Convergence Across Castes*

Viktoria Hnatkovska
University of British Columbia

Chenyu(Sev) Hou
Simon Fraser University

Amartya Lahiri
University of British Columbia

May 27, 2026

Abstract

India witnessed a sharp education and wage catch-up by the historically disadvantaged scheduled castes and tribes (SC/STs) towards non-SC/ST levels during the period 1983-2024. We provide a structural explanation for the catch-up using a multi-sector, heterogeneous agent model where individuals differ in ability and their caste identity. Castes differ in the costs of schooling and accessing sectoral labor markets which results in caste-based talent misallocations. We show that exogenous productivity growth can explain 64 percent of the observed wage convergence. The primary driver of convergence in the model is the fall in real costs of schooling with growth. We provide independent evidence in support of this mechanism.

JEL Classification: J6, R2

Keywords: Castes, convergence, growth

1 Introduction

Caste identities are fundamentally enmeshed in the social, economic and political lives of people in India. These identities, which are determined by birth, often dictate where they grow up, where

*We would like to thank the editor Mathias Doepke, two anonymous referees, Tasso Adamopoulos, Paul Beaudry, Satyajit Chatterjee, Rana Hasan, Chang-Tai Hsieh, Ashok Kotwal, Devashish Mitra, Dilip Mookherjee, B. Ravikumar, Richard Rogerson, and seminar participants at the CMSG-Montreal, IGC conference (Delhi), FRB St Louis-LAEF-Human Capital conference in Santa Barbara, NBER Summer Institute, IIT-Delhi, IIT-Kanpur, UCSD, Peking University, Pennsylvania State University, FRB Philadelphia, University of Maryland and USC for helpful comments and discussions. We also thank IGC for providing funding to support this research.

they study, where they work, who they marry and who they network with. Given the rigid nature of birth-based caste hierarchies, it was often viewed as an immovable barrier to socio-economic mobility.[1] Indeed, in order to create a level playing field, the constitution of India mandated reservations for the most disadvantaged castes, identified in the constitution as Scheduled Castes and Tribes (SC/STs), in higher education, public sector jobs and political representation.

Work by Hnatkovska et al. (2012) has shown that the period since 1983 has witnessed a sharp reduction in education and wage disparities between non-SC/STs and SC/STs with most of the wage convergence being empirically accounted for by education convergence.[2] These trends represent a remarkable turnaround in the fortunes of SC/STs after centuries of disadvantage.

This paper examines the roles of economic growth and affirmative action policies together in accounting for the declining caste gaps during the period 1983-2024. We develop a three-sector model with heterogeneous agents who face caste-based barriers to schooling and labor market access. These caste barriers create sorting effects in schooling and sectoral employment choices which create talent misallocations and caste gaps. Productivity growth reduces sectoral caste gaps in wages and labor allocations in the model as long as the barriers rise at a slower rate than growth. Our quantitative implementation of the model suggests that productivity growth can explain around 64 percent of the observed wage convergence between non-SC/STs and SC/STs during the period.

Affirmative action policies, which lower the barrier to sectoral entry for SC/STs relative to non-SC/STs, have mostly a level effect on the size of the caste gaps at any point in time but do not directly have any dynamic effects unless the policies themselves are changed. Since there have been no changes in job reservations during the period under study, these policies do not have any direct effect on convergence. [3]

Our counterfactual quantitative experiments on the model show that the primary driver of the convergence is the decrease in the education costs of SC/STs relative to non-SC/STs. Intuitively, real costs of schooling decline with aggregate growth. Since SC/STs start with higher costs of schooling in the model, their schooling costs fall proportionately faster with growth. This sparks

[1] Munshi (2019) provides an excellent background and overview of the role of castes in India.

[2] On a related theme, Hnatkovska et al. (2013) show that the intergenerational mobility rates of SC/STs in terms of education and wages have also caught up to non-SC/ST rates.

[3] Munshi (2019) conjectures that affirmative action policies as well as caste-based labor networks may have been contributing factors to convergence. Munshi and Rosenzweig (2016) shows evidence for the effects of caste networks on migration decisions in India. Their results suggest that caste networks may have slowed down urban migration. Bertrand et al. (2010) examines the impact of reservations on enrolment and outcomes in engineering colleges in one Indian state in 1996. However, these papers do not explore the time series evolution of aggregate caste wage gaps, which is the focus of this paper.

the relatively faster increase in SC/ST schooling and wages in the model.

We provide three independent pieces of evidence on schooling costs in India in support of the main mechanism in the model. First, using national and district level education price data we show that: (a) the relative price of education fell during this period; and (b) it fell faster in SC/ST dominated districts relative to non-SC/ST dominated districts. Second, using panel data on states in India we show that the cost of schooling (proxied by teacher salaries) rose less than proportionately with per capita incomes.[4] This provides further evidence for declining real costs of education with growth. Third, using census data we show that while initial school provisioning was lower in SC/STs dominated villages in India in 1991, school provisioning increased relatively faster in SC/STs dominated villages during 1991-2011.[5]

The education price, the schooling cost and the school provisioning data provide evidence of the key mechanisms embedded in the model: schooling costs are higher for SC/STs; schooling costs of SC/STs declined faster over time than that for non-SC/STs; and that the relative cost of schooling declines with growth.

There are important policy implications of our assessment of the role of growth. If growth accounts for a significant share of caste convergence, then policies that sustain broad-based growth can play an important role in narrowing inter-group disparities. At the same time, this conclusion should not be read as implying that caste-based welfare and affirmative action policies are irrelevant. In the model, these policies mainly affect the level of caste gaps, while the observed convergence over time is driven more by growth and the associated decline in the real burden of schooling and entry barriers.

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), 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 caste networks impact labor

[4]This result echoes a similar finding in the cross-country data reported by Banerjee and Duflo (2005). Teacher salaries represent the largest component of education spending, comprising 80-90 percent of education budgets in advanced countries.

[5]One might view the evidence on school provisioning as being indicative of the time costs of schooling in contrast to our model where schooling costs are paid out of goods. In an extension of the baseline model, we also include time in the schooling technology. We show that also predicts quantitative convergence along the same lines as the model with only goods costs of schooling.

mobility, education choices and employment. Our focus on aggregate caste dynamics and economic growth distinguishes our work from this literature.[6]

A second literature that is related to our paper is the extensive work on structural transformation of countries along the development path wherein countries gradually switch their economic focus from agriculture to non-agricultural sectors. This is a voluminous literature that spans both empirical and theoretical work. Key contributions in this are Kongsamut et al. (2001), Ngai and Pissarides (2007) and Acemoglu and Guerrieri (2008). An excellent overview of this literature can be found in Herrendorf et al. (2014). Our work is most closely related to papers in this area that have emphasized the importance of human capital for structural transformation (Porzio et al. (2022), Buera et al. (2022)). We differ from this work in our focus on the distributional effects of the transformation.

Our work also relates to the literature that has examined the effect of human capital and labor misallocations on productivity and growth. While this literature is long, the paper closest to our interest 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 due to discrimination or other factors though their focus is on occupational misallocation while we focus on sectoral misallocation. Also, like Erosa et al. (2010), we emphasize the importance of human capital investments for productivity, but our focus is on the heterogeneity of these investments within a country.

The next section describes the key facts on caste gaps in India. Section 3 presents the model and some analytical results. Section 4 presents the calibration and quantitative results; Section 4.1 uncovers the main mechanism at play while Section 6 provides some independent evidence in support of the mechanism. Section 4.2 discusses the importance of affirmative action policies. The last section concludes.

2 Empirical regularities

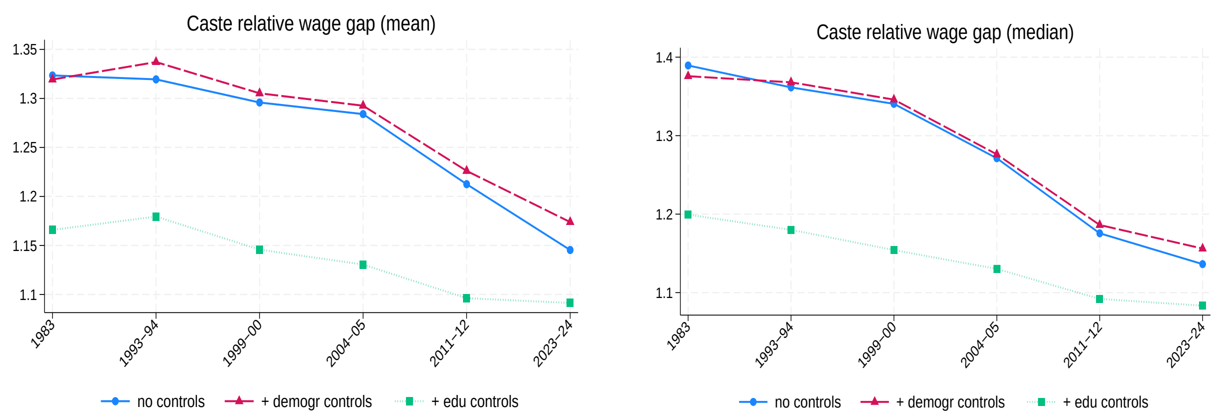
We start by reporting some aggregate and sectoral facts regarding the wage gaps between SC/STs and non-SC/STs during the period 1983-2024. These facts extend the results reported in Hnatkovska

[6] 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.

et al. (2012) to 2024 and provide additional cuts of the data. They serve as the empirical motivation of the paper. Our data for 1983-2012 comes from various rounds of the National Sample Survey (NSS) employment-unemployment household surveys, while the data for 2023-24 is from the Periodic Labor Force Survey (PLFS) conducted by the National Statistical Office of India starting from 2017. Details on the data are contained in the Appendix.[7]

Figure 1 reports the wage gaps between the castes across the 1983-2012 NSS rounds and 2023-24 PLFS round. Panel (a) shows the mean wage gaps between the groups, while panel (b) shows the corresponding median gaps. The solid lines depict the unconditional wage gaps, while the dashed line shows the wage gaps after controlling for demographic characteristics of workers (+demogr controls) and the dotted lines show the wage gaps after also controlling for the years of education (+edu controls).[8] Both plots reveal an unambiguous pattern of wage convergence between the two groups since 1983, with the unconditional mean wage gap declining by 17.8% and the unconditional median gap falling by 25.3%.

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-SC/ST to SC/ST) from the 1983 to the 2011-12 NSS rounds and 2023-24 PLFS round. Panel (b) shows the corresponding median wage gaps. The dashed lines in the two panels show the computed wage gaps after controlling for the demographic characteristics of workers (age, age squared, religion, and rural/urban sector) (+demogr), while the dotted lines also add years of education (+edu) as a control. Solid lines are without such controls.

[7]We should note that PLFS sampling design is different from the larger NSSO sampling, and thus they are not strictly comparable. However, since we focus on relative differences between caste groups computed within each round, we believe it facilitates comparability.

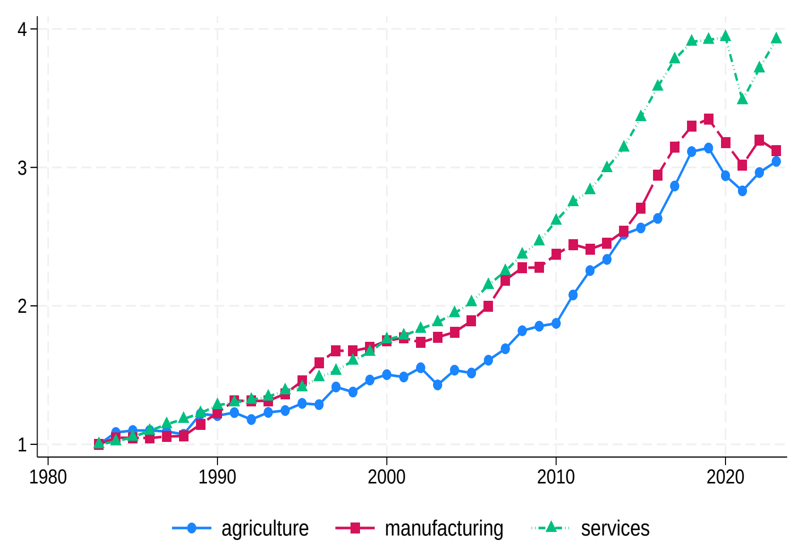
[8]Specifically, to obtain unconditional wage gaps we estimated an OLS regression (for mean) and a Recentered Influence Function (RIF) regression (for median) of log real wages on a constant and an SC/ST dummy. The conditional gaps (on demographics) are computed from the same regression with age, age squared, religion, and rural/urban location controls; while the conditional gaps (on education) are computed by also adding years of education to the regressions.

Figure 1 also shows that the conditional wage gaps that control for age, age squared, religion, and rural/urban sector of residence, move closely with the unconditional gaps. These demographic controls therefore do not account for much of the observed convergence. In contrast, adding years of education to the regressions reduces caste wage gaps dramatically. This pattern is consistent with the finding in Hnatkovska et al. (2012) that education convergence is the main proximate driver of caste wage convergence.

The trends in Figure 1 raise the logical question about the deeper reasons behind the observed convergence between the groups during this period since education is clearly an endogenous choice. While there may have been multiple factors operating simultaneously, in this paper we focus on the biggest change that occurred in the Indian economy during 1983-2024: the period saw a growth takeoff with average annual per capita GDP growth rising from 3.5 to 6 percent.

Much of this transformation was associated with rapid productivity growth across sectors as can be seen from Figure 2. It shows sectoral output per worker since 1983, computed from the KLEMS dataset for India. All series are normalized by their values in 1983. The plot also reveals a rank-ordering of sectoral labor productivity growth during 1983-2024: services grew the fastest while agriculture was the slowest growing sector.

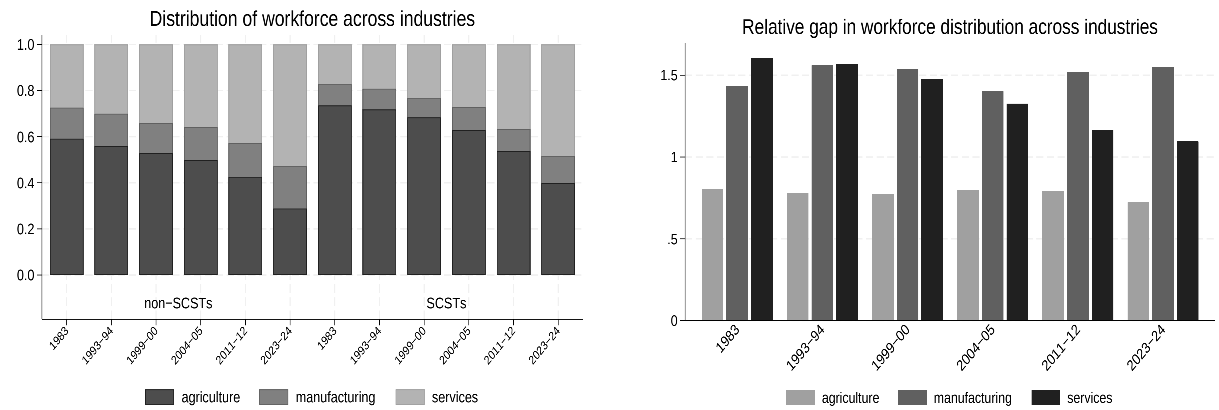
Figure 2: Sectoral labor productivity measures



Notes: The Figure shows the sectoral labor productivity computed from the KLEMS database for India. All series are normalized by their 1983 values.

So, how did growth during 1983-2024 affect the two social groups? Figure 3 reports the industry distribution of SC/ST and non-SC/ST workers, and the relative gaps in this distribution. SC/STs were, and remain, more likely to be employed in agriculture than non-SC/STs. 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. Manufacturing shows a small divergence in the employment shares of the two groups.

Figure 3: Industry employment distribution across castes



(a) (b)

Notes: Panel (a) presents the distribution of workers across the industry categories for different NSS and PLFS rounds. The left set of bars refers to non-SC/STs, while the right set is for SC/STs. Panel (b) presents the ratio of non-SC/STs to SC/STs shares reported in Panel (a) for each industry and year.

Figures 4 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 also declined in all three sectors but particularly sharply in services.

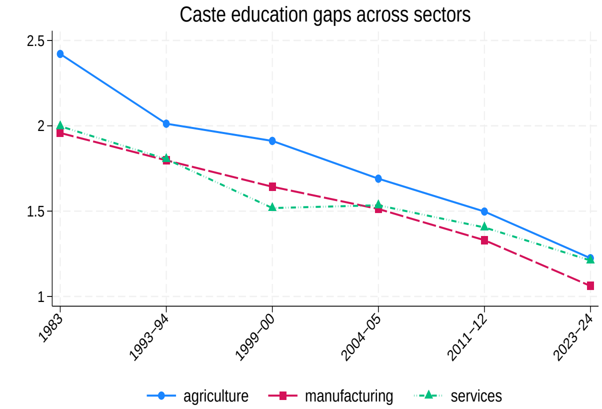
To summarize, the period 1983-2024 was characterized by high aggregate growth, rising output per worker and declining education and wage gaps between castes in all three sectors.

3 Model

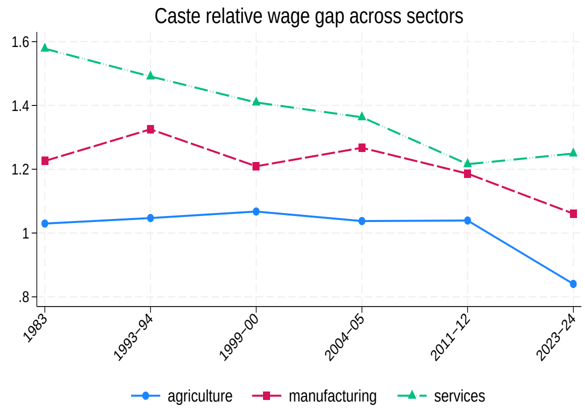
We now ask whether productivity shocks can have a differential impact on the two groups and cause the education and wage gaps between the castes to fall? If so, what are the conditions under which that can happen? Would such an environment also induce sectoral outcomes that are consistent with the facts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

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

Figure 4: 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 sectoral ratios of mean wages of non-SC/STs to SC/STs .

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[9]

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

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 service-sector good. $\bar{y}$ is the minimum required level of the a good.[10]

[9]Equivalently, this block can be interpreted as a household consumption aggregator over three intermediate goods. The final-good formulation is a convenient decentralization and does not affect the equilibrium objects we study.

[10]The general homothetic CES specification induces structural transformation towards the slowest growing sector under the assumption of the elasticity of substitution between sectors being less than one. This has been used by a number of authors to generate the observed structural transformation in the industrial countries (see Ngai and Pissarides (2007) and Acemoglu and Guerrieri (2008)). But that specification would induce a counterfactual expansion of the agricultural sector in India since it was the slowest growing sector during 1983-2024. We proceed with a non-homothetic Cobb-Douglas aggregator instead as it generates the observed structural transformation in India without us having to take a sharp stand on the specific value of the inter-sectoral elasticity of substitution.

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

$$p^a y^a_{ij} + p^m y^m_{ij} + p^h y^h_{ij} = w_{ij}$$

The optimal expenditures on intermediate goods by an agent i are

$$p^a y^a_{ij} = \theta\left(w_{ij} - p^a \bar{y}\right) + p^a \bar{y} \tag{3.1}$$

$$p^m y^m_{ij} = \eta\left(w_{ij} - p^a \bar{y}\right) \tag{3.2}$$

$$p^h y^h_{ij} = (1-\theta-\eta)\left(w_{ij} - p^a \bar{y}\right) \tag{3.3}$$

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

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

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

$$P = \frac{(p^a)^\theta (p^m)^\eta (p^h)^{1-\theta-\eta}}{\theta^\theta \eta^\eta (1-\theta-\eta)^{1-\theta-\eta}} \tag{3.4}$$

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

$$y_{ij} = w_{ij} - p^a \bar{y} \tag{3.5}$$

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.

3.1 Ability and Human Capital

Each agent i in caste j is born with an endowment of ability a_{ij} 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

$$e_{ij} = a_{ij} q_{ij}^{\chi}, \ \chi \in (0,1) \tag{3.6}$$

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

Acquiring human capital is expensive with the cost of acquiring q units of schooling being $\lambda_j q$ where $\lambda_j, \ j = n, s$ is the marginal cost of schooling which is denominated in terms of the final good. Note that the marginal cost of education is constant and caste specific. This is the first difference between individuals belonging to different castes.[11]

3.2 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.[12] 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:

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

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, e_{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

[11] In Section 5 below, we also study an extension of the model which includes both time and goods in the schooling technology. The qualitative results are robust to that extension.

[12] We view the entry cost as a way to capture a combination of sectoral discrimination against particular caste, caste-based networks as in Munshi and Rosenzweig (2006) and Munshi and Rosenzweig (2016), and the constitutionally mandated affirmative action policies that make entry into public sector jobs easier for SC/STs. One can imagine the discrimination and networks may make the entry costs for SC/STs relatively higher than that for the non-SC/ST workers, whereas affirmative action works in the opposite direction. In light of this, we do not take a stand on which caste group has a higher entry cost and leave these costs to be calibrated freely in our quantitative analysis.

that has no qualitative effect on the results but is useful for quantitative purposes.[13]

Assumption 2 implies that the fixed cost of entry into sector-h is greater than the entry cost for sector-m for both castes. This ensures an ability rank order where the highest ability individuals work in sector-h (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.

3.3 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 human capital 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 service sector good according to

$$y_i^h = He_i$$

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

3.4 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.

[13]The second component of the sectoral entry cost, e_{ij}, is not required for any of the qualitative results on caste gaps that we derive below. However, we allow for this second term, which is independent of caste, to allow for the fact that schooling creates network of connections that is broader than the individual's immediate family and caste connections or networks.

In this benchmark model we formalize schooling as a technology which only requires goods. Time is also likely an important input into the production of schooling. We explore a more general schooling technology with both goods and time as required inputs in Section 5 below.

3.4.1 The schooling choice

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

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

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

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

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:

$$q_{ij}^{a} = \left(\frac{\chi a_{ij} p^{a} A}{\lambda_j}\right)^{\frac{1}{1-\chi}} \tag{3.7}$$

$$q_{ij}^{m} = \left(\frac{\chi a_{ij}\left(p^{m} M + \phi\right)}{\lambda_j}\right)^{\frac{1}{1-\chi}} \tag{3.8}$$

$$q_{ij}^{h}=\left(\frac{\chi a_{ij}\left(p^{h}H+\phi\right)}{\lambda_{j}}\right)^{\frac{1}{1-\chi}} \tag{3.9}$$

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.

3.4.2 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 3.5 and f_{ij}^{k} is given by Assumption 1.

The sector-specific schooling levels in equations 3.7-3.9 above imply consumption levels for agents contingent on their decisions regarding schooling and sector of employment:

$$c_{ij}^{a}=(1-\chi)\left(\frac{\chi}{\lambda_{j}}\right)^{\frac{\chi}{1-\chi}}\left(a_{ij}p^{a}A\right)^{\frac{1}{1-\chi}}-p^{a}\bar{y} \tag{3.10}$$

$$c_{ij}^{m}=(1-\chi)\left(\frac{\chi}{\lambda_{j}}\right)^{\frac{\chi}{1-\chi}}\left\{a_{ij}\left(p^{m}M+\phi\right)\right\}^{\frac{1}{1-\chi}}-\phi\gamma_{j}^{m}-p^{a}\bar{y} \tag{3.11}$$

$$c_{ij}^{h}=(1-\chi)\left(\frac{\chi}{\lambda_{j}}\right)^{\frac{\chi}{1-\chi}}\left\{a_{ij}\left(p^{h}H+\phi\right)\right\}^{\frac{1}{1-\chi}}-\phi\gamma_{j}^{h}-p^{a}\bar{y} \tag{3.12}$$

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:

$$\hat{a}_{j}^{m}=\left[\frac{\phi\gamma_{j}^{m}}{(1-\chi)\left(\frac{\chi}{\lambda_{j}}\right)^{\frac{\chi}{1-\chi}}\left\{\left(p^{m}M+\phi\right)^{\frac{1}{1-\chi}}-\left(p^{a}A\right)^{\frac{1}{1-\chi}}\right\}}\right]^{1-\chi} \tag{3.13}$$

$$\hat{a}_j^h = \left[\frac{\phi\gamma_j^h}{(1-\chi)\left(\frac{\chi}{\lambda_j}\right)^{\frac{\chi}{1-\chi}} \left\{ (p^h H + \phi)^{\frac{1}{1-\chi}} - (p^a A)^{\frac{1}{1-\chi}} \right\}} \right]^{1-\chi} \tag{3.14}$$

$$\tilde{a}_j^h = \left[\frac{\phi(\gamma_j^h - \gamma_j^m)}{(1-\chi)\left(\frac{\chi}{\lambda_j}\right)^{\frac{\chi}{1-\chi}} \left\{ (p^h H + \phi)^{\frac{1}{1-\chi}} - (p^m M + \phi)^{\frac{1}{1-\chi}} \right\}} \right]^{1-\chi} \tag{3.15}$$

Equation 3.13 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 $p^h H + \phi > p^m M + \phi > p^a A$

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 3.1. *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. ■

3.4.3 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 3.2. *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 3.2 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 $\hat{a}^h \gtrless \hat{a}^m$, the following Proposition characterizes the mapping of the abilities to sectoral employment under both these cases:

Proposition 3.1. *(a) When $\hat{a}_j^h > \hat{a}_j^m$, $j = n, s$, the sectoral distribution of abilities is*

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

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

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

Proof. See Appendix. ■

While the message of Proposition 3.1 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 3.1 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 $j = n, s$.[14]

3.5 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:

$$Y^a = L\left[s\int_{\underline{a}}^{\bar{a}} y_{is}^a dG(a) + n\int_{\underline{a}}^{\bar{a}} y_{in}^a dG(a)\right] \tag{3.16}$$

[14]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.

$$Y^m = L\left[s\int_{\underline{a}}^{\bar{a}} y_{is}^m dG(a) + n\int_{\underline{a}}^{\bar{a}} y_{in}^m dG(a)\right] \tag{3.17}$$

$$Y^h = L\left[s\int_{\underline{a}}^{\bar{a}} y_{is}^h dG(a) + n\int_{\underline{a}}^{\bar{a}} y_{in}^h dG(a)\right] \tag{3.18}$$

where Y^k denotes total production of intermediate good $k = a, m, h$. Note that in equations 3.16-3.18, sectoral output of individual i belonging to caste $j = n, s$ whose ability is outside the relevant sectoral ability thresholds given in Proposition 3.1 will be zero.

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

$$C + Q + F = Y = L\left[s\int_{\underline{a}}^{\bar{a}} y_{is} dG(a) + n\int_{\underline{a}}^{\bar{a}} y_{in} dG(a)\right] \tag{3.19}$$

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.

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.*

3.6 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:

$$\Delta s^a = \frac{\hat{a}_n^m - \underline{a}}{\hat{a}_s^m - \underline{a}} \tag{3.20}$$

$$\Delta s^m = \frac{\tilde{a}_n^h - \hat{a}_n^m}{\tilde{a}_s^h - \hat{a}_s^m} \tag{3.21}$$

$$\Delta s^h = \frac{\bar{a} - \tilde{a}_n^h}{\bar{a} - \tilde{a}_s^h} \tag{3.22}$$

To derive the sectoral caste wage gaps from the model, note that the ability thresholds and the sector-contingent schooling choices given by equations 3.7-3.9 imply that the mean sectoral wages of agents belonging to caste $j = n, s$ are

$$\begin{aligned}
w_j^a &= (p^a A)^{\frac{1}{1-\chi}} \left(\frac{\chi}{\lambda_j}\right)^{\frac{\chi}{1-\chi}} \int_{\underline{a}}^{\hat{a}_j^m} a^{\frac{1}{1-\chi}} \frac{dG(a)}{G(\hat{a}_j^m)} \\
w_j^m &= p^m M \left(p^m M + \phi\right)^{\frac{\chi}{1-\chi}} \left(\frac{\chi}{\lambda_j}\right)^{\frac{\chi}{1-\chi}} \int_{\hat{a}_j^m}^{\tilde{a}_j^h} a^{\frac{1}{1-\chi}} \frac{dG(a)}{G(\tilde{a}_j^h) - G(\hat{a}_j^m)} \\
w_j^h &= p^h H \left(p^h H + \phi\right)^{\frac{\chi}{1-\chi}} \left(\frac{\chi}{\lambda_j}\right)^{\frac{\chi}{1-\chi}} \int_{\tilde{a}_j^h}^{\bar{a}} a^{\frac{1}{1-\chi}} \frac{dG(a)}{1 - G(\tilde{a}_j^h)}
\end{aligned}$$

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:

$$\Delta w^a = \left(\frac{\lambda_s}{\lambda_n}\right)^{\frac{\chi}{1-\chi}} \left(\frac{(\hat{a}_n^m)^{\frac{1}{1-\chi}+1} - (\underline{a})^{\frac{1}{1-\chi}+1}}{(\hat{a}_s^m)^{\frac{1}{1-\chi}+1} - (\underline{a})^{\frac{1}{1-\chi}+1}}\right) \left(\frac{\hat{a}_s^m - \underline{a}}{\hat{a}_n^m - \underline{a}}\right) \tag{3.23}$$

$$\Delta w^m = \left(\frac{\lambda_s}{\lambda_n}\right)^{\frac{\chi}{1-\chi}} \left(\frac{(\tilde{a}_n^h)^{\frac{1}{1-\chi}+1} - (\hat{a}_n^m)^{\frac{1}{1-\chi}+1}}{(\tilde{a}_s^h)^{\frac{1}{1-\chi}+1} - (\hat{a}_s^m)^{\frac{1}{1-\chi}+1}}\right) \left(\frac{\tilde{a}_s^h - \hat{a}_s^m}{\tilde{a}_n^h - \hat{a}_n^m}\right) \tag{3.24}$$

$$\Delta w^h = \left(\frac{\lambda_s}{\lambda_n}\right)^{\frac{\chi}{1-\chi}} \left(\frac{\bar{a}^{\frac{1}{1-\chi}+1} - (\tilde{a}_n^h)^{\frac{1}{1-\chi}+1}}{\bar{a}^{\frac{1}{1-\chi}+1} - (\tilde{a}_s^h)^{\frac{1}{1-\chi}+1}}\right) \left(\frac{\bar{a} - \tilde{a}_s^h}{\bar{a} - \tilde{a}_n^h}\right) \tag{3.25}$$

where the thresholds $\hat{a}_j^m, \tilde{a}_j^h$ are given by equations 3.13 and 3.15, 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 3.13 and 3.15 which can be used to get

$$\frac{\hat{a}_n^m}{\hat{a}_s^m} = \left(\frac{\lambda_n}{\lambda_s}\right)^{\chi} \left(\frac{\gamma_n^m}{\gamma_s^m}\right)^{1-\chi} \tag{3.26}$$

$$\frac{\tilde{a}_n^h}{\tilde{a}_s^h} = \left(\frac{\lambda_n}{\lambda_s}\right)^{\chi} \left(\frac{\gamma_n^h - \gamma_n^m}{\gamma_s^h - \gamma_s^m}\right)^{1-\chi} \tag{3.27}$$

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.

To see how these sectoral caste labor and wage gaps map into the overall caste wage gap it is useful to decompose the overall wage gap as

$$\Delta w = (\Delta s^a \Delta w^a) \frac{l_s^a w_s^a}{w_s} + (\Delta s^m \Delta w^m) \frac{l_s^m w_s^m}{w_s} + \left(\Delta s^h \Delta w^h\right) \frac{l_s^h w_s^h}{w_s} \tag{3.28}$$

where l_s^k is the fraction of caste s workers employed in sector $k = a, m, h$. $\frac{l_s^j w_s^j}{w_s}$, $j = A, M, H$ denote the sectoral wage weights for the decomposition. This expression makes clear that eliminating the sectoral wage and labor gaps ($\Delta s^k = 1$ and $\Delta w^k = 1$) would also eliminate the overall wage gap ($\Delta w = 1$) since the weights must sum to one.[15]

4 A Quantitative Evaluation

We now turn to a quantitative implementation of the model. The exercise has three goals. First, we ask whether the calibrated model can match the 1983 caste gaps in education, sectoral employment, and sectoral wages. Second, holding the 1983 caste-specific barriers fixed, we ask how much of the observed 1983–2024 caste convergence can be generated by sectoral productivity growth. Third, we use counterfactuals to separate the role of growth-induced changes in education and sorting from the level effects of caste-specific access barriers, including those associated with affirmative action policies.

The quantitative strategy of this section is to first calibrate the model to 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 2024 by matching the change in sectoral labor productivities in the model with the corresponding changes in the sectoral output per unit of labor reported in the KLEMS data for India. We then feed the calibrated sectoral productivity for 2024 into the model and recompute the equilibrium for 2024. The resulting distributional implications of the model in 2024 are then compared to the data in order to evaluate the explanatory power of sectoral productivity growth for the caste wage gap dynamics.

Our focus is on eight key data moments for 1983: the three sectoral caste employment gaps;

[15] Online Appendix A provides the exact Shapley decomposition of the change in the aggregate wage gap into sectoral wage-gap, sectoral labor-gap, and sector-weight components.

Table 1: Calibration of Key Variables

Variable	Value	Variable	Value
Fixed variables			
$\bar{y}$	0.50	θ	0.46
η	0.15		
$\underline{a}$	1.00	$\bar{a}$	50.00
M/A in 1983	1.20	H/A in 1983	1.10
L	1.00	S	0.25
Calibrated variables			
γ_s^m	23.54	γ_n^m	24.30
γ_s^h	307.90	γ_n^h	404.77
λ_s	2.56	λ_n	1.92
ϕ	0.56	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.

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 $\left(\gamma_s^m, \gamma_n^m, \gamma_s^h, \gamma_n^h\right)$, the two education cost parameters (λ_s, λ_n), the scaling parameter ϕ and the schooling elasticity of human capital χ.

Table 1 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. We chose $\bar{y} = 0.5$ by following Anand and Prasad (2010) who estimated minimum consumption requirement value to be 50% of food consumption for a sample of six emerging economies, including India. The parameters θ and η were chosen to match the output shares of agriculture and manufacturing in 1983. The parameters $\underline{a}$ and $\bar{a}$ define the bounds on the ability distribution which are common to both castes. They affect the scale of production and wages in the economy but do not have distributional effects since the ability distribution is common to both castes and invariant over time. We set these, with no loss of generality, to $\underline{a} = 1$ and $\bar{a} = 50$. Lastly, $L = 1$ (the total population) is a normalization and $S = 0.25$ is set to match the average population share of SC/STs in 1983.

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 and also choose their sector of employment. This educational and sectoral sorting impacts their productivity. Consequently, sectoral labor productivity reflects the joint effects of exogenous sectoral productivity, endogenous human capital of the sectoral labor force and the endogenous sectoral sorting by workers. This is true both in the data and the model.

We 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. The numbers for relative sectoral productivities are reported in the top panel of Table 1.[16]

The lower panel of Table 1 reports parameter values that were calibrated to match the moments of the 1983 caste distribution. There are three features to note about them. First, in order to match the sectoral caste gaps in 1983 the model demands that $\lambda_s = 2.56$ and $\lambda_n = 1.92$, so that the schooling cost parameter for caste-s is about 33 percent higher than that for caste-n. This 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.[17]

Second, the entry cost for services exceeds the entry cost for manufacturing for both SC/STs and non-SC/STs, i.e., $\gamma_k^h > \gamma_k^m,\ k = n, s$. This reflects the fact that average years of schooling of service sector workers is greater than the average schooling years of manufacturing workers in all our sample rounds. Figure 5 in the Appendix shows this.

Third, matching the caste gaps in 1983 also requires the fixed costs of entry into sectors m and h to be lower for caste-s. These are 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. From the model perspective, given the schooling gap between SC/STs and non-SC/STs, the model would predict counterfactually few SC/STs in the higher skill sectors. The higher schooling costs faced by SC/STs would also *reduce* the average wage gap in manufacturing and services since only the highest-ability and highly educated SC/STs would work in those sectors. But that is counterfactual since the wage gaps in these two sectors are higher than in agriculture. Having lower sectoral entry costs for SC/STs in manufacturing and services allows the model to simultaneously match the sectoral employment and wage gaps between the castes in the data.

[16]This specification for the Mincer regression retains consistency with the model where there are neither lifecycle effects nor effects of experience or tenure. The specification does impose returns to be constant within education categories.

[17]The higher schooling costs for SC/STs reduce the share of SC/ST workers who transit to the higher skill sectors, thereby raising the average ability of SC/STs in agriculture. However, the lower levels of schooling of the SC/STs who remain in agriculture lowers the labor productivity of SC/ST workers in agriculture enough to allow the model to simultaneously generate $\Delta s^A < 1$ and $\Delta w^A > 1$.

Table 2 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.[18]

Table 2: Data and Model Moments

Variable	Notation	1983 Data	1983 Model	2024 Data	2024 Model
		Targeted		Non-Targeted	
Wage Gap Agriculture	Δw^a	1.04	1.04	0.90	1.04
Wage Gap Manufacture	Δw^m	1.20	1.20	1.03	1.21
Wage Gap Service	Δw^h	1.45	1.45	1.26	1.14
Labor Share Gap Agri	Δs^a	0.80	0.85	0.72	0.85
Labor Share Gap Manuf	Δs^m	1.43	1.43	1.55	2.47
Labor Share Gap Serv	Δs^h	1.61	1.61	1.09	1.28
Mean educ SC/ST	$\bar{q}_s$	1.81	1.83	8.89	4.21
Mean educ Non-SC/ST	$\bar{q}_n$	4.08	4.07	9.99	7.18
		Non-Targeted		Non-Targeted	
Total wage gap	Δw	1.32	1.34	1.15	1.22
Pareto shape para: Schooling SC/ST	k_s	0.57	0.79	2.18	1.24
Pareto shape para: Schooling Non-SC/ST	k_n	1.12	1.19	2.31	1.65

Notes: The top panel of the table reports the sectoral caste gaps in employment and wages with all gaps being the ratio of Non-SC/ST to SC/ST. The bottom panel reports selected non-targeted moments generated by the data and the model.

How well does the model perform with respect to the non-targeted moments for the two castes in 1983? The bottom panel of Table 2 shows the fit of the model with respect to three non-targeted caste gaps. 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 32 percent non-SC/ST wage premium in the data, we consider the fit to be very good. We should note that we measure the overall wage gap using the wage gap formula given in equation (3.28).

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

[18]Schooling in the model is continuous, while schooling in the data is reported in years. To make the two comparable, we scale schooling in the model so that the maximum non-SC/ST schooling level in the 1983 model economy corresponds to 18 years of schooling and then compute the reported schooling moments using this common scale.

Table 2 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. 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 2024.[19] Since the model has no intrinsic dynamics, each new level for productivity generates a new equilibrium.

Notice that since our caste schooling and sectoral entry costs are denominated in fixed units of the final good, any changes in productivity would make the effective costs lower. To discipline the relationship between these costs and productivity, we scale the schooling cost parameters $\lambda_j,\ j = n, s$, as well as the entry cost parameter ϕ by the factor

$$P_t = \left(\frac{A_t^{\theta} M_t^{\eta} H_t^{1-\theta-\eta}}{A_{1983}^{\theta} M_{1983}^{\eta} H_{1983}^{1-\theta-\eta}} \right)^{\epsilon}$$

The scaling factor P_t is equal to one for $t = 1983$ but rises with the growth rate of the geometric mean of sectoral productivities between 1983 and 2024 with elasticity ϵ. When $\epsilon = 0$ schooling and entry costs are invariant with growth while $\epsilon = 1$ is the other extreme where costs are completely scaled to productivity growth.

To calibrate parameter ϵ, we need evidence on the behavior of these costs with growth. While there is no direct evidence on sectoral entry costs, there is evidence on schooling costs in the form of teacher salaries. This follows the approach of Banerjee and Duflo (2005) who examined a cross-country panel using teacher salaries as a proxy for schooling costs since teacher salaries tend to account for 80-90 percent of the cost of providing education. The teacher salary data for India comes from various rounds of the NSS for 1983-2012 period, and from the PLFS for 2023-24. The surveys report teachers under seven different occupation codes which we detail in the Appendix.

[19] An alternative approach would be to change education and entry costs as well as productivity growth in 2024. This approach allows for both exogenous changes in the costs and the endogenous changes of these costs through the impact of growth. We perform this exercise in Online Appendix B. Our results suggest that growth plays a dominant role in creating both wage and education convergence as observed in the data.

We compute the average teacher salary across all the teaching occupations for each state in India for each round of the survey. We then regress the log of the average state teacher salary on log real per capita state domestic product (SDP) using a panel of India states from 1983 to 2024. Since we are interested in capturing how schooling costs change with productivity, we control for the capital input in the regression.[20] State fixed effects are also included. Table 3 summarizes the results.

Table 3: Teacher salaries and productivity

	ln(mean teacher salary)
ln(sdp_pc)	0.289**
	(0.141)
capital income	1.226***
	(0.236)
State FE	yes
N	180
R2	0.805

Note: The Table reports results from a regression of log average teacher salary on log per capita state domestic product – ln(sdp_pc) – controlling for capital input. State fixed effects are included. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$

The estimated coefficient on log per capita SDP is 0.289 and implies that schooling costs rise less than proportionately with productivity, a result that corroborates the findings in Banerjee and Duflo (2005) based on cross-country data. Based on this estimate, we set the elasticity of the scaling factor $\epsilon = 0.289$ in our quantitative exercises for 2024.

To get the growth rates between 1983 and 2024 of the exogenous sectoral productivities A, M, and H, we pick the exogenous sectoral productivity growth rates such that the implied growth rates of sectoral output per worker between 1983 and 2024 in the model exactly match the corresponding growth rates in the data.[21] This procedure yields the following sectoral productivity levels in 2024

$$A_{2024} = 1.59 \quad M_{2024} = 2.27 \quad H_{2024} = 3.85$$

Table 2 also gives the labor and wage gaps across castes in the model and the data in 2024. In the data, the wage gap between non-SC/STs and SC/STs declined by 13.4 percent between 1983

[20]We construct capital input using India KLEMS data as capital income share multiplied by the log capital-labor ratio. More details about the data source and variable construction is provided in the Appendix.

[21]In our data analysis, labor productivity is computed as average output per worker for each sector in constant 2011 prices with associated gross growth rates of labor productivity in agriculture, manufacturing and services of $g^a = 3.045, g^m = 3.12, g^h = 3.924$, respectively.

and 2024. The corresponding reduction generated by the model is about 8.6 percent. Thus, the baseline model can explain 64 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 qualified success in generating the observed dynamics of the sectoral caste gaps in both wages and employment shares. In agriculture, the wage and employment share gaps were predicted to remain relatively unchanged in the model, similar to their dynamics in the data during this period. The model's performance on the manufacturing sector is mixed: it is able to reproduce the widening labor gap between 1983 and 2024 but is unable to reproduce the declining wage gap. In contrast, the model reproduces the sharp decreases in the wage and labor share gaps in services during this period. This last feature is particularly important because the service labor share gap is the gap that converged the most in the data. Given that the average wage of the service sector is the highest among all sectors, the shrinking of the labor share gap in the service sector plays one of the most important roles in creating total wage convergence.[22]

An interesting feature of the data is the switch in the relative rank order of the labor share gaps between manufacturing and services. While services had the largest caste gap in labor shares in 1983, manufacturing had the largest caste labor gap by 2024. The model successfully reproduces this switch.

Table 2 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.[23]

4.1 Mechanism Underlying Convergence

The results above show that sectoral productivity growth generates caste convergence in the model. We now unpack the mechanism behind this result by focusing on the two margins that generate

[22] See Online Appendix A for a more detailed discussion.

[23] In the Appendix we also report the fit of the model in terms of aggregate prices and quantities. The noteworthy feature of this exercise is that the model is able to match the observed increase in the relative price of agriculture between 1983 and 2024. Most models of structural transformation have the opposite prediction for the relative price of agriculture. The model also induces talent misallocations due to caste-based schooling and sectoral entry costs. Online Appendix C shows that growth-induced re-sorting accounts for 48 percent, 39 percent, and 11 percent of overall sectoral labor productivity growth in agriculture, manufacturing, and services, respectively, during 1983–2024. Online Appendix D shows that eliminating all caste-based distortions would generate welfare gains of around 10% of per capita consumption.

caste gaps in the model: schooling costs and the costs of accessing sectoral labor markets. Recall that castes differ in the cost of schooling and the costs of accessing sectoral labor markets. These two costs induce a caste-specific sorting of agents into schooling and sectors which generates caste gaps in sectoral wages and employment. Changes in the caste wage gaps then are the result of differential changes in these caste specific schooling and labor market access costs which alter the schooling and sectoral choices by the two castes.

The two important cost parameters are the schooling costs λ_j and the entry cost parameter ϕ. Both of these are denominated in terms of the final good, and are *constant*. Hence, absent any scaling of these costs, growth reduces the *real* costs of access to schooling and sectoral labor markets. The decline in these costs changes the schooling and sectoral employment decisions of agents. Consequently, if these costs change at different rates for the two castes, then the sectoral caste gaps in employment and wages would change since the two groups would respond differently in their schooling and employment decisions.

We examine the individual importance of the schooling and labor market frictions by varying the elasticity of the scaling variable P_t. In our baseline case we scaled the schooling cost λ and the entry cost parameter ϕ by a common scaling factor $P_{2024} = \left(\frac{A_{2024}^{\theta} M_{2024}^{\eta} H_{2024}^{1-\theta-\eta}}{A_{1983}^{\theta} M_{1983}^{\eta} H_{1983}^{1-\theta-\eta}}\right)^{\epsilon}$ and we set $\epsilon = 0.289$. We now examine the effects of setting the elasticity differentially for the education (ϵ) and entry (ϵ_{ϕ}) cost and varying them from 0 to 1. We conduct six experiments and the results are reported in Table 4.

The last column of Table 4 shows that when the scaling elasticity is set to one for both costs, then the overall wage gap in 2024 is 1.34, which is the same as the gap in the model in 1983. The same logic applies to the other listed gaps and education moments: when both education and entry costs are scaled completely by the factor of productivity growth, the 2024 model reproduces the 1983 model moments because scaling both costs one-for-one with productivity leaves real schooling and entry barriers unchanged. Hence, the relevant ability thresholds also remain unchanged relative to the 1983 economy. The opposite extreme is when the elasticity is set to zero in both sectors so that the costs are fixed at the 1983 level. In this case the model produces a smaller wage gap in 2024 of 1.14 relative to the baseline case. In this case, growth erodes the real value of the schooling and entry barriers, thereby creating convergence.

In the column "$\epsilon_{\phi} = 0$" we set the scaling parameter for the entry cost to zero but leave the elasticity of the scaling variable for schooling at the baseline level of 0.289. This case produces a larger wage gap in 2024 than the baseline. Intuitively, here the real costs of entry fall much faster with growth while real schooling costs decline at a slower rate since they are scaled at a higher elasticity. Since non-SC/STs start with larger entry barriers relative to SC/STs due to affirmative action policies, growth reduces their real entry costs faster than those of SC/STs. Consequently, the wage gap declines at a slower rate. On the other hand, when $\epsilon_\phi = 1$ the wage gap declines to below 1 because in this case entry barriers remain unchanged in real terms but schooling costs decline in real terms as those are only scaled with growth elasticity of 0.289. SC/STs, who face higher schooling costs than non-SC/STs, benefit disproportionately in this case since growth reduces schooling costs faster for them. The cases of $\epsilon = 0$ and $\epsilon = 1$ can be understood similarly.[24]

The main takeaway from the results in Table 4 is that the decline in real schooling costs are the key driver of wage convergence in the model.

Table 4: Schooling and Sectoral Re-sorting

Object	Baseline model	$\epsilon_\phi = 0$	$\epsilon_\phi = 1$	$\epsilon = 0$	$\epsilon = 1$	both = 0	both = 1
Δw^a	1.04	1.04	1.04	1.08	1.04	1.06	1.04
Δw^m	1.21	1.19	1.34	–	1.19	–	1.20
Δw^h	1.14	1.26	1.05	1.05	1.45	1.06	1.45
Δs^a	0.85	0.85	0.85	0.86	0.85	0.86	0.85
Δs^m	2.47	2.49	5.98	–	2.07	–	1.43
Δs^h	1.28	1.44	0.71	0.75	1.71	0.85	1.61
$\bar{q}_s$	4.21	3.40	7.21	6.90	0.91	6.05	1.83
$\bar{q}_n$	7.18	6.46	9.60	9.44	2.05	8.79	4.07
Δw	1.22	1.31	0.99	1.10	1.41	1.14	1.34

Notes: The baseline model uses $\epsilon = \epsilon_\phi = 0.289$. A dash denotes an undefined sectoral ratio because the relevant sector has no workers from SC/ST caste in the counterfactual equilibrium.

4.2 Affirmative Action

The Indian constitution mandates reservations of seats in public institutions of tertiary education, in public sector employment and in political representation for SC/STs. How important were these reservations for the observed caste convergence between 1983 and 2024?

Recall that our calibration of the model for 1983 dictated lower fixed costs of accessing manufacturing and service sector employment for SC/STs. We view these lower sectoral entry costs of SC/STs as the proxy for reservations in the model. To examine the importance of reservations, we conduct three counterfactual simulations: (a) set $\gamma_s^m = \gamma_n^m$; (b) set $\gamma_s^h = \gamma_n^h$; and (c) set both

[24]A dash in the table indicates that the corresponding sectoral ratio is undefined because the counterfactual equilibrium leaves the relevant caste-sector cell empty.

$\gamma_s^m = \gamma_n^m$ and $\gamma_s^h = \gamma_n^h$. In 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/ST levels in each sector thereby *eliminating the advantage* of reservations for SC/STs. All other baseline parameters remain unchanged.

Table 5: Role of Affirmative Action

	1983					2024				
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	0.72	0.85	0.84	0.85	0.84
Δs^m	1.43	1.43	1.53	0.81	0.84	1.55	2.47	2.96	0.80	0.87
Δs^h	1.61	1.61	1.59	–	–	1.09	1.28	1.27	3.66	3.61
Δw^a	1.04	1.04	1.00	1.04	1.01	0.90	1.04	1.00	1.04	1.00
Δw^m	1.20	1.20	1.19	1.01	1.00	1.03	1.21	1.19	1.02	1.01
Δw^h	1.45	1.45	1.45	–	–	1.26	1.14	1.14	1.00	1.00
Δw	1.32	1.34	1.31	1.63	1.59	1.15	1.22	1.20	1.31	1.29

Notes: For $j = a, m, h$, Δs^j is the ratio of the fraction of all non-SC/STs working in sector j to the fraction of all SC/STs working in sector j; Δw^j 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. In these experiments, the relevant costs for SC/STs are raised to the non-SC/ST level. A dash denotes an undefined sectoral ratio because the relevant caste-sector cell is empty.

The left panel of Table 5 shows the effects of equalizing sectoral entry costs in 1983 while the right panel shows the corresponding effects in 2024. Comparing the "both" and "Baseline" columns in the Table reveals that when both sectoral entry costs are equalized, the overall wage gap in 1983 rises to 1.59 from the baseline level of 1.34 while for 2024 the gap rises to 1.29 from the baseline of 1.22. Clearly, reservations reduced the level of the wage gap at all dates. However, since the level of reservations remains unchanged, they do not have a direct effect on the *dynamics* of caste gaps.

In summary, we view these results as indicating that affirmative action policies may have affected the level of the wage gaps. However, the dynamic behavior of caste wage gaps during 1983-2024 has been more significantly impacted by economic growth.

5 Model with Time and Goods Cost of Schooling

Our model formalized schooling as a technology which only required goods. A natural critique of this is that schooling typically also requires inputs of time. In such environments, rising productivity of market work would raise the opportunity cost of school which, in turn, would reduce the growth of human capital. Since one of our key results is that education convergence was the primary driver of caste wage convergence, a valid concern is whether our convergence result would carry over to a more general schooling technology with both goods and time as required inputs. In this section we introduce this extension as a robustness check.

Consider the same economy as in the baseline case except for the fact that the schooling technology is now

$$s_{ij} = \mu_j (1 - n_{ij})^{\nu} g_{ij}^{1-\nu}, \qquad h_{ij} = a_{ij} s_{ij}^{\chi}, \tag{5.29}$$

where n_{ij} is working time, $1 - n_{ij}$ is schooling time, and g_{ij} is the goods input in schooling. The formal calibration below imposes a common schooling time share ν across castes. This keeps the extension disciplined. To distinguish this extension from the baseline notation, s_{ij} corresponds to q_{ij} which was schooling in the baseline model. Similarly, h_{ij} corresponds to e_{ij} which was human capital in the baseline model.

In the Appendix we describe the solution to this version of the model in greater detail. The key feature to note is that the extension nests the baseline model exactly when $\nu = 0$. In that case $n_{ij} = 1$, $s_{ij} = \mu_j g_{ij}$, and the education cost is

$$P_t g_{ij} = \frac{P_t}{\mu_j} s_{ij}. \tag{5.30}$$

Hence the baseline schooling cost parameter is

$$\lambda_{jt} = \frac{P_t}{\mu_j}. \tag{5.31}$$

At the 1983 normalization $P_{1983} = 1$, the exact baseline map is $\mu_j = 1/\lambda_j$. With positive common ν, the exact nesting is broken, but the schooling cost comparison remains transparent through $\lambda_{jt} = P_t/\mu_j$. The calibrated value $\mu_s < \mu_n$ implies $\lambda_s > \lambda_n$, as in the baseline model.

We calibrate this model similarly to the baseline case. Table 6 reports the calibrated 1983 parameters. The upper panel lists normalizations and externally fixed parameters. The lower panel reports the parameters chosen to match the eight 1983 moments. The absolute levels of the entry cost parameters are not directly comparable to the baseline levels because the scale of the optimized schooling value changes once schooling time is introduced.

The calibrated common time share is small, $\nu = 0.067$. Since goods enter schooling with exponent $1 - \nu$, the curvature of schooling with respect to the goods input in the worker's indirect value is $\kappa_g = (1 - \nu)\chi = 0.625$, close to the baseline schooling curvature $\chi = 0.607$. In terms of the schooling cost parameters, the calibration implies $\lambda_s = 2.38$ and $\lambda_n = 1.85$, close to the baseline values $\lambda_s = 2.56$ and $\lambda_n = 1.92$. The entry cost parameters have the same ordering as in the baseline: entry costs are higher in services than in manufacturing for both castes, and non-SC/ST entry costs exceed SC/ST entry costs. These similarities suggest that this model is not a different economy but a version of the baseline economy in which part of schooling is paid for with time.

Table 6: Calibration of Key Variables: Good and Time Cost of Education

Fixed variables			
Variable	Value	Variable	Value
$\bar{y}$	0.50	θ	0.46
η	0.15		
$\underline{a}$	1.00	$\bar{a}$	50.00
M/A in 1983	1.20	H/A in 1983	1.10
L	1.00	S	0.25
P_{1983}	1.00		
Calibrated variables			
γ_s^m	169.33	γ_n^m	175.43
γ_s^h	413.28	γ_n^h	504.59
ϕ	0.68	χ	0.67
μ_s	0.42	μ_n	0.54
ν	0.07	$\kappa_g = (1-\nu)\chi$	0.62

Starting from the 1983 calibration, sectoral productivity growth is calibrated to match sectoral labor productivity growth in 2024. The cost parameters remain at their 1983 values except for the same baseline scaling terms, with $\epsilon = \epsilon_\phi = 0.289$. The scaling of entry costs and schooling costs is implemented as a change in the goods price of schooling P_t and in the entry cost parameter ϕ. The calibration gives the 2024 sectoral productivity levels as

$$A_{2024} = 1.55 \; M_{2024} = 2.29 \; H_{2024} = 3.65$$

Table 7 compares the model moments with the data. Education is measured using the same normalization as in the baseline calibration: the maximum generated 1983 non-SC/ST schooling level is mapped to 18 years of schooling, and average schooling is reported on that common scale.

The 1983 fit is close to the formal baseline fit. The dynamic implications differ in a useful way. With a positive time cost of education, schooling becomes more expensive when market wages rise because schooling uses time away from work. Productivity growth still raises the return to human capital, but it also raises the opportunity cost of the time spent acquiring schooling. This dampens

Table 7: Data and Model Moments

Variable	Notation	1983 Data	1983 Model	2024 Data	2024 Model
		Targeted		Non-Targeted	
Wage Gap Agriculture	Δw^a	1.04	1.04	0.90	1.04
Wage Gap Manufacture	Δw^m	1.20	1.21	1.03	1.20
Wage Gap Service	Δw^h	1.45	1.46	1.26	1.27
Labor Share Gap Agri	Δs^a	0.80	0.85	0.72	0.85
Labor Share Gap Manuf	Δs^m	1.43	1.45	1.55	2.01
Labor Share Gap Serv	Δs^h	1.61	1.62	1.09	1.39
Mean educ SC/ST	$\bar{q}_s$	1.81	1.84	8.89	3.38
Mean educ Non-SC/ST	$\bar{q}_n$	4.08	4.07	9.99	6.27
		Non-Targeted		Non-Targeted	
Total wage gap	Δw	1.32	1.35	1.15	1.28
Pareto shape para: Schooling SC/ST	k_s	0.57	0.75	2.18	1.10
Pareto shape para: Schooling Non-SC/ST	k_n	1.12	1.14	2.31	1.50

Notes: The top panel of the table reports the sectoral caste gaps in employment and wages with all gaps being the ratio of Non-SC/ST to SC/ST. The bottom panel reports selected non-targeted moments generated by the data and the model.

the education response relative to the baseline model. The model therefore produces lower mean education in 2024 than the formal baseline model.

This muted schooling response also explains why total wage convergence is weaker than in the baseline growth exercise. The total wage gap falls from 1.35 in 1983 to 1.28 in 2024. The direction of convergence is the same as in the baseline model, but the magnitude is smaller.

The exercise shows that allowing schooling to require time as well as goods does not overturn the main mechanism of the baseline model. Productivity growth still raises the return to human capital and generates caste wage convergence. The difference is that schooling time introduces an additional opportunity cost margin: as market wages rise, time spent in school becomes more costly relative to time spent working. This moderates the schooling response which produces weaker wage convergence than in the baseline goods-only schooling model. Thus, the extension delivers the same qualitative force as the baseline, but highlights that the quantitative strength of the education channel depends on how schooling costs are modelled.

6 Evidence on Schooling Costs

The model has three features that are key for explaining both the caste wage gap as well as the decline in that gap over time: (a) real costs of schooling declined with growth; (b) schooling costs are higher for SC/STs relative to those for non-SC/STs; and (c) schooling costs declined relatively faster for SC/STs. We now examine the evidence on these features of the model.

6.1 Schooling costs and growth

Did the real costs of schooling in India decrease over the past three decades? We already presented some indirect evidence on this with estimated elasticity of 0.289 of teacher salaries with respect to growth. We now examine this issue using education price data.

The data on the Consumer Price Index (CPI) for education comes from the CPI for industrial workers which is collected by the Labor Bureau, Ministry of Labour and Employment of the Government of India. This data is at monthly frequency, covers 2008-2020 period, and is available across 85 centers located across India.[25]

We focus on the education and recreation index of the CPI for industrial workers as this is the highest level of disaggregation available. We first compare the growth rates of education prices relative to the aggregate CPI across all districts. Columns 1 and 2 of Table 8 report the results. The education and recreation price index in India rose by 3.20 percent annually as compared to the 6.83 percent annual increase in the overall CPI during 2008-2020. Hence, the price of education relative to the price of the overall consumption basket declined by 3.64 percent annually during this period. This is exactly what the model demands.

Did real education costs decline faster for SC/STs? To answer this question, we exploit the geographic variation in SC/ST population shares across districts. We compute district-level population shares of SC/STs from the 2011 Census of India and use the threshold of 23.7 percent SC/ST population share (which is the mean SC/ST population share in our dataset) to split the districts into SC/ST and non-SC/ST dominant districts.[26] We then map the 85 price centers from the Labor Bureau to these districts. This allows us to compare the growth of the education price index relative to the overall CPI in SC/ST dominated districts with that in non-SC/ST dominated districts.

Column 3 of Table 8 shows that SC/ST dominant districts experienced a greater decline in the relative price index of education compared to districts that are predominantly non-SC/ST. These results provide support to the basic mechanism in the model.[27]

[25]The monthly CPI data release from the Ministry of Statistics and Programme Implementation (MOSPI) also contains indices on disaggregated categories including education at both the national and state levels. However this

Table 8: Annual growth rate of education and overall price indices in India, 2008-2020

	CPI edu	CPI overall	CPI edu/CPI overall
all districts	3.199	6.834	−3.635
	(0.039)	(0.014)	(0.040)
non-SC/ST districts			−3.359
			(0.055)
SC/ST districts			−3.992
			(0.059)
difference (SC/ST–non-SC/ST)			−0.632***
			(0.081)

Note: The Table reports average growth rates (in percent) of education and recreation CPI, overall CPI, and their ratio. Standard errors in parentheses. *** $p < 0.01$.
Sample: monthly Labour Bureau CPI-IW data (base 2001=100), Jan 2008–Aug 2020, 78 centres mapped to 85 (centre, district) pairs via the Census 2011 crosswalk. Centres are classified as SC/ST dominant if their district's SC/ST population share exceeds 23.7%.

6.2 Relative schooling costs of SC/STs

Our model generated caste wage gaps through a higher relative cost of schooling for SC/STs and caste wage convergence through a faster reduction in the schooling cost for SC/STs. We saw some evidence for the latter in the relative education price index movements of the two groups reported in Table 8. Assessing differences in education costs across SC/STs and non-SC/STs households is difficult since the levels of these costs are not directly observable.[28]

We address this issue by using a two pronged approach. We first compare the price **levels** of several education categories for SC/ST and non-SC/ST dominated districts in India. This is a direct approach to inferring relative education costs. We then examine the evidence on school provisioning in SC/ST and non-SC/ST dominated districts in India since 1991. This is an indirect approach to inferring the evolution of schooling costs for the two caste groups.

data is only available starting January 2011.

[26]We are limited to 2011 Census since this is the latest census available for India.

[27]As a supplementary check, we also examined how household consumption expenditures on education change with household income in India during 1983-2012. Using NSS consumption expenditure surveys we computed state-level averages of household education expenditures per household member for disaggregated education categories (books, tuition, tutoring, stationery, other), as well as for aggregate household education expenditure. We then regressed the log of these state-level household education expenditures per household member on log per capita state domestic product. The coefficients were below 1. Since expenditures combine prices and quantities, we do not use this evidence to identify education price changes; it only provides a complementary check that education spending rose less than proportionately with income during this period.

[28]A comparison of education consumption expenditures is one proxy, but it is problematic because expenditures can differ both due to their composition in the consumption baskets of the two social groups, and due to the differential prices that the two groups pay for education goods and services.

6.2.1 Education prices across India

To examine differences in education costs across castes, we used detailed micro level data on prices of various education goods and services in India during 2006-2020 period across 85 centers. These data underlie education price index that we discussed in Section 6.1.

Here we focus on the monthly 7th and 9th grade tuition fees in different districts in India during 2006-2020 period.[29] To examine how levels of prices differ across SC/ST and non-SC/ST dominated districts we combine this price data with district-level population shares of SC/STs from the 2011 India Census.

Table 9 reports average log tuition fees for the 7th and 9th grades during 2006-2020 period. The rows show average log fees for all districts, and separately for SC/ST and non-SC/ST dominated districts. We see that the 7th grade tuition fees are significantly higher in SC/ST dominated districts though the 9th grade tuition fees are not significantly different.

Table 9: Monthly tuition fees in India, 2006-2020

	7th grade tuition fees	9th grade tuition fees
all districts	2.094	2.894
	(0.014)	(0.011)
non-SC/ST districts	1.802	2.888
	(0.018)	(0.016)
SC/ST districts	2.465	2.903
	(0.019)	(0.015)
difference (SC/ST-non-SC/ST)	0.662***	0.015
	(0.027)	(0.022)

Note: The Table reports average (log) tuition fees for the 7th and 9th grades. Standard errors in parentheses. *** $p < 0.01$

To better exploit the geographic variation in our dataset, we regress the log of tuition fees on the SC/ST population shares across districts. Table 10 reports the results – the relationship between the SC/ST population shares and both grade 7th and 9th tuition fees is positive and significant, indicating that districts with higher SC/ST population also had higher tuition fees. These results suggest that SC/STs indeed faced higher costs of education, in line with our model mechanism.

[29] We focus on these categories since they are the most homogeneous across centers and thus allow for a meaningful spatial comparison.

Table 10: Monthly tuition fees and SC/ST population share, 2006-2020

	7th grade tuition fees	9th grade tuition fees
SC/ST population share	2.392***	1.080***
	(0.202)	(0.088)
N	4,870	11,616
R^2	0.069	0.029

Note: The Table reports results from a regression of average (log) tuition fees for the 7th and 9th grades on the SC/ST population share across Indian districts during 2006-2020 period. Standard errors in parentheses. *** $p < 0.01$

6.2.2 School provisioning

An alternative approach to determining schooling costs of the two caste groups is to examine the provisioning of schools in districts where each is dominant. We use Census data from India for 1991 and 2011 to examine the distribution of schools across towns and villages in India.[30] Our data comes from the SHRUG open data platform made available by the Development Data lab. Details about the data can be found in Asher et al. (2021).

We are especially interested in two questions: (a) were there fewer schools in SC/ST dominated villages and towns relative to non-SC/ST dominated area? (b) did school provisioning increase faster during 1991-2011 in SC/ST dominated areas relative to non-SC/ST areas? If the answers to these two questions are affirmative then it provides indicative evidence that schooling costs were indeed higher for SC/STs but also declined at a faster rate than the schooling costs for non-SC/STs.

Table 11 reports the key statistics on school provisioning. We follow Bailwal and Paul (2021) and define a village or town to be dominated by caste k if the majority of the population in the village or town belongs to caste k where $k = Non - SC/ST, SC, ST$.

There are two takeaways from Table 11. First, the top panel of the Table shows that in 1991 non-SC/ST dominated geographic areas had a higher probability of having schools of all types. School provisioning in SC and ST villages and towns has improved over time but the gap with non-SC/ST areas still remained in 2011. [31]

Second, the bottom panel of the Table reports the fraction of the different groups that live in areas that provide the various kinds of schools. As in the top panel, the results show that relative

[30]Digitized census data for India are available from 1991 onwards. This precludes the evaluation of school provisioning from 1981, which would have been closer to our household survey data start date of 1983. 2011 Census is also the last census conducted in India so far, so the school provisioning data cannot be extended beyond that year.

[31]We estimate these probabilities by running logit regressions of a binary (1,0) variable indicating availability of school of type $j = Primary, Middle, Secondary$ in the town or village on a constant and dummy variables for SC and ST domination of the area.

Table 11: Provisioning of Schools

	1991			2011		
Area Dominance:	SC	ST	non-SC/ST	SC	ST	non-SC/ST
	Probability of having school in the village or town					
Primary	0.56	0.55	0.71	0.76	0.83	0.84
Middle	0.09	0.11	0.24	0.31	0.33	0.49
Secondary	0.04	0.04	0.11	0.11	0.10	0.21
	Fraction of people having school in the village or town					
Primary	90.1%	84.1%	91.4%	95.5%	96.1%	96.1%
Middle	45.9%	38.2%	52.9%	71.1%	59.6%	72.4%
Secondary	27.8%	22.6%	33.8%	41.9%	32.6%	46.7%
Obs	36,243	53,446	306,971	50,037	110,011	423,067

to non-SC/STs, a smaller fraction of SCs and STs live in areas which have schools for all three categories of schools. Importantly, the gaps were much smaller relative to 1991 indicating a faster increase in school availability for SCs and STs as compared to non-SC/STs. [32]

We view these results as indicating that: (a) relative to non-SC/STs, schooling costs were greater for SC/STs in 1991; and (b) schooling costs declined relatively faster for SC/STs during 1991-2011. We interpret these findings as being supportive evidence for the schooling cost calibration for 1983 as well as their faster decline for SC/STs over time.[33]

An alternative interpretation of the schooling data above is that the faster increase in school provisioning in SC/ST dominated geographies after 1991 was due to public policy measures. Indeed, there were quite a few public policy initiatives since the 1990s that could have had this effect. The 73rd Amendment (1992) of the constitution provided for reservations for women and SC/STs in local governance. This could have improved local provisioning for education and resulted in differential outcomes in predominantly SC/ST areas. The District Primary Education Program (1993) and Sarva Shiksha Abhiyan (2000) could also have decreased the relative costs for SC/STs.

There is, however, considerable evidence that the spread of schooling after the 1990s was driven by a rapid expansion of private schools. Thus, Muralidharan and Kremer (2008) conducted a

[32]Note that this measure is *not tied to whether a village or town is SC/ST dominated or not*. Instead, it directly measures the share of people that have school access where they live.

[33]In related work, Bailwal and Paul (2021) examine the distance to the nearest school from villages in India in 2001 and 2011 and find that (a) the distances to the nearest primary and middle schools are increasing in the village's SC and ST population shares; and (b) the positive correlation between distance to the nearest primary and middle schools and the SC/ST population share of the village declined between 2001 and 2011. While their sample period is different from our paper, nevertheless their finding (a) corroborates our calibration estimate of higher costs of schooling for SC/STs while their finding (b) provides support for a faster decrease in the cost of schooling for SC/STs during the sample.

nationally representative survey in 2003 to document that: (a) 28 percent of rural Indians had access to a private school in their village; (b) most of the private schools were founded in the five years preceding 2003; (c) 40 percent of private school enrolment was in these newly founded schools; (d) the presence of private schools was *negatively* correlated with state and district per capita GDPs; and (e) the presence of a private school in a village was positively correlated with teacher absence rates in government schools in the village.

The results in Muralidharan and Kremer (2008) indicate that the growth of private schools was mainly a response to the absence of functioning public schools. We interpret this as evidence suggesting that there were important factors unrelated to public policy driving the expansion of school provisioning in India post-1991.[34]

7 Conclusion

The paper has examined the role of growth in accounting for the observed convergence in the education, sectoral employment and wages of scheduled castes and tribes (SC/STs) in India toward the levels of non-SC/STs during 1983-2024.

We formalized a tractable multi-sector, heterogeneous agent model where all individuals draw their innate ability from the same ability distribution but their costs of acquiring schooling and accessing sectoral labor markets depend on their caste. We examined the dynamic effects of exogenous productivity growth on caste gaps in this environment with caste-based talent misallocations. Our quantitative experiments on the model suggest that exogenous sectoral productivity growth can account for 64 percent of the observed wage convergence between SC/STs and non-SC/STs during 1983-2024.

The main mechanism driving the caste convergence in the model is SC/STs increasing their relative education levels in response to decreasing real costs of schooling. We provided independent evidence in support of this mechanism using India-wide data on education prices, teacher salaries and school provisioning. In particular, we showed that: (a) the education CPI grew slower than the overall CPI so that the relative price of education in India declined; (b) the price of education as measured by tuition fees declined faster in SC/ST dominated districts; (c) the cost of schooling

[34] One could argue that post-1990s regulatory reform may have facilitated the growth of private schools. However, the major thrust of the criticisms of education policy changes during this period has been that they made the operation of private schools more onerous rather than less. For an in-depth review of the role of private schools in India, see Muralidharan (2019).

proxied by teacher salaries declined with growth in India; and (d) villages and towns dominated by SC/STs saw a faster increase in provisioning of schools since 1991.

The findings of the paper indicate that growth during 1983-2024 may have succeeded in breaking down millennia of the socio-economic disparities induced by caste-based distortions. This points to growth as an important dynamic complement to group-based policies: affirmative action affects the level of caste gaps, while growth that lowers the relative burden of barriers can drive convergence over time.

The caste convergence in India provides a sharp contrast to persistent between-group differences in other settings, such as racial gaps as well as gaps between the children of college and high school graduates in the US and other countries. Why haven't these gaps declined over time with growth? Our model does point to two conditions that are important for growth to generate convergence. First, growth must be large enough to materially reduce the relative burden of barriers. Second, the barriers must not rise one-for-one with wages or income. In India, the sharp growth acceleration after the 1980s and the evidence that schooling costs rose less than income make this mechanism quantitatively relevant. In other settings, if the relevant barriers are tied closely to wages, local housing costs, school quality, credit constraints, or social segregation, growth need not generate the same convergence. We believe this would be an interesting line of future work.

A related issue to caste gaps is gender gaps. This has attracted a lot of attention in India over recent years particularly due to large gender gaps in labor force participation rates. We believe our approach can be adapted to address that issue as well.

References

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

Anand, R. and E. Prasad (2010, August). Optimal price indices for targeting inflation under incomplete markets. IZA Discussion Papers 5137, Institute for the Study of Labor (IZA).

Asher, S., T. Lunt, R. Matsuura, and P. Novosad (2021). Development Research at High Geographic Resolution: An Analysis of Night Lights, Firms, and Poverty in India using the SHRUG Open Data Platform. *The World Bank Economic Review*.

Bailwal, N. and S. Paul (2021). Caste discrimination in provision of public schools in rural india. *Journal of Development Studies 57*(11), 1830–1851.

Banerjee, A. and E. Duflo (2005). Growth theory through the lens of development economics. In P. Aghion and S. Durlauf (Eds.), *Handbook of Economic Growth* (1 ed.), Volume 1, Part A, Chapter 07, pp. 473–552. Elsevier.

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.

Bertrand, M., R. Hanna, and S. Mullainathan (2010). Affirmative action in education: Evidence from engineering college admissions in india. *Journal of Public Economics 94*(1-2), 16–29.

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

Buera, F. J., J. P. Kaboski, R. Rogerson, and J. I. Vizcaino (2022, 03). Skill-biased structural change. *The Review of Economic Studies 89*(2), 592–625.

Erosa, A., T. Koreshkova, and D. Restuccia (2010, 10). How important is human capital? a quantitative theory assessment of world income inequality. *The Review of Economic Studies 77*(4), 1421–1449.

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.

Munshi, K. (2019, December). Caste and the indian economy. *Journal of Economic Literature 57*(4), 781–834.

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.

Muralidharan, K. (2019). The State and the Market in Education Provision: Evidence and the Way Ahead. SIPA Working Papers 2019-06, Columbia—SIPA.

Muralidharan, K. and M. Kremer (2008). Public and Private Schools in Rural India. In P. P. . R. Chakrabarti (Ed.), *School Choice International*. MIT.

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

Porzio, T., F. Rossi, and G. Santangelo (2022, August). The human side of structural transformation. *American Economic Review 112*(8), 2774–2814.

A Appendix

A.1 Data

Our primary data sources are: (i) the National Sample Survey (NSS) employment-unemployment household surveys from 1983 to 2011-12; and (ii) the Periodic Labor Force Survey (PLFS) for 2023-24. 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.

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 per survey round in the NSS data, and 32,000 individuals in the PLFS data. 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. This limits the sub-sample with wage data to about 48,000 individuals on average across the NSS rounds, and just over 18,000 in the PLFS data.

In the text we group the reported industry codes into three broad industry categories: Ind 1 refers to Agriculture, Hunting, Forestry and Fishing; Ind 2 collects Manufacturing and Mining and Quarrying; Ind 3 refers to all Service industries. These groupings are detailed in Table 12.

Table 12: Industry categories

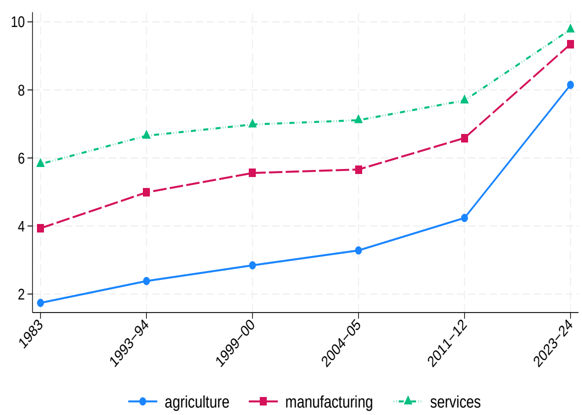
Industry code	Industry description	Group
A	Agriculture, Hunting and Forestry	Ind 1
B	Fishing	Ind 1
C	Mining and Quarrying	Ind 2
D	Manufacturing	Ind 2
E	Electricity, Gas and Water Supply	Ind 3
F	Construction	Ind 3
G	Wholesale and Retail Trade; Repair of Motor Vehicles, motorcycles and personal and household 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

We also use India KLEMS dataset which contains aggregate and industry-level measures of productivity, employment, and capital formation across the Indian economy during 1980-2024 period. We use this dataset to construct measures of sectoral labor productivity used in the model calibration, and a measure of capital input for the teacher salary regression. To obtain a measure of capital input we use the following variables from KLEMS: capital income share in value added, capital stock at constant 2011-2012 prices (in Crores of Rp.), and number of persons employed (in 1000s). The measure of capital input is constructed as a product of capital income share and (ln) capital-employment ratio.

A.2 Sectoral education levels

Figure 5 shows that there is clear rank-order in the average years of education of workers in the three sectors in our sample. Specifically, for all the sample rounds, the average years of education is the highest for service sector workers followed by manufacturing workers which is followed by agricultural workers.

Figure 5: Sectoral Educational Levels



A.3 Teacher occupation data

The NSSO and PLFS data classifies the teaching profession under 3 primary National Classification of Occupations (NCO) codes and 4 teaching associate professional codes. The details are provided in the table below. Different survey rounds use different NCO code classification. We provide the codes and their concordance in Table 13.

Table 13: Teacher occupation categories

NCO68 code	NCO04 code	NCO15 code	Description
150	231	231	College University and High School education teaching professionals
151	232	233	Secondary education teaching professional
159	233	235	Other teaching professional
153	331	234	Middle and primary teaching associate professional
154	332	235	Pre-primary teaching associate professional
155	333	232	Special education teaching associate professional
156	334	235	Other teaching associate professional

A.4 Proofs of Lemmas 3.1-3.2 and Proposition 3.1

To ease notation, throughout this section we will use the definition:

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

Lemma 3.1 *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. The agent will choose the sector that gives the highest c_{ij}^k. It is easy to see that the agent prefers sector a to m if and only if $c_{ij}^a \geq c_{ij}^m$. Similarly, she prefers a to h iff $c_{ij}^a \geq c_{ij}^h$ and m to h if and only if $c_{ij}^m \geq c_{ij}^h$ where c_{ij}^a, c_{ij}^m and c_{ij}^h are given by equations 3.10, 3.11 and 3.12, respectively. We can rewrite these three conditions and define:

$$z_j^m(a_{ij}) \equiv \frac{\phi\gamma_j^m}{a_{ij}^{\frac{1}{1-\chi}}} \geq \Psi_j(p^m M+\phi)^{\frac{1}{1-\chi}} - \Psi_j(p^a A)^{\frac{1}{1-\chi}} \tag{A.32}$$

$$z_j^h(a_{ij}) \equiv \frac{\phi\gamma_j^h}{a_{ij}^{\frac{1}{1-\chi}}} \geq \Psi_j(p^h H+\phi)^{\frac{1}{1-\chi}} - \Psi_j(p^a A)^{\frac{1}{1-\chi}} \tag{A.33}$$

$$z_j^h(a_{ij}) - z_j^m(a_{ij}) \equiv \frac{\phi(\gamma_j^h-\gamma_j^m)}{a_{ij}^{\frac{1}{1-\chi}}} \geq \Psi_j(p^h H+\phi)^{\frac{1}{1-\chi}} - \Psi_j(p^m M+\phi)^{\frac{1}{1-\chi}} \tag{A.34}$$

With $0<\chi<1$, $\phi, \gamma_j^k > 0$ and Assumption 2, it is obvious that $z_j^m(a_{ij})$, $z_j^h(a_{ij})$ and $z_j^h(a_{ij}) - z_j^m(a_{ij})$

are strictly decreasing in a_{ij}. Since $p^h H + \phi > p^m M + \phi > p^a A$ (Assumption 3), we have:

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

■

Lemma 3.2: *The rank order of the three ability thresholds are*

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

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 3.14 and 3.15 above, $\tilde{a}^h_j > \hat{a}^h_j$ can be rewritten as

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

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 $\tilde{a}^h_j > \hat{a}^h_j > \hat{a}^m_j$. ■

Proposition 3.1: *(a) When $\hat{a}^h_j > \hat{a}^m_j$, $j = n, s$, the sectoral distribution of abilities is*

$$a_{ij} \in \begin{cases} [\underline{a}, \hat{a}^m_j) & : \ i \in A \\ [\hat{a}^m_j, \tilde{a}^h_j) & : \ i \in M \\ [\tilde{a}^h_j, \bar{a}] & : \ i \in H \end{cases}$$

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

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

Proof. (a) When $\hat{a}_j^m < \hat{a}_j^h$, Lemma 3.2 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 3.13, 3.14, 3.15, and Lemma 3.1. 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 3.15 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 3.15.

(b) When $\hat{a}_j^h < \hat{a}_j^m$, from Lemma 3.2 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 3.13-3.14 and Lemma 3.1. 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 3.13 says that sector-m dominates sector-a while equation 3.15 says that working in sector-h is strictly preferred by these types over sector-m employment. ■

A.5 Sectoral prices and quantities

Table 14 shows the percent change in sectoral prices and quantities in the data and their model counterparts during the period 1983-2024.

Table 14: Sectoral Prices and Quantities

Variable	Notation	Data	Model
Relative price Agri	p^a	19%	13.2%
Relative price Manuf	p^m	-7%	95.8%
Relative price Serv	p^h	-11%	-33.3%
Output Share Agri	y^a	-61%	-17.3%
Output Share Manuf	y^m	14%	-52.1%
Output Share Serv	y^h	59%	40.6%

Notes: The table reports the percent changes of sectoral prices and quantities in the data and the model.

Two features of the results in Table 14 are noteworthy. First, the model does well in matching the dynamics of the relative prices and quantities of agriculture and services. The predicted dynamics of the agricultural relative price is particularly important in this context. As the Table shows, the relative price of agriculture actually rose during 1983-2024 in India. The model matches this fact. We view this as a particular strength of the model since standard models of structural transformation which generate a declining share of agriculture over time have difficulty in simultaneously generating a rising agricultural relative price.[35]

Second, the model encounters difficulties in reproducing the dynamics of the manufacturing sector, both in quantities and prices. It predicts an increase in the relative price of manufacturing and a decrease in its output share. Both are counterfactual. This aspect of the model is similar to its relative underperformance in matching the dynamics of the caste gaps in manufacturing.

A.6 Goods and Time Cost Model

Let $\pi_k = p_k X_k$ be the sector price times sector productivity, and set $\beta_A = 0$ and $\beta_M = \beta_H = \phi$. Using $x_{ij} = 1 - n_{ij}$ for schooling time, the sector-k problem can be written as

$$\max_{x_{ij},g_{ij}} a_{ij}\mu_j^{\chi} x_{ij}^{\nu\chi} g_{ij}^{(1-\nu)\chi}\left[\pi_k(1-x_{ij})+\beta_k\right] - P_t g_{ij} - \phi\gamma_j^k. \tag{A.35}$$

The first-order conditions give transparent expressions for the new education choices. Let

$$r = \nu\chi, \qquad \kappa_g = (1-\nu)\chi. \tag{A.36}$$

For an interior solution,

$$x_{jk}^* = \frac{r(\pi_k+\beta_k)}{\pi_k(1+r)}, \qquad n_{jk}^* = \frac{\pi_k - r\beta_k}{\pi_k(1+r)}. \tag{A.37}$$

Given schooling time, the optimal goods input is

$$g_{jk}^*(a) = \left[\frac{\kappa_g a\mu_j^{\chi}(x_{jk}^*)^r\left[\pi_k(1-x_{jk}^*)+\beta_k\right]}{P_t}\right]^{1/(1-\kappa_g)}. \tag{A.38}$$

[35] Standard models of structural transformation based on non-homothetic demand for the agricultural good predict that the relative price of agriculture declines in response to productivity growth since its demand rises less than proportionately with income. Models that generate structural transformation through inelastic elasticity of substitution across sectors predict that resources flow towards the slower growing non-agricultural sectors as their relative prices rise (see Ngai and Pissarides (2007)). But this is counterfactual in the Indian data during 1983-2024 when agriculture was the slowest growing sector.

Substituting these choices into the worker problem gives the indirect value

$$V_{jk}(a) = \Omega_{jk} a^{1/(1-\kappa_g)} - \phi \gamma_j^k, \tag{A.39}$$

where

$$\Omega_{jk} = (1-\kappa_g)\kappa_g^{\kappa_g/(1-\kappa_g)} P_t^{-\kappa_g/(1-\kappa_g)} \left\{ \mu_j^{\chi} (x_{jk}^*)^r \left[\pi_k (1 - x_{jk}^*) + \beta_k \right] \right\}^{1/(1-\kappa_g)}. \tag{A.40}$$

Thus the cutoff logic remains the same as in the baseline model: workers sort across sectors by comparing sector values of the form in A.39. The difference is that the return to ability now includes both the goods input and the opportunity cost of schooling time.

Online Appendix for “Convergence of Castes”

Viktoria Hnatkovska
University of British Columbia

Chenyu(Sev) Hou
Simon Fraser University

Amartya Lahiri
University of British Columbia

May 27, 2026

Appendices

A Total Wage Gap Decomposition

Equation (3.28) shows that the aggregate caste wage gap is a weighted sum of sectoral wage gaps and sectoral labor allocation gaps. This appendix decomposes the change in the aggregate wage gap between 1983 and 2023/24 into these sectoral gaps and the corresponding sectoral weights.

Let $\bar{w}_{c,k,t}$ denote the average wage of caste group $c \in \{s, n\}$ in sector $k \in \{a, m, h\}$ at date t, and let $l_{c,k,t}$ be the share of caste group c employed in sector k. The aggregate wage of caste group c is

$$\bar{W}_{c,t} = \sum_k \bar{w}_{c,k,t} l_{c,k,t}. \tag{A.41}$$

*We would like to thank the editor Mathias Doepke, two anonymous referees, Tasso Adamopoulos, Paul Beaudry, Satyajit Chatterjee, Rana Hasan, Chang-Tai Hsieh, Ashok Kotwal, Devashish Mitra, Dilip Mookherjee, B. Ravikumar, Richard Rogerson, and seminar participants at the CMSG-Montreal, IGC conference (Delhi), FRB St Louis-LAEF-Human Capital conference in Santa Barbara, NBER Summer Institute, IIT-Delhi, IIT-Kanpur, UCSD, Peking University, Pennsylvania State University, FRB Philadelphia, University of Maryland and USC for helpful comments and discussions. We also thank IGC for providing funding to support this research.

The aggregate non-SC/ST to SC/ST wage gap can therefore be written as

$$\Delta W_t = \frac{\bar{W}_{n,t}}{\bar{W}_{s,t}} = \sum_k \frac{\bar{w}_{n,k,t}}{\bar{w}_{s,k,t}} \frac{l_{n,k,t}}{l_{s,k,t}} \frac{\bar{w}_{s,k,t} l_{s,k,t}}{\bar{W}_{s,t}}$$
$$= \sum_k \Delta w_{k,t} \Delta l_{k,t} \omega_{k,t}, \tag{A.42}$$

where $\Delta w_{k,t}$ is the sectoral wage gap, $\Delta l_{k,t}$ is the sectoral labor gap, and

$$\omega_{k,t} = \frac{\bar{w}_{s,k,t} l_{s,k,t}}{\bar{W}_{s,t}}$$

is the SC/ST wage-income weight of sector k.

Since equation (A.42) is multiplicative, the contribution of each term depends on the order in which the wage gaps, labor gaps, and sector weights are allowed to change. We therefore use a Shapley decomposition, following the Shapley value of Shapley (1953) and its application to distributional accounting in Shorrocks (2013). The Shapley decomposition averages each component's marginal contribution over all possible orders of the transition, which makes the accounting exact and independent of an arbitrary ordering.

Table 15 reports the resulting decomposition. Positive entries indicate forces that reduce the aggregate non-SC/ST to SC/ST wage gap. The six-gap channel is the sum of the three sectoral wage-gap contributions and the three sectoral labor-gap contributions. The composition term is the sum of the changes due to the sectoral weights ω_k.

Table 15: Contribution to Total Wage Gap Convergence, 1983–2023/24

Component	Data	Model
Agriculture wage gap	0.055	0.000
Agriculture labor gap	0.039	0.000
Manufacturing wage gap	0.034	−0.001
Manufacturing labor gap	−0.017	−0.120
Services wage gap	0.093	0.132
Services labor gap	0.261	0.125
Six-gap channel	0.464	0.135
Composition weights	−0.286	−0.020
Total convergence	0.178	0.115

Notes: Positive entries reduce the aggregate non-SC/ST to SC/ST wage gap.

The decomposition shows that the six sectoral wage and labor gaps are the main convergence force in the data. The services sector is especially important: the services wage and labor gaps together account for most of the positive six-gap contribution. The model generates the same qualitative mechanism, with the services wage and labor gaps providing the main positive force toward aggregate convergence. The model does not match the full magnitude of the data six-gap channel, partly because it over-predicts the widening of the manufacturing labor gap. At the aggregate level, however, the model accounts for a large share of the observed decline in the total wage gap.

The main remaining difference is the composition channel. In the data, changes in sectoral weights offset convergence because the service sector receives a larger weight over time while still having sizeable caste gaps. The model produces a much smaller composition offset. Thus, the decomposition clarifies that the model's main success is in reproducing the qualitative sectoral six-gap mechanism, especially the services-sector wage and labor-gap channel, whereas the residual accounting difference is concentrated in sectoral composition weights and the manufacturing labor-gap response.

B Growth, Education and Entry Costs

In our model SC/STs and non-SC/STs differ along two margins: the cost of education and the costs of sectoral labor market entry. Our baseline calibration strategy was to calibrate these cost parameters to target the 1983 sectoral caste gaps. We then evaluated the role of growth during 1983-2024 in generating caste convergence by allowing sectoral productivities to change while keeping the calibrated caste-specific cost parameters fixed at their 1983 levels, apart from the baseline partial scaling with aggregate productivity. In our model growth therefore affects these costs through their value relative to the final good.

One concern with this strategy is that there could have been changes in policy or social conventions during 1983-2024 that might have changed the caste-specific education and sectoral entry costs directly. For example, policy initiatives such as Operation Blackboard (1987) and the Right to Education Act (2002) were aimed directly at deepening education pathways for the populace. In as much as these policies aided SC/STs more than non-SC/STs, they may have directly lowered the costs of education for SC/STs relative to non-SC/STs. Extension of job reservation policies to Other Backward Castes (1992) could have directly reduced the relative sectoral entry costs for non-SC/STs.

In this section, we examine the importance of direct changes in education and entry costs relative to the role of growth by allowing these costs to change between 1983 and 2024. Specifically, we conduct an alternative quantitative exercise where we re-calibrate the sectoral growth rates as well as the entry and education cost parameters in 2024. There are nine parameters involved: three sectoral growth rates, three levels of costs and three relative cost summaries. We calibrate them targeting nine moments in 2024: three sectoral labor productivity growth rates, the three sectoral relative labor gaps, and the three sectoral relative wage gaps.[1] The recalibration is done over the 3 growth rates of sectoral productivities, 4 caste-specific fixed entry costs and 2 caste-specific education costs. To summarize the relative changes in these parameters, we define the relative costs for the manufacturing sector, service sector, and education as:

$$\psi_m = \frac{\gamma_n^m}{\gamma_s^m}, \quad \psi_h = \frac{\gamma_n^h - \gamma_n^m}{\gamma_s^h - \gamma_s^m}, \quad \psi_e = \left(\frac{\lambda_s}{\lambda_n}\right)^{\chi/(1-\chi)}. \tag{B.43}$$

The first two objects summarize the relative entry costs. The last object is the relative education cost term that enters the wage gap and cutoff formulas; the underlying schooling cost parameters remain λ_s and λ_n.

Table 16: Parameters

Calibrated variables		
Variable	baseline	2024
Cost Parameters		
γ_s^m	23.54	10.05
γ_s^h	307.90	51.09
λ_s	2.56	3.09
ψ_m	1.03	1.00
ψ_h	1.34	1.16
ψ_e	1.56	1.24
Sectoral Productivity Growth		
A_g	1.00	1.65
M_g	1.00	2.09
H_g	1.00	3.70

Notes: Red indicates an increase relative to the 1983 value and blue indicates a decrease. The productivity rows report growth factors relative to 1983.

Table 16 summarizes the calibrated parameters in 2024 as well as the corresponding parameters in our baseline calibration where the cost variables are fixed at 1983 levels. The key differences

[1] We re-calibrate the sectoral productivity growth rates because when we allow the costs to change, the implied labor productivity growths in the model differ from our baseline when the costs are fixed.

relative to the 1983 baseline parameters are that the relative education cost disadvantage of SC/STs, ψ_e, is lower in 2024, and the relative entry cost summaries ψ_m and ψ_h are also lower. Thus the recalibration reduces the relative caste differences in both entry and education costs, while allowing sectoral productivity growth to match the labor productivity targets.

Table 17 below shows the key moments generated from the re-calibrated model. Relative to the baseline growth exercise with fixed cost parameters, the fit improves most clearly in the non-agricultural labor gaps and wage gaps. The manufacturing labor gap no longer rises as sharply, and the service labor gap converges more. The manufacturing wage gap also falls toward the data, while the service wage gap still converges but no longer falls as much as in the baseline.

The mechanism is transparent from the recalibrated cost parameters. Lower SC/ST entry costs make manufacturing and service entry easier for SC/ST workers, reducing the labor gaps in both sectors. At the same time, the relative education cost disadvantage of SC/STs falls, which raises their schooling and tends to reduce wage gaps in both non-agricultural sectors. The difference between manufacturing and services comes from changes in the relative entry cost. ψ_m changes little, from 1.03 to 1.00, while ψ_h falls more sharply, from 1.34 to 1.16. Since ψ_h measures the non-SC/ST to SC/ST relative cost of moving from manufacturing into services, this larger fall makes service entry relatively easier for non-SC/ST workers. Higher ability non-SC/ST workers therefore sort into services rather than remaining in manufacturing. This lowers the manufacturing wage gap and raises the service wage gap relative to the baseline, which moves both sectoral wage gaps closer to the data.

To assess the relative contributions of growth and caste-specific costs to the caste wage convergence, we proceed in two stages. First, we eliminate the impact of changing costs by holding the education and entry costs at their 1983 values while allowing productivity growth and the baseline partial cost scaling to operate. Any wage convergence in this case is attributable to growth under the baseline cost structure. These results are included in column (1) of Table 18.

Then we isolate the role of direct cost changes. To remove the indirect real-cost effect of growth, we scale costs by the compound productivity factor $\frac{A_{2024}^{\theta} M_{2024}^{\eta} H_{2024}^{1-\theta-\eta}}{A_{1983}^{\theta} M_{1983}^{\eta} H_{1983}^{1-\theta-\eta}}$. Furthermore, to examine the roles of education and entry costs separately, in column (2), we only change the education cost parameters while keeping entry costs at the 1983 levels. In column (3), we change the entry costs but keep education costs at 1983 levels.

Table 17: Data and Model Moments

Variable	Notation	1983 Data	1983 Model	2024 Data	2024 Model
		Baseline		Targeted	
Wage Gap Agriculture	Δw^a	1.04	1.04	0.90	1.01
Wage Gap Manufacture	Δw^m	1.20	1.20	1.03	1.09
Wage Gap Service	Δw^h	1.45	1.45	1.26	1.18
Labor Share Gap Agri	Δs^a	0.80	0.85	0.72	0.92
Labor Share Gap Manuf	Δs^m	1.43	1.43	1.55	1.58
Labor Share Gap Serv	Δs^h	1.61	1.61	1.09	1.14
Labor Prod Growth Agri	$\frac{Ey^a_{24}}{Ey^a_{83}}$	–	–	3.04	3.04
Labor Prod Growth Manuf	$\frac{Ey^m_{24}}{Ey^m_{83}}$	–	–	3.12	3.11
Labor Prod Growth Serv	$\frac{Ey^h_{24}}{Ey^h_{83}}$	–	–	3.92	3.92
		Baseline		Non-Targeted	
Mean educ SC/ST	$\bar{q}_s$	1.81	1.83	8.89	4.26
Mean educ Non-SC/ST	$\bar{q}_n$	4.08	4.07	9.99	5.97
Total wage gap	Δw	1.32	1.34	1.15	1.15

Notes: The top panel reports the sectoral caste gaps in employment and wages, with all gaps being the ratio of non-SC/ST to SC/ST, and the sectoral labor productivities. The bottom panel reports selected non-targeted moments.

Table 18: Model Moments with Growth or Relative Cost Changes

Variable	Notation	Growth	Education	Entry
		(1)	(2)	(3)
Wage Gap Agriculture	Δw^a	1.04	1.03	1.01
Wage Gap Manufacture	Δw^m	1.22	1.20	1.09
Wage Gap Service	Δw^h	1.11	1.28	1.37
Labor Share Gap Agri	Δs^a	0.85	0.93	0.84
Labor Share Gap Manuf	Δs^m	3.04	1.53	1.15
Labor Share Gap Serv	Δs^h	1.19	0.78	1.75
Labor Prod Growth Agri	$\frac{Ey^a_{24}}{Ey^a_{83}}$	3.30	1.01	1.64
Labor Prod Growth Manuf	$\frac{Ey^m_{24}}{Ey^m_{83}}$	3.60	1.34	1.92
Labor Prod Growth Serv	$\frac{Ey^h_{24}}{Ey^h_{83}}$	4.16	2.46	3.02
Mean educ SC/ST	$\bar{q}_s$	4.51	1.18	2.00
Mean educ Non-SC/ST	$\bar{q}_n$	7.45	1.62	4.21
Total wage gap	Δw	1.20	1.06	1.26

Notes: All sectoral caste gaps in employment and wages are the ratio of non-SC/ST to SC/ST. Growth changes sectoral productivities and applies the baseline partial cost scaling while leaving the 1983 cost summaries in place. Education isolates changes in the relative education-cost term by keeping entry costs at their 1983 real levels. Entry isolates entry-cost changes by keeping the relative education-cost term at its 1983 level.

From Table 18 we see that with only growth, the total wage gap falls from 1.34 to 1.20. This reinforces the main message that productivity growth is a strong convergence force. Productivity growth raises schooling and creates convergence in the education gap. The main weakness of the growth-only case is sectoral allocation: it creates too large an increase of Δs^m and too much compression of Δs^h.

In column (2), we fix the entry cost at the 1983 levels and isolate the change in education costs. The lower relative education-cost term for SC/STs generates strong total wage convergence. However, because this exercise removes the broad real-cost decline that comes from growth, education levels and labor-productivity growth remain far below the data. Education-cost changes alone therefore capture an important convergence force, but cannot discipline the aggregate productivity levels.

Finally, when we only change entry costs, the total wage gap changes less. This channel works mainly through sectoral sorting rather than through human-capital accumulation. It helps repair the sectoral allocation problem by lowering the manufacturing labor gap and raising the service labor gap relative to the growth-only case, but it cannot by itself generate sizable education growth or labor-productivity growth. In light of these patterns, we think that growth plays the more significant role in creating the wage and education gap movements in line with the data, while entry-cost changes help the model fit the sectoral allocation margins.

C Misallocations and Productivity

A key aspect of our model is that labor productivity responds to both exogenous and endogenous factors. The endogenous response arises anytime agents change their schooling and sectoral employment decisions in response to exogenous shocks. This re-sorting changes the human capital of workers as well as the sectoral distribution of the human capital, both of which affect the sectoral and aggregate levels of labor productivity. Put differently, productivity affects talent misallocation but misallocation itself affects productivity in the model. How big is this latter effect?

Worker re-sorting in the model occurs due to changing costs of schooling and sectoral employment which also change the talent misallocations and caste gaps. We evaluate the quantitative importance of the decreasing caste misallocation for labor productivity by comparing sectoral labor productivity growth rates under three scenarios: (i) sectoral entry costs are scaled to aggregate growth; (ii) schooling costs are scaled to aggregate growth; and (iii) both entry costs and schooling costs are scaled to growth. In each experiment, we hit the model with the imputed exogenous productivity growth rates in the baseline case.

Table 19 reports the sectoral productivity growths under the three scenarios as well as the numbers in the baseline case. Comparing the column "Scale both" with the last column shows that the overall and exogenous sectoral productivity growth rates become identical when both costs are scaled. In this case, there is no change in misallocations as the relative real costs of schooling and sectoral employment remain unchanged for the two castes. Hence, the difference between the exogenous sectoral productivity growth and the overall sectoral productivity growth in the baseline case (column "Baseline") is due to changing misallocations.

Table 19: Changing Misallocations and Productivity Growth

Variable	Data	Baseline	Scale entry	Scale educ	Scale Both	Exogenous Growth
Ey^a_{24}/Ey^a_{83}	3.04	3.05	3.61	1.30	1.59	1.59
Ey^m_{24}/Ey^m_{83}	3.12	3.12	3.42	1.32	1.89	1.89
Ey^h_{24}/Ey^h_{83}	3.92	3.93	3.84	2.11	3.50	3.50

Notes: The baseline column uses the formal dynamic cost scaling, $\epsilon = \epsilon_\phi = 0.289$. Exogenous growth is the calibrated sectoral productivity growth factor.

The numbers in Table 19 imply that declining misallocations due to endogenous education and sectoral sorting account for 48 percent, 39 percent and 11 percent of overall labor productivity growth in Agriculture, Manufacturing and Services, respectively.

D 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:

$$\lambda_s = \lambda_n + \tau_\lambda$$

$$\gamma^k_s = \gamma^k_n + \tau^k_\gamma, \quad k = m, h$$

where τ_λ is the tax on schooling and $\tau^k_\gamma, k = m, h$ 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 Table 1, $\tau_\gamma^k < 0,\ k = m, h$, 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

$$L\left[s\int_{\underline{a}}^{\bar{a}} T_i dG(a) + n\int_{\underline{a}}^{\bar{a}} T_i dG(a)\right] = L\left[s\int_{\underline{a}}^{\bar{a}} \tau_\lambda q_{i,s}^* dG(a)\right] + L\left[s\int_{\hat{a}_s^m}^{\tilde{a}_s^h} \tau_\gamma^m \phi dG(a) + s\int_{\tilde{a}_s^h}^{\bar{a}} \tau_\gamma^h \phi dG(a)\right] \quad \text{(D.44)}$$

where $q_{i,s}^*$ stands for the optimal choices of schooling given by equations 3.7-3.9.

This formulation of the cost differences as tax distortions leaves unchanged the production details of the model since we retain the same calibrated $\lambda_n, \lambda_s, \gamma_n^k, \gamma_s^k$ as in Table 1. The consumption side of the model however does get affected by this reformulation since taxes could be either rebated to the public or consumed by the government. We shall examine both possibilities below.

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 would eliminate all caste gaps.

Table 20: Welfare Costs of Caste Distortions Under No Rebate

	1983			2024		
Variable	Baseline	γ's equal	all equal	Baseline	γ's equal	all equal
C_s	105.72	102.54	168.59	320.54	313.15	490.39
C_n	168.63	168.91	168.59	490.40	490.61	490.39
C	152.90	152.32	168.59	447.94	446.25	490.39
Y_a	133.12	133.09	145.79	423.57	422.56	454.52
Y_m	234.70	238.70	256.50	445.31	445.40	478.16
Y_h	302.09	295.90	334.50	1605.90	1590.00	1725.70
Y_f	199.17	198.06	219.03	717.26	713.73	770.22

Notes: The table reports average consumption of each caste as well as per capita outputs of the sectoral and final goods when taxes are not rebated.

Table 20 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 that 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 59.5 percent in 1983 and 53.0 percent in 2024. Non-SC/STs are essentially unaffected.

Aggregate output, Y_f, rises by 10 percent in 1983. This is the static gain from removing caste distortions. The corresponding output gain in 2024 is 7.4 percent. The increase in average per capita consumption, C, from removing all caste distortions in this economy is 10.3 percent in 1983 and 9.5 percent in 2024.

How do these estimates change when the caste taxes are rebated back to the public in the form of lump-sum transfers? Table 21 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 20 above.

Table 21: Welfare Costs of Caste Distortions Under Lump-Sum Rebates

	1983			2024		
Variable	Baseline	γ's equal	all equal	Baseline	γ's equal	all equal
C_s	115.94	112.31	168.59	351.50	344.57	490.39
C_n	178.85	178.69	168.59	521.37	522.03	490.39
C	163.12	162.10	168.59	478.90	477.67	490.39

Notes: The table reports average consumption when caste-tax revenues are fully rebated to households as lump-sum transfers. The output rows are identical to Table 20 and are omitted.

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 20. Consequently, the welfare gains for SC/STs from removing all distortions are smaller than in the no-rebate case. The average per capita consumption gains for SC/STs are 45.4 percent in 1983 and 39.5 percent in 2024.

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 in both rebate regimes. The aggregate gains are larger when the distortions are treated as resource costs and smaller when tax revenues are fully rebated, but in both cases the exercise shows that caste-based distortions impose substantial welfare costs on SC/STs and on the aggregate economy.

References for the Online Appendix

Shapley, Lloyd S. (1953), "A Value for n-Person Games," in Harold W. Kuhn and Albert W. Tucker, eds., *Contributions to the Theory of Games II*, Princeton University Press, 307–317.

Shorrocks, Anthony F. (2013), "Decomposition Procedures for Distributional Analysis: A Unified Framework Based on the Shapley Value," *Journal of Economic Inequality*, 11(1), 99–126.