}$$

The Proposition illustrates that the sectoral wage gaps in the a and h sectors depend on the trade-offs between the relative fixed costs of skill acquisition and the relevant relative ability mark-ups. Clearly, if $\frac{\gamma_n^h}{\gamma_s^h} > \frac{\bar{e}_n}{\bar{e}_s}$ and $\frac{\gamma_n^m}{\gamma_s^m} > \frac{\underline{e}_n}{\underline{e}_s}$ then the wage gap in both sectors a and h will co-move positively with the ability threshold $\hat{e}_s^m$ and $\hat{e}_s^h$. Thus, consider aggregate shocks that reduce the ability thresholds $\hat{e}_j^m$ and $\hat{e}_j^h$ and thereby induce more individuals to get skilled. This will reduce the wage gaps in the a and h sectors only if the relative fixed cost of getting skilled for the s caste is sufficiently low so as to overcome their initial skill gaps at both the low and top ends of the ability distributions. In the $m-$sector, changes in the ability thresholds have no effect on the wage gap because the cost mark-up of training to move up from sector m to sector h is the same for both castes. Hence, the sectoral wages of both castes react symmetrically.

4 A two-sector illustration

The analysis above has described how changes in the ability thresholds of the two groups affect the sectoral wage gaps between the groups. The key aspect that we have been silent on thus far is the effect of exogenous productivity shocks on the ability thresholds. This is key since a goal of the model is to assess the role of aggregate productivity shocks in accounting for the process of wage and education convergence between the castes that we have seen over the past three decades.

In order to gain some analytical insights on this issue, we now specialize the three-sector model developed above to the two-sector case. In particular, we assume that there are only two sectors – a and m, i.e., we eliminate the h sector. We should note that in this two-sector example there is only one cut-off ability threshold for each group. Hence, in the following we drop the sectoral superscripts from the notation for the thresholds and use $\hat{e}_j$ to denote the threshold ability of caste $j = s, n$ so that all individuals with ability levels greater than $\hat{e}_j$ will get skilled in order to work in the $m-$sector.

Under these functional form assumptions, the equilibrium of the economy is determined by the system of equations:

$$p_m = \frac{\left(\frac{1-\theta}{\theta}\right)\left[y^A - \bar{c}L\right]}{y^M - F}$$
$$p_m = \frac{A\hat{e}_s}{M\hat{e}_s - \phi\left(\gamma_s - a\hat{e}_s\right)}$$

$$\frac{\hat{e}_n}{\hat{e}_s} = \frac{\gamma_n}{\gamma_s}$$

where y^A, y^M and F are given by equations (3.12), (3.13) and (3.15) above (without the h-sector terms). The first equation above is the market clearing condition for the agricultural good while the second equation gives the ability threshold for group s members to get skilled in order to work in sector m. The third equation comes from the relation $z_s(\hat{e}_s) = z_n(\hat{e}_n)$. Under the assumed linear skill cost technology, this condition implies that the relative ability thresholds of the two castes are proportional to the relative fixed costs of getting skilled. Specifically, if

Combining these three relations gives the key equilibrium condition

$$\frac{A\hat{e}_s}{M\hat{e}_s - \phi(\gamma_s - a\hat{e}_s)} = \frac{\left(\frac{1-\theta}{\theta}\right)\left[y^A - \bar{c}L\right]}{y^M - F} \tag{4.16}$$

which involves only one unknown $\hat{e}_n$ since $\hat{e}_s = \frac{\gamma_s}{\gamma_s}\hat{e}_n$. Note that in this case we have

$$\begin{aligned}
y^A - \bar{c}L &= \frac{A}{2}\left[S\frac{\left(\frac{\gamma_s}{\gamma_s}\hat{e}_n\right)^2 - \underline{e}_s^2}{\bar{e}_s - \underline{e}_s} + N\frac{\hat{e}_n^2 - \underline{e}_n^2}{\bar{e}_n - \underline{e}_n} - \frac{2\bar{c}L}{A}\right] \\
y^M &= \frac{M}{2}\left[S\frac{\bar{e}_s^2 - \left(\frac{\gamma_s}{\gamma_s}\hat{e}_n\right)^2}{\bar{e}_s - \underline{e}_s} + N\frac{\bar{e}_n^2 - \hat{e}_n^2}{\bar{e}_n - \underline{e}_n}\right] \\
F &= \phi S\left(\frac{\bar{e}_s - \hat{e}_s}{\bar{e}_s - \underline{e}_s}\right)\left[\gamma_s - \frac{a}{2}\left(\bar{e}_s + \frac{\gamma_s}{\gamma_s}\hat{e}_n\right)\right] + \phi N\left(\frac{\bar{e}_n - \hat{e}_n}{\bar{e}_n - \underline{e}_n}\right)\left[\gamma_n - \frac{a}{2}(\bar{e}_n + \hat{e}_n)\right]
\end{aligned}$$

A key question of interest to us is whether the aggregate changes in the Indian economy over the past two decades can explain, at least partly and qualitatively, the wage and education convergence across the castes. Toward that end, we define

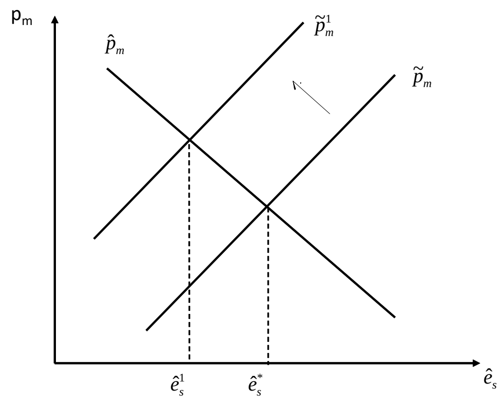
$$A = \mu\bar{A} \tag{4.17}$$

$$M = \mu\bar{M} \tag{4.18}$$

This specification nests sectoral and aggregate productivity changes with changes in μ being aggregate shocks while changes in $\bar{A}$ and $\bar{M}$ are sector-specific productivity shocks. Moreover, to avoid scale effects we also set

$$\phi = \frac{\mu}{\bar{\phi}} \tag{4.19}$$

Figure 9: An aggregate productivity shock



If the skill acquisition cost were not indexed to the aggregate productivity parameter μ, the cost of acquiring skills would become progressively smaller as a share of total output of the economy simply in response to aggregate productivity growth. The specification avoids this scale effect of growth.

In order to determine the effect of aggregate productivity growth on the economy, it is useful to define the following:

$$\hat{p}_m = \frac{A\hat{e}_s}{M\hat{e}_s - \phi\left(\gamma_s - a\hat{e}_s\right)} \tag{4.20}$$

$$\tilde{p}_m = \frac{\left(\frac{1-\theta}{\theta}\right)\left[y^A - \bar{c}L\right]}{y^M - F} \tag{4.21}$$

Figure 9 plots the two equations. Clearly, $\hat{p}_m$ is a downward sloping function of $\hat{e}_s$ while $\tilde{p}_m$ is an upward sloping function. The equilibrium threshold ability is $\hat{e}_s^*$. All ability types above this critical level get skilled and work in the $m-$sector while the rest work in the $a-$sector. Recall that $\hat{e}_n = \frac{\gamma_n}{\gamma_s}\hat{e}_s$, so this solves for the ability threshold for type-n individuals as well.

Our primary interest is in determining the effect of an aggregate productivity shock on this economy. The following Proposition summarize the effects of a TFP shock on this economy:

Proposition 4.2 *An increase in aggregate labor productivity μ decreases the ability threshold $\hat{e}_s$. This (i) reduces the caste wage gap in sector a if and only $\frac{\gamma_n}{\gamma_s} > \frac{\underline{e}_n}{\underline{e}_s}$; and (ii) reduces the caste wage* *gap in sector m if and only if* $\frac{\gamma_n}{\gamma_s} > \frac{\bar{e}_n}{\bar{e}_s}$.

The logic behind Proposition 4.2 is easiest to describe using Figure 9 which shows the effect of an aggregate TFP shock on the equilibrium system of equations 4.20-4.21. A rise μ leaves the $\hat{p}_m$ locus unchanged but shifts the $\tilde{p}_m$ locus up and to the left. As a result the equilibrium threshold ability level $\hat{e}_s$ declines. Intuitively, the aggregate TFP shock leaves unchanged the relative gains and losses from getting skilled since the productivity of all sectors (including the education sector) are affected symmetrically. On the hand, a higher μ raises the aggregate supply of the agricultural good *net* of the subsistence amount $\bar{c}L$ while leaving the aggregate supply of the manufacturing good net of the training cost unchanged. The resultant excess supply of the agricultural good induces a terms of trade worsening of the agricultural good. As agents increase their demand for good m its relative price p_m rises. All else equal, this increases the attractiveness of working in the $m-$sector. Consequently, the threshold ability falls and agents with lower ability now begin to get trained. Part (b) of the Proposition follows directly from Proposition 3.1.

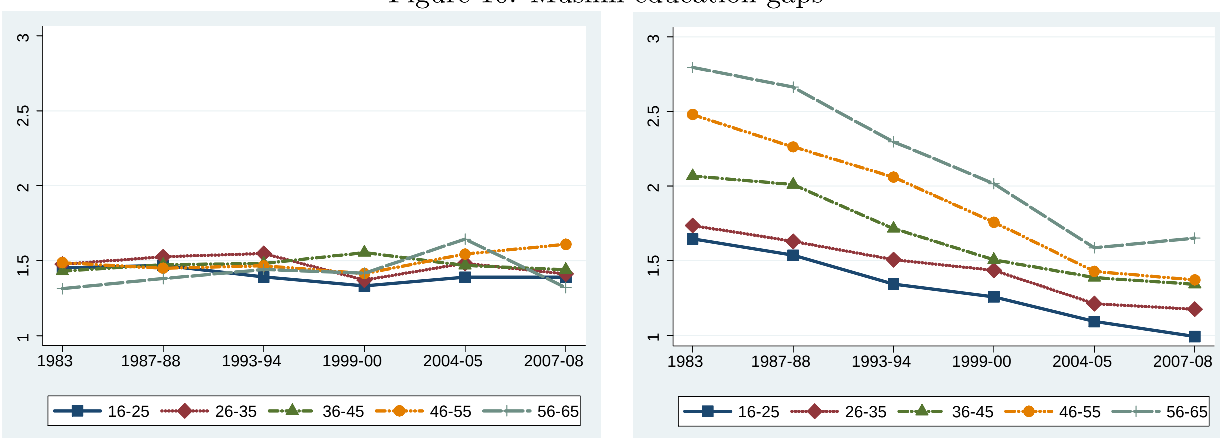
Before closing this section it is worth also examining the effect of productivity changes that are biased against the agricultural sector, a feature that characterizes India during this period. Specifically, suppose A remains unchanged while M rises. The direct effect of this shock would be to shift the $\hat{p}_m$ schedule down and to the left while simultaneously shifting the $\tilde{p}_m$ schedule down and to the right. The effect of these changes would be an unambiguous decline in the relative price of the manufacturing good, i.e., p_m falls. The effect on $\hat{e}_s$ is ambiguous and depends on the net strength of the two shifts. The key feature to note though is that the structure is perfectly consistent with both an improvement in the agricultural terms of trade as well as an increase in the share of each group getting skilled.

5 Some Independent Evidence: Muslims

The model that we outlined above predicts that a key necessary feature for there to be convergence between the groups is the presence of a pre-existing subsidy to acquiring skills for SC/STs. The direct connection of such subsidies to actual policies in India are the reservations in jobs and education that were provided to SC/STs in the Indian constitution when it came into effect in 1951. Alongside SC/STs, another group that was worse off relative to the mainstream in terms of education and income were the Muslims. However, the Constitution of India does not provide any reservations for Muslims. If the margin identified by the model is correct then the aggregate productivity rise in India since the mid 1980s should have led to a strong catch-up of the education and wage levels of SC/STs to the Muslim levels..

Figure 10 shows the education attainment levels by age groups of Non-SC/STs relative to Muslims (Panel (a)), and Muslims relative to SC/STs (Panel (b)). Panel (a) of the The Figure clearly shows that Muslims had lesser education relative to non-SC/STs to start with. Moreover, over the sample period, their education gaps relative to non-SC/STs marginally worsened while the gaps with SC/STs declined sharply.

Figure 10: Muslim education gaps



(a) (b)

Notes: Panel (a) of this Figure presents the gap in years of education between non-SC/STs and Muslims for different age groups. Panel (b) presents the gap in years of education between Muslims and SC/STs by age-groups.

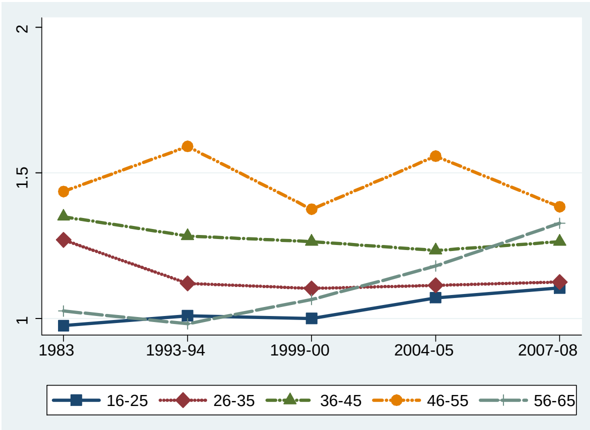
Figure 11 shows the wage gaps between Muslims and the other two groups. The Muslim wage dynamics are similar to the education dynamics. They were worse off relative to non-SC/STs at the beginning of the sample period and better off relative to SC/STs. Over the period 1983-2008, their wage gaps with non-SC/STs marginally widened while simultaneously declining relative to SC/STs.

We consider these patterns to be independent evidence in support of the role of a pre-existing affirmative action policy in accounting for the wage and education convergence of SC/STs that was suggested by our model.

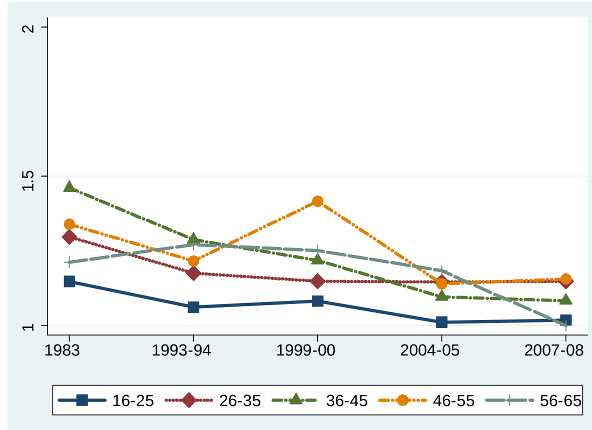
6 A Quantitative Evaluation (to be completed)

We now turn to a quantitative implementation of the model. The main exercise is to solve for the group-specific threshold ability levels for each type of skill as functions of the underlying structural

Figure 11: Muslim wage gaps



(a)



(b)

Notes: Panel (a) of this Figure presents the wage gap by age-group between non-SC/STs and Muslims. Panel (b) presents the wage gap by age-group between Muslims and SC/STs.

and policy parameters of the model. We calibrate the model to the mimic the 1983 distribution of skills and sectoral output. Next, we estimate aggregate and sectoral productivity changes from the National Income and Product Accounts data and feed those estimated paths one at a time 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.

7 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 to 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 caste convergence as well as the large scale structural transformation in the economy observed in the data. Using a multi-sector, heterogenous agent model we find that aggregate changes can induce convergence across the two groups if there are some pre-existing institutions in place to lower the costs of acquiring education/skills for the SC/STs relative to non-SC/STs. Given that reservations in education for SC/STs were incorporated into the Indian constitution in 1950 in order to offset their historical disadvantage, this condition appears to have some support in the facts. We provide some indirect evidence on other minorities (Muslims) that were not covered by these affirmative action programs which is supportive of the channel formalized here.

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8 Data Appendix

Table 1 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 1.

Table 1: 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