Structural Transformation and Decline in Caste Based Frictions in India

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Abstract

I investigate the barriers hindering structural transformation. The paper documents that between 1993 and 2012, there was labor reallocation from the agriculture sector to non-agricultural sectors in India. This shift was led by workers from marginalized groups, as their proportional share in non-agricultural sectors increased during this period. Additionally, I find that the sectoral returns to education vary for workers belonging to different caste groups and employ a multi-sectoral model to elucidate this. When examining the existing barriers that elevate the mobility cost to switch across sectors, the model focuses on barriers arising from unobserved (innate abilities) and observed (formal years of schooling) human capital. Using data on wage gains from moving to non agriculture sectors, I determine that the data is more aligned with model implied barriers in the former case, and that unobserved innate abilities play a role. Moreover, I discover that even though barriers declined for both caste groups we observe only workers from the disadvantaged caste groups moving into the non agriculture sectors (especially service sector). The findings suggest a potential influence of policies promoting vocational or non-formal education, aiding in the upskilling of SC/ST workers and facilitating their transition to more productive sectors. In contrast to the United States, I also observe sizable barriers to labor reallocation towards more productive non-agriculture sectors in India.

Keywords: Structural Transformation, Barriers, Caste discrimination

JEL Classification: J24, I26, O15, J71, J31

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1 Introduction

The service sector has played a pivotal role in recent Indian economic growth. The share of the service sector in GDP rose from 44% in the 1990s (post-liberalization) to 54% in the 2000s.[1] Simultaneously, during this period, India also witnessed the reallocation of labor from agriculture to the construction and service sectors.[2] The movement of labor and economic activity between sectors is crucial to structural transformation. What were the characteristics of the Indian economy that facilitated this transformation? Existing research highlights factors such as increase in productivity of consumer services, increase in demand for service intensive goods (due to increase in income growth), technological and infrastructure advancements along with relative decline of land market frictions, and skill development.[3] In this chapter, I use a multi-sectoral model to re-examine some of these factors and quantify the barriers to mobility. Primarily, data on sectoral wage ratios is used to quantify the barriers defined in the model.

At the outset, the chapter first documents the trend of growth, the labor movement towards sectors, and distribution by caste and gender across sectors during 1993-2012 to highlight patterns of structural transformation in India. The stylized facts show that as India experienced growth led by the service sector, there was a notable shift of labor from agriculture to non-agricultural sectors, particularly construction and services. Focusing on the distribution of workers transitioning out of agriculture by caste group reveals that, compared to those from general castes, a higher proportion of workers from marginalized groups moved into the non-agricultural sector between 1993 and 2012. This suggests that the observed labor reallocation predominantly involved individuals from these marginalized groups. While examining the Mincer returns by sector and caste group, I find variation in Mincer returns by sector and caste group. I then rely on the theoretical framework of Herrendorf and Schoellman (2018) to define barriers to structural transformation and use micro-level data on wage gains from switching to the non-agriculture sector and educational data to shed light on the relevance of unobserved factors such as ability playing an essential role in structural transformation. This analysis aims to provide insights into the reasons behind the variation in sectoral Mincer returns among workers from different caste groups. From an empirical standpoint, I quantify the barriers using IHDS panel data and extend the results by disaggregating the sample of switchers by caste to relate the patterns of transformation in the period 1993-2012 with a decline in caste-based frictions.[4]

[1] Whereas for agriculture it fell from 29% to 22% and for manufacturing from 27% to 24% (Singh, 2012). Serrano-Quintero (2022) provides plausible explanation of this service-led growth rather than the initial manufacturing growth in structural transformation which has been observed for developed nations. The paper suggests that it was skill biased technical change which contributed to the difference in high productivity between services and manufacturing.

[2] Source: NSS-EUS 50^{th} (1993) and 68^{th} round (2012), for employed individuals aged 25-60 years, based on usual principal activity status and occupation. Refer to stylized fact 2 and Figure 2.

[3] See Fan et al. (2023), Mehta (2022), and Dehejia and Panagariya (2016) among others.

[4] Jodhka (2017), Vaid (2014), Munshi (2020), Munshi (2019), Deshpande (2011), Cassan et al. (2021) among others have focused on changes in caste based frictions over time.

Using the model, I express the barriers to labor reallocation, which are implicitly defined using wage differentials across sectors. In the model, unobserved (innate abilities) or observed human capital (formal education) can be two potential reasons behind why workers do not move out of agriculture and into a more productive sector in the presence of sectoral wage differences.[5]

The key results in the chapter can be summarised as follows. Using wage ratios, I explain the factors that influence individuals in choosing their sectoral focus, specifically, innate abilities and formal schooling. To examine which among these factors play an important role, I compare the wage ratios for each factor with the wage gains of those who transitioned from agricultural to non-agricultural sectors. For India, the wage gains from moving out of agriculture are closer to the sectoral wage ratios indicating that unobservable innate abilities play a role. However, relative to the barriers in the United States, I observe sizable barriers in India.[6] I also observe that these barriers decline over time, even when I further divide the sample by caste groups. This is true for both historically marginalized groups (scheduled caste and tribe- SC/ST) and the advantaged caste group (General). However, the data shows more workers from the SC/ST groups relative to the General group, moving into non-agriculture sectors, especially the service sector.

Relating the increase in productivity in the service sector in India over time (Fan et al., 2023) to the results of the model suggesting that unobserved abilities play a role, it could be that individuals from marginalized groups engaged in the service sector were more productive or had attained skills (such as vocational education) that helped them become more productive over time compared to other groups. To explore this further, I examine the relationship between policies providing vocational education and the sectoral job choices of workers belonging to different caste groups. Using the triple difference-in-difference estimation, I find a significant positive relationship between the uptake of vocational education and sectoral choice for those belonging to the marginalized caste group. This suggests that vocational training has positively affected and enhanced the pool of skilled SC/ST workers, which is positively related to their transition into non-agricultural sectors. Another reason for the movement of SC/ST workers to more productive sectors could be that, over time, firms might hire workers from marginalized groups due to their higher productivity (thus reducing discrimination) but could still be paying them the same or less than workers from the general caste group.[7] More opportunities in the service sector and the decline in caste-based discrimination in the education and labor market might have aided better allocation of talent across sectors.

[5] In the model and in the chapter, human capital refers to formal years of education in school and college. This is important to note because in the latter part of the chapter there is a discussion on the role played by vocational education.

[6] This was true in comparison to the United States (Herrendorf and Schoellman, 2018), Brazil (Alvarez, 2020) and Indonesia (Hamory et al., 2021). Refer to Table A7 in Appendix A for estimation of barriers for these nations.

[7] Figures 5 and A9 indicate this finding. If we compare the level of returns to education by sector for each caste, we do observe individuals belonging to the General group earn higher relative returns in comparison to those from the SC/ST group.

Related literature: This chapter contributes to the literature on structural transformation and barriers restricting perfect labor movement across sectors in Buera et al. (2022) and Lagakos and Waugh (2013). These papers shed light on why there are cross-country productivity differences. Herrendorf and Schoellman (2018) go one step ahead and quantify barriers to mobility. I extend their analysis by shifting the perspective from cross-country analysis to zooming in on India and relating them with caste-based discrimination while focusing on the service sector. Ngai and Petrongolo (2017) assesses the pattern of differences in productivity within the agriculture and non-agriculture sectors by focusing on the self-selection of heterogeneous workers. With respect to this paper, the results in my study also suggest that how workers sort into sectors makes a difference, specifically by their social identity, such as their caste category.

This chapter contributes to the literature on structural transformation in India (Sommers, 2024; Fan et al., 2023; Dehejia and Panagariya, 2016; Lahiri et al., 2014; Nayyar et al., 2021; Mondal, 2019; Basole, 2022). This chapter complements by documenting stylized facts on structural transformation. Also, it shows that the size of barriers to mobility differs for caste groups, thus hinting towards the role of the evolution of caste-based discrimination. While there are studies that establish a connection between frictions, such as the *hukou* system in China and structural transformation (Tombe and Zhu, 2019), but to the best of my knowledge, this is the first attempt to link frictions based on social identity with structural change in the Indian context.

The chapter contributes to the strand of literature focusing on human capital accumulation driving the pace of structural transformation by adopting advanced technology studied by Ngai and Pissarides (2007) and Porzio et al. (2022). Buera and Kaboski (2012) link the importance of skilled labor, hence skill premium (wages), with a rise in demand for skill-intensive services in the United States since 1950. For India, between 1987 and 2011, Sommers (2024) shows that the decline in trade cost and Fan et al. (2023) argue that the growth in consumer services (within the service sector) contributed to structural transformation. During this period, they also observed a skill premium growth in India. This highlights the role of human capital. A rise in skill or education levels could be one of the reasons for the increase in service sectoral productivity. The prevalence of caste-based discrimination in the labor and educational sectors accentuates the significance of our study. Especially because discrimination hinders the pace of structural transformation, thus impeding growth (Donovan and Schoellman, 2023). Life cycle wage growth among different caste groups and the nature of workers' occupations also show variations specific to caste. Hence, it highlights the interlinkages between wage growth and educational attainment and the role of human capital in occupational sorting (Caselli and Coleman Ii, 2001). Finally, this chapter also adds to the literature centered on misallocation of workers (or talent) across sectors (Gollin et al., 2014; Hsieh et al., 2019).

Layout of the chapter: The remainder of the chapter is organized as follows. Section 2.2 describes the data and empirical observations to motivate the model discussed in Section 2.3. Following

the description of the theoretical framework, I estimate the model implied barriers from the data in Section 2.4. The role of vocational education is then discussed in Section 2.5, followed by the contribution and potential mechanism in Section 2.6. The additional tables and figures are contained in the Appendix.

2 Data and Stylized Facts

Data

I make use of two available datasets which collect data across India. The first is the India Human Development Survey (IHDS), a panel survey for 2005 and 2012. The nationally representative survey tracks more than 40,000 households in both waves. I use the data set to estimate the wage gains for individuals re-allocating from agriculture to the non-agriculture sector.[8]

To give perspective to the findings from the panel data and for robustness checks, I use the most recent rounds of Employment and Unemployment Surveys (EUS) conducted by the National Sample Survey Organization (NSSO). It is a cross-sectional data, with more than 100,000 households surveyed in seven quinquennial EUS rounds conducted between 1993-2012.[9]

Both data sets capture demographic characteristics, including the caste and gender groups to which workers belong and their labor earnings, which I utilize to determine daily wages. Additionally, these data sets provide information on occupations and sectors in which individuals are employed, along with their residence's state and location (rural/urban).[10] I club individuals into two broad caste groups: the General and Schedule Caste and Tribe (SC/ST) groups. The remaining variable of interest includes information on age and educational categories, also used to define potential experience.[11]

Stylized Facts

To motivate the research question, this section first presents some stylized facts on the Indian economy before discussing the theoretical model in the next section.

[8] I classify workers into three broad non-agriculture sectors: construction, services (skilled and unskilled) and manufacturing. I use Herrendorf and Schoellman (2018) classification to divide service sector into unskilled and skilled services listed in Appendix A.

[9] NSS Rounds: 50^{th} (1993 -'94), 55^{th} (1999 -2000), 61^{st} (2004 -'05), 62^{nd} (2005 -'06), 64^{th} (2007 -'08), 66^{th} (2009 -'10) and 68^{th} (2011 -'12).

[10] To map sectors across NSS rounds I refer to the concordance list by Fan et al. (2023) in WA8-WA10.

[11]

$$\text{Potential experience} = \begin{cases} age - schooling - 6, & \text{if schooling} \geq 12, \\ age - 18, & \text{if schooling} \leq 12. \end{cases}$$

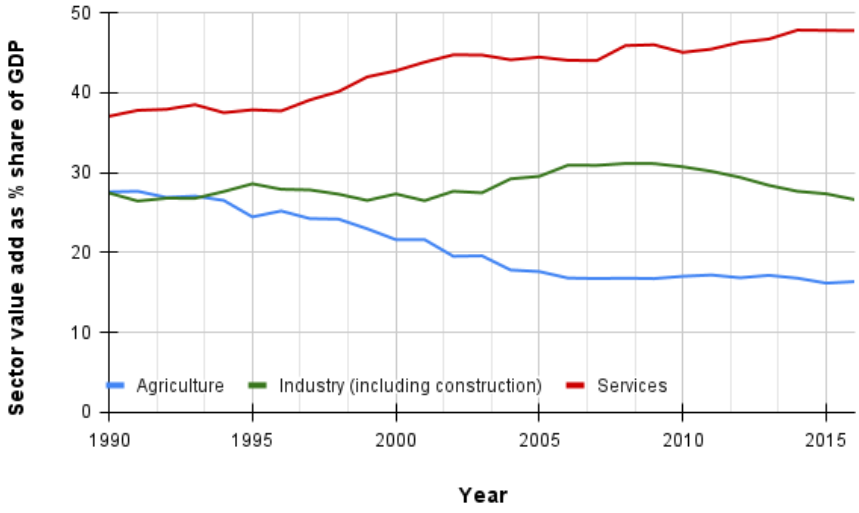


Figure 1: Economic sectors as a share of GDP (value added as a % GDP) in India in 1991-2019 (Source: World Bank Data)

Stylized fact 1: Value-added share of the service sector increased

Figure 1 plots the share of each sector (value added) as a percentage of GDP in India from 1991 to 2016. The graph shows that in the 1990s, there was a rise in the service sector's share and a decline in the agriculture sector's share.[12] This stylized fact echoes the findings of the literature on structural transformation in India (Dehejia and Panagariya, 2016; Basole, 2022; Eichengreen and Gupta, 2013; Eichengreen and Gupta, 2011). Share of industry (manufacturing and construction) sector increased till 2010 but then declined and remained stagnant.

Stylized fact 2: Movement of labor out of agriculture and into non-agriculture sectors

Figure 2 plots the share of workers across various industries.[13] Though over time, employment share in manufacturing has roughly remained the same. However, I observe an increase in employment in construction and services (by 6 percentage points).[14] Employment in agriculture declined in India

[12]Refer to Figure A12 and A11 in Appendix A for further analysis on the trend of the size of specific services. Over the years trade, financial services, education and trade has grown rapidly and has a larger share as a % of GDP among other sectors within services. Fan et al. (2023) and Serrano-Quintero (2022) finds that business and financial services, real estate, trade, retail were high productive sub-sectors within services.

[13]I use Employment and Unemployment Surveys (EUS) conducted by the National sample survey organization (NSSO) which includes detailed information on socioeconomic and background characteristics at both individual and household level. I map the industry codes (NIC) between 1993 (NIC 1987) and 2012 (NIC 2008) and club them into 3 broad sectors- Agriculture, Industry (Manufacturing and construction), and Services. The figure includes a limited sample of individuals aged 25-60 who are currently employed and have reported their years of education.

[14]Refer to Figure A1 in the Appendix for the distribution across four broad sectors, with industry divided into manufacturing and construction.

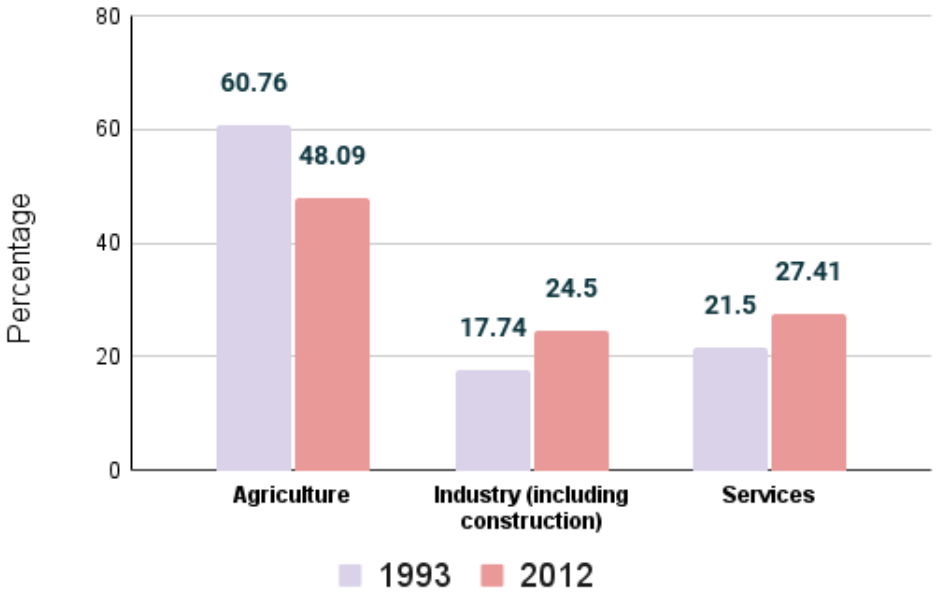


Figure 2: labor re-allocation across sectors over time

between 1993 and 2012.

Stylized fact 3: Movement of workers of SC/ST caste into the service sector

Figure 3 suggests that there have been caste-based changes in sectoral distribution. Even though, over time, there has been no equalization of the share across sectors between caste groups. However, there has been a convergence in them for the service sector between 1993 and 2012.[15]

If we note the patterns for gender groups within the SC/ST caste group's share in the service sector, I observe that both men and women moved towards the service sector.[16] For men, the increase was 44% (an increase of 11.69 percentage points), and for women, it was a 50% increase (3.78 percentage points). There is a possibility that the increase in the labor share of the SC/ST group in the service sector could be driven by female workers' movement into the service sector. However, their absolute values are smaller than those of SC/ST men.[17]

[15]Potential case reflecting this would be if: $E_{1993}^{Service,General} = E_{2012}^{Service,General}$ and $E_{1993}^{Service,SC/ST} < E_{2012}^{Service,SC/ST}$ then, the proportion $\frac{E_{2012}^{Service,General}}{E_{2012}^{Service,General}+E_{2012}^{Service,SC/ST}}$ declines.

[16]Refer to Figure A10 in Appendix A for a graph showing overtime distributional patterns in the service sector for men and women by both caste groups. Also, refer to Figure A2 and A3 in Appendix A for distributional changes by caste groups in the remaining non agriculture sectors, i.e., manufacturing and construction.

[17]If I segregate the increase into skilled and unskilled sector I find that women's share increased by 5.76 percentage points (199%) in the unskilled services and 2.11 percentage points (44%) in the skilled services. Refer to Figure A4 and A5 in Appendix A.

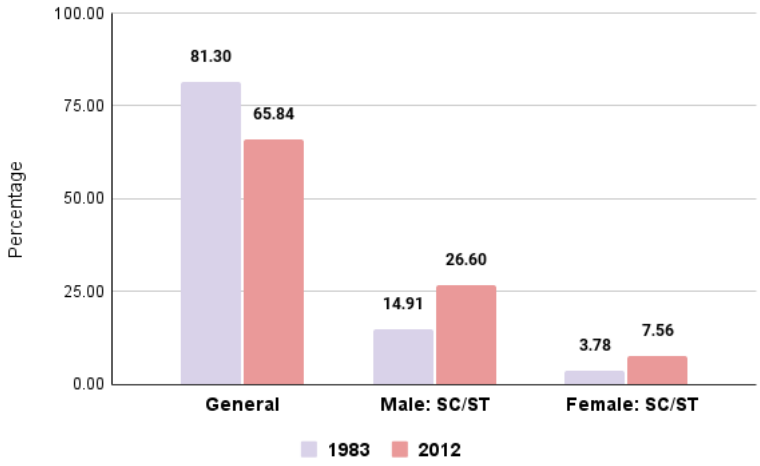


Figure 3: Changes in share of workers in service sector over time by caste

Stylized fact 4: Returns to schooling are highest in the service sector for all (caste) workers

I further explore sectoral analysis by estimating sector-specific Mincer returns (while accounting for experience and schooling) and visually represent the wage schedules in Figure 4.[18] Running Mincer regressions by sectors, I find that the sectoral Mincer returns differ significantly from each other and the aggregate Mincer returns. Hence, this suggests that aggregate Mincer returns do not capture all information relevant to determining wages at the sectoral level.

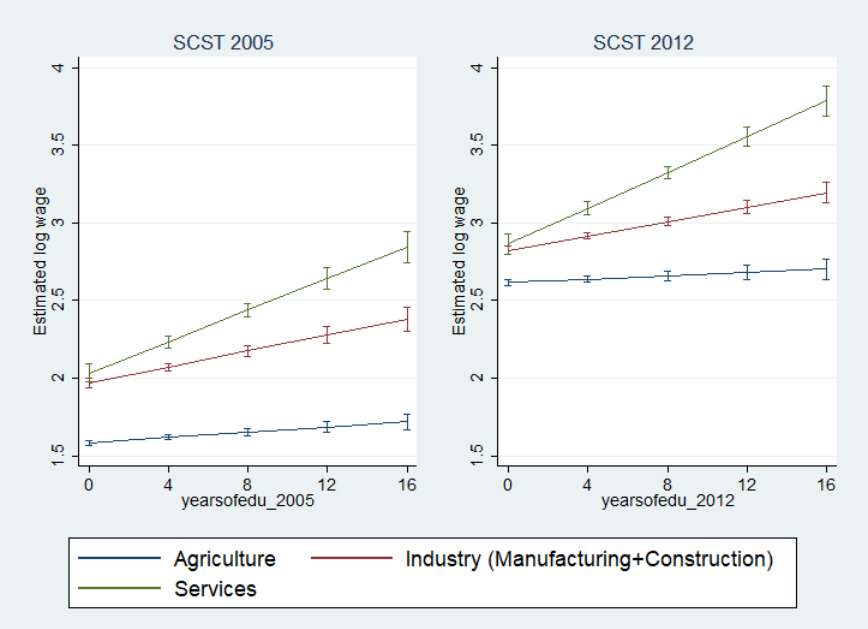
I plot sectoral wage schedules for agriculture and service sector for both SC/ST & General caste groups in 2005 and 2012.[19] Figure 4 plot the estimated log wage function ($\log(w_j(n))$) against years of schooling n for each sector after netting out demographics, gender, and potential experience. If we only focus on service and the agriculture sector, Figure 5 indicate that the highest returns are for those engaged in skilled services for both caste groups for the two IHDS waves. However, in 2012, compared to 2005, returns of the skilled service sector relative to other sectors indicated by a steeper slope for the SC/ST group, as the remaining non agriculture sectors became flatter (relatively). Indicating, that the increase in earnings was more substantial for each additional unit of education for those engaged in skilled service sector in 2012 relatively to those who were engaged in the same sector in 1983 and those engaged in the agriculture sector. Meanwhile, for the General group, returns in 2012 for the remaining non-agriculture sectors remain similar (or the slope has remained as steep) as in 2005.[20] Table A1 (in Appendix A) tabulates the sectoral returns to schooling by caste

[18] I estimate sectoral Mincer returns by estimating: $log(w_{ij}) = \beta_j d_j + \beta_x X_{ij} + \gamma_j s_{ij} d_j + \epsilon_{ij}$, where X_{ij}= experience (potential), state, gender; s_{ij}= schooling of worker 'i' in sector 'j'; d= sector dummy. For the Figures I plot: $log(w_{ij}) = \hat{\beta}_j + \hat{\gamma}_j s$.

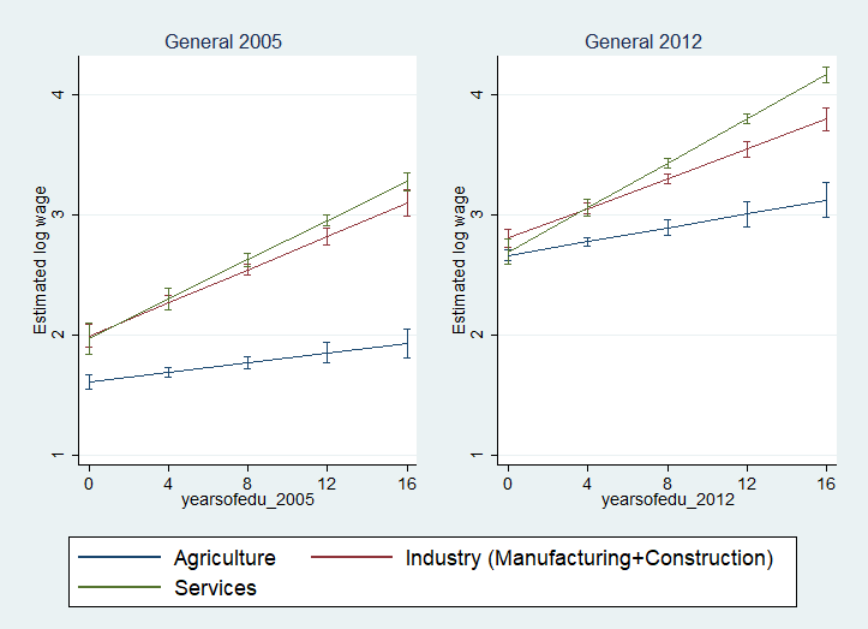
[19] Figures A6 and A7 in Appendix A presents returns for four sectors individually, where industry is further divided into construction and manufacturing.

[20] Refer to Figure A8 and A9 for quadratic returns to schooling. We observe that for workers from both caste groups, in 2012, non linear relationship of attaining higher education with higher wages was more

groups, indicating that over time, there was a convergence



Panel A: SC/ST group

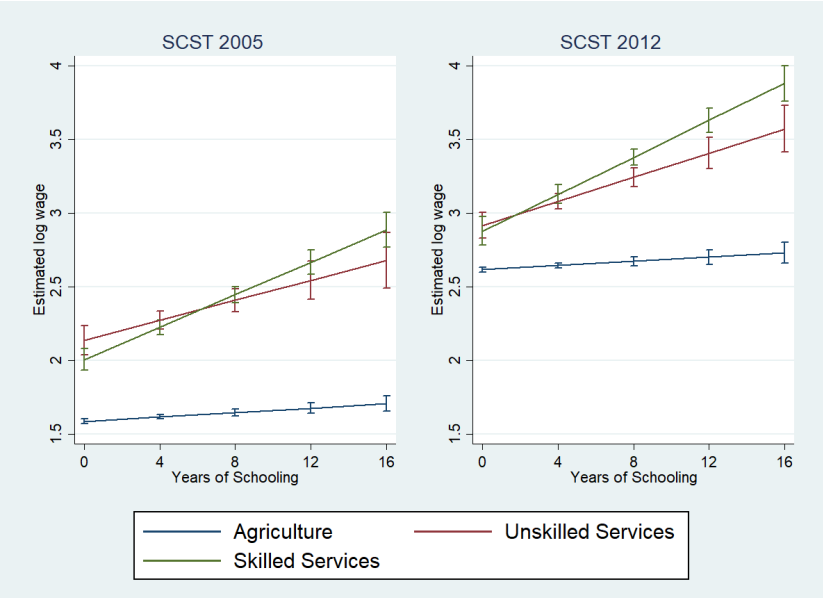


Panel B: General group

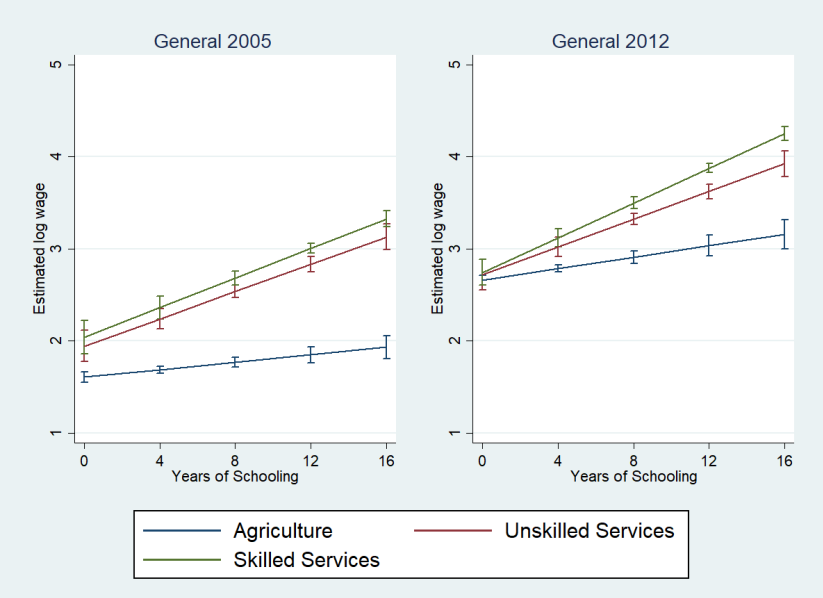
Figure 4: Linear returns to education by sectors: Agriculture, Industry and Services

Notes: Panel A presents the sectoral wages for agriculture, industry (manufacturing and construction), and the service sector (skilled and unskilled) for SC/ST workers in both wave IHDS I (2005) and II (2012) and for workers from the General category in Panel B over different years of education. 95% confidence intervals bands are shown as error bars.

pronounced in the unskilled service sector than the skilled service sector.



Panel A: SC/ST group



Panel B: General group

Figure 5: Linear returns to education by sectors: Agriculture, Skilled and Unskilled Service

Notes: Panel A presents the sectoral wages for agriculture and service sector (skilled and unskilled) for SC/ST workers in both wave IHDS I (2005) and II (2012) and for workers from the General category in Panel B over different years of education. 95% confidence intervals bands are shown as error bars.

between the SC/ST and general group non-agriculture sectoral returns. In both years, the difference between the returns was statistically significant.

The stylized facts discussed above indicate that the service sector contributed the most to India's GDP from 1993 to 2012 among the non-agricultural sectors. During this time, I also observed the redistribution of labor from agriculture into more productive sectors, such as the service sector. However, the workers from the SC/ST group were moving towards these sectors. In the next section, I analyze these facts and the reasons behind them using a theoretical model. In the model, there

are two potential reasons which can explain variation in sectoral returns, the first is workers' unobserved characteristics or ability and the second is formal years of education. Similar to Herrendorf and Schoellman (2018), I use wage gaps to quantify the model implied barriers under each case, and compare them with the wage gains of workers moving from agriculture to non agriculture sectors to pin point which among these two factors play a much more significant role in India.

3 Model

The previous section discussed several stylized facts on structural transformation with a focus on the service sector. I observed that there was variation in Mincer returns by sector. In this section, I build on Herrendorf and Schoellman (2018) multi-sectoral model to quantify the gains of switching occupations from agriculture to the non-agriculture sector and estimate model implied barriers using data on observables (wages). I aim to extend the analysis by disaggregating (quantitatively) according to caste groups. This section briefly explains the partial equilibrium model to estimate unobserved barriers in the reallocation of labor across industries from Mincer returns in the section before proceeding to the results for the Indian economy.

The model's environment includes two sectors (j): the agriculture sector (a) and the non-agriculture or the service sector (na).[21] Workers are endowed with $(x) \in [0, \bar{x}]$, indicating the inherent ability, and $(s) \in [0, \bar{s}]$ as years of schooling. The density function $m(x, s)$ refers to the distribution of worker types, which is exogenously given in the model.

The human capital of a worker type (x, s) is defined as $h(x, s) = exp(xs)$, and individuals value working (wages) and not leisure.

Sectors produce value added:

$$\int_{(x,s)} h(x,s)^{\gamma_j} m_j(x,s) dx ds,$$

where γ_j is the human capital intensity of sector j. The model focuses on two types of barriers to re-allocation, which are teased out from γ_j. Under the first type or case 1 (described in detail in later section), it is hypothesized that the differences in observed sectoral Mincer returns are due to variations in workers' unobserved characteristics or abilities ($\gamma_{na} = \gamma_a$). In contrast, the second barrier suggests (case 2) the differences in Mincer returns are because schooling generates more human capital for a worker with the same characteristics in the service sector than in the agriculture sector ($\gamma_a < \gamma_{na}$). The model examines both of these cases.

In the model, the cost of relocating to a sector is quantified by τ_j, where, given the equilibrium

[21] I estimate barriers and present the results for both the non-agriculture sector (clubbed manufacturing, construction and services) and also show disaggregated results for the service sector. The Appendix includes results for the remaining sectors individually.

allocation of workers to the two sectors, if a worker moves from sector a to na (this is our case of interest), then the wage in the destination sector is "taxed" at rate $\tau_{na} \in [0, 1)$.[22]

Competitive Equilibrium

Equilibrium is defined such that prices of goods (p_j), wage rates for efficient labor units $(w_j(x, s))$, tax rates (τ_j) such that the following conditions are satisfied:

- Workers are paid their marginal value products in each sector:

$$W_j(x, s) = P_j h(x, s)^{\gamma_j}. \tag{1}$$

- If $m_j(x, s) > 0$, then in sector i worker (x, s) does not earn a higher wage net of moving costs:

$$W_j(x, s) \geq (1 - \tau_i) W_i(x, s). \tag{2}$$

- Sectoral efficiency units of labor:

$$L_j \equiv \int_{(x,s)} h(x, s)^{\gamma_j} m_j(x, s) dx ds. \tag{3}$$

- Average sectoral wages for all workers:

$$W_j \equiv P_j L_j. \tag{4}$$

- Average sectoral wages for workers with 's' yrs of schooling:

$$W_j(s) \equiv P_j \frac{\int_{(x)} h(x, s)^{\gamma_j} m_j(x, s) dx}{\int_{(x)} m_j(x, s) dx}, \tag{5}$$

  Average wages of workers with 0 yrs of schooling can be written as:

$$W_j(0) = P_j \frac{\int_{(x)} h(x, 0)^{\gamma_j} m_j(x, 0) dx}{\int_{(x)} m_j(x, 0) dx}, \tag{6}$$

  $h(x, 0) = exp(x^*0) = 1$ then

$$W_j(0) = P_j. \tag{7}$$

[22] In our analysis, the costs or the value of τ would be higher for disadvantaged caste group than those from the General caste group. Many studies focused around the literature on discrimination quantify barriers describing as a wedge indicating differences in relative wages (labor market discrimination) or costs of attaining education between the groups (Becker, 1971; Hsieh et al., 2019; Aigner and Cain, 1977).

- The labor market clears in both sectors:

$$m(x,s) = m_a(x,s) + m_{na}(x,s). \tag{8}$$

The objective is to quantify the model implied barriers using sectoral wage ratios across sectors and compare them with the wage gains of workers moving from agriculture to the service sector. In the remaining section, I explain both cases in detail.

Case 1: Role of Innate Ability

In this case, there exists variation in sectoral returns due to workers' unobservable characteristics, i.e., it assumes that schooling generates the same human capital in each sector, but workers sort based on innate ability (and therefore learned more per year of schooling work in services).
From equation (4) we know that the average sectoral wages can be written as:

$$W_j = P_j L_j,$$

$$\frac{W_j}{L_j} = P_j.$$

Substituting equation (7) in the above we get:

$$\frac{W_j}{L_j} = W_j(0).$$

Then the ratio of sectors' average wages can be written as:

$$\frac{W_{na}/L_{na}}{W_a/L_a} = \frac{W_{na}(0)}{W_a(0)}. \tag{9}$$

I quantify barriers under this case for those with 0 years of education. These would be the same for workers with higher education, given the assumption of equality of formal education requirement (or human sectoral intensities) under this case. Assuming the service sector pays higher wages than the agriculture sector, i.e., $W_{na}(0) > W_a(0)$, workers with 0 schooling to be in agriculture require $(1-\tau_{na})W_{na}(0) \leq W_a(0)$. Given that schooling generates the same human capital in all sectors (assumption in this case, i.e., $\gamma_{na} = \gamma_a$: $(1-\tau_{na})W_{na}(0)h(x,s)^{\gamma} \leq W_a(0)h(x,s)^{\gamma}$), then the smallest barriers that keep workers of all years of schooling in agriculture (or prevents workers from moving

to the service sector) is:[23]

$$\frac{1}{1-\tau_{na}} = \max\left\{1, \frac{W_{na}/L_{na}}{W_a/L_a}\right\} = \max\left\{1, \frac{W_{na}(0)}{W_a(0)}\right\},$$

or

$$\tau_{na} = 1 - \frac{1}{\max\left\{1, \frac{W_{na}/L_{na}}{W_a/L_a}\right\}} = 1 - \frac{1}{\max\left\{1, \frac{W_{na}(0)}{W_a(0)}\right\}}. \tag{10}$$

The barrier is increasing with an increase in adjusted average wage gaps or wage differentials $\left\{\frac{W_{na}/L_{na}}{W_a/L_a}\right\}$. Another way to describe this would be, if for example $\frac{W_{na}/L_{na}}{W_a/L_a} > 1$ then it would encourage workers to move into the service sector, however, one reason behind workers not moving could be due to presence of frictions.

Case 2: Role of Human Capital (formal years of education)

In this case, it is assumed there is variation in Mincer returns because schooling generates more human capital for a worker with the same characteristics in the service sector than in the agriculture sector. I assume workers have the same ability and workers with the highest years of schooling $(\bar{s})$ have maximum gains from moving out of the agriculture sector. In the case of $W_{na}(\bar{s}) > W_a(\bar{s})$, the barriers faced by those with the highest years of schooling are also encountered by workers with lower education. Then we can define the smallest barrier which prevents workers with $\bar{s}$ from moving out of agriculture can be written as:[24]

$$\frac{(1-\tau_{na})W_{na}(\bar{s})}{W_a(\bar{s})} = 1.$$

Depending on the value of τ_{na} I can re-write the above relation as:

$$W_{na}(\bar{s}) = W_a(\bar{s}), \text{if } \tau_{na} = 0,$$
$$W_{na}(\bar{s}) > W_a(\bar{s}), \text{if } \tau_{na} < 1.$$

[23] In the presence of no barriers, there is no movement of worker from agriculture to service sector when the wages equalize and hence no incentive to move.

[24] Smallest because, if barriers are 0, there is wage equality, which makes the worker indifferent between moving across sectors. If the barrier is larger than this, the workers will not move at all, and if the barrier is slightly lower, they will move.

Thus, the barrier under this case can be written as:

$$\begin{aligned} \frac{1}{1-\tau_{na}} &= \max\left\{1, \frac{W_{na}(\bar{s})}{W_a(\bar{s})}\right\}, \\ &\text{or} \\ \tau_{na} &= 1 - \frac{1}{\max\left\{1, \frac{W_{na}(\bar{s})}{W_a(\bar{s})}\right\}}. \end{aligned} \tag{11}$$

Now that the barriers are defined in both cases, the subsequent section involves measuring them through the lens of the model.

4 Quantifying the Model

Herrendorf and Schoellman (2018) use estimates of wage gains and relate them with the estimated model implied barriers for the United States. I do the same for India and extend the estimation for caste groups.

Estimating Wage Gains

I estimate wage gains $log(w_{it})$ for workers (i) who switched to non-agriculture sectors (na) from agriculture (a) and control for time effects (d_t).

$$\triangle log(w_{it}) \equiv log(w_{inat}) - log(w_{iat-1}), \tag{12}$$

$$\triangle log(w_{it}) = \beta_{an} d_i + \beta_t d_t + \epsilon_{it}.^{25} \tag{13}$$

Table 1 displays wage gains for those switching their industries to non-agriculture in the two waves of IHDS data. Column (2) displays sectoral wage gaps adjusted for demographics, indicating the highest wage gaps between the agriculture and service sectors. Column (3) presents wage gains for workers switching sectors. Panel A displays the estimated wage gains for all sample, and Panel B and C for SC/ST and the General group. The estimates for all sample indicate positive and small wage gains from leaving agriculture. Data suggests that the highest gains are for those switching to construction, followed by the service sector and then manufacturing from agriculture. Panel B and C in Table 1 indicate that gains for SC/ST caste groups from agriculture to the non-agriculture sector are higher than workers from the General caste group (except for the unskilled service sector). The results suggest that there were still gains in switching to non-agriculture sector for marginalized groups.

[25] d_i is the sector pair, for example 12 would mean those who were in sector 1 in 2005 but switched to sector 2 in 2012.

In the remaining section, I estimate the model implied barriers to move from the agriculture sector to more productive sectors and compare it to the above estimated wage gains.

Estimating Wage Differentials Under Both Cases

To contextualize the results, I estimate barriers and wage differences under both channels over time and link them with the wage gains determined above. To quantify each barrier, I estimate the following for each worker i in sector j:

$$\begin{aligned}\log\left(wage\right)_{ij} =& \beta_0 sectors_j + \beta_1(sectors_j * years\ of\ schooling_{ij}) + \beta_2 potential\ \ exp_i + \\ & \beta_3 potential\ \ exp_i^2 + \beta_4 potential\ \ exp_i^3 + \beta_5 potential\ \ exp_i^4 + \beta_6 X_{ij} + \epsilon_{ij}.\end{aligned} \tag{14}$$

The quadratic (and higher-order) term in the above equation is included to capture changes in life cycle wage growth across sectors with potential experience. This inclusion addresses the non-linear relationship between experience and wages, as documented in Murphy and Welch (1990) and Mincer (1974). X_{ij} includes controls such as state and gender. Estimates of β_0 display sectoral wage gap $\left\{\frac{W_n(0)}{W_a(0)}\right\}$, which will help in quantifying the first type of channel, i.e., ability, and β_1 presents the premium achieved in each sector due to schooling quantifying the second channel, i.e., human capital. These estimates are presented in Table 2.Columns (4) and (5) of Table 2 indicate the wage gaps, whereas columns (6) and (7) display the estimated barriers from the corresponding wage gaps. To examine which among these factors play a more significant role, I compare the wage ratios for each factor (columns (4) and (5) of Table 2) with the wage gains (column (3) of Table 1) of those who transitioned from agricultural to non-agricultural sectors.

Given, in comparison to the wage gaps under case 2, the estimated values of wage gaps under case 1 (columns (4) of Table 2) are closer to the wage gains (column (3) of Table 1), this, suggests that the barriers from the wage differences in the first type of channel, i.e., unobserved ability plays a much more significant role than observed formal educational requirements. This was also true for the United States, as shown in Herrendorf and Schoellman (2018). Consequently, this suggests that observed differences in sectoral Mincer returns vary due to differences in unobserved sectoral abilities and not because of differences in human capital or formal education requirements.

The wage gains for workers moving out of agriculture are closer to the model implied barriers sectoral under case 1, indicating that sectoral differences in innate ability plays a role. The model implied values also suggest that the values of barriers to structural transformation are sizable, however declining over time. The results highlight the importance of the role of sectoral unobserved innate abilities, as the data indicates a 58% decline in sizable barriers over time under case 1 for

Table 1: Changes in wages for those who switch industries from Agriculture

Switched from Agriculture to Sector (1)	Raw Wage Gaps (2)	Wage Changes of Switchers (3)	Observations (4)
Panel A: All Sample			
Non-Agriculture	1.72	1.08	3,943
Manufacturing	1.53	1.07	562
Construction	1.50	1.09	2,760
Services	2.06	1.03	621
1. Unskilled	1.77	1.00	285
2. Skilled	2.28	1.06	336
Panel B: General Caste Group			
Non-Agriculture	2.28	0.98	330
Manufacturing	1.98	0.84	44
Construction	1.75	1.02	224
Services	2.62	1.00	62
1. Unskilled	2.04	1.18	28
2. Skilled	3.02	0.88	34
Panel C: SC/ST Caste Group			
Non-Agriculture	1.59	1.10	1,964
Manufacturing	1.44	1.19	267
Construction	1.46	1.10	1,384
Services	1.88	1.05	313
1. Unskilled	1.73	1.01	131
2. Skilled	1.97	1.09	182

Note: The table presents the wage gains from moving out of agriculture (net of time fixed effects). Panel A includes all sample. Panel B and C displays results for those workers belonging to the SC/ST and General caste group. Col (2) displays wage gaps (after controlling for state and time fixed effects). Col (3) displays wage gaps for those workers who switched from agriculture to non-agriculture sectors.

Table 2: Barriers to mobility for those switching to non-agriculture industry (IHDS I and II)

	Switched from Agriculture to Sector	Wage gaps				Barriers		Count
		Raw	Adjusted	Case 1 (ability)	Case 2 (human capital)	Case 1 (ability)	Case 2 (human capital)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
Panel A: All Sample								
2005 (IHDS Wave I)	Non-Agriculture	2.04	1.56	1.28	2.62	0.22	0.62	12,713
	Services	2.38	1.69	1.23	2.93	0.19	0.66	6,050
	1. Unskilled	2.16	1.52	1.35	2.17	0.26	0.54	2,271
	2. Skilled	2.53	1.85	1.23	3.28	0.19	0.70	3,779
2012 (IHDS Wave II)	Non-Agriculture	1.61	1.29	1.10	2.25	0.09	0.56	16,586
	Services	2.09	1.48	1.01	2.85	0.01	0.65	6,048
	1. Unskilled	1.77	1.25	1.11	1.91	0.10	0.48	2,547
	2. Skilled	2.36	1.66	1.03	3.16	0.03	0.68	3,501
% Decline in barrier	Non-Agriculture					58%	10%	
	Services					95%	1%	
	Unskilled					62%	12%	
	Skilled					84%	2%	
Panel B: General Caste Group								
2005 (IHDS Wave I)	Non-Agriculture	2.76	1.85	1.31	3.29	0.24	0.70	2,283
	Services	3.07	1.96	1.28	3.43	0.22	0.71	1,477
	1. Unskilled	2.53	1.75	1.22	2.88	0.18	0.65	530
	2. Skilled	3.42	2.29	1.39	3.64	0.28	0.73	947
2012 (IHDS Wave II)	Non-Agriculture	2.03	1.35	1.03	2.38	0.03	0.58	2,694
	Services	2.39	1.49	0.96	2.64	-0.04	0.62	1,570
	1. Unskilled	1.84	1.25	0.99	1.96	-0.01	0.49	558
	2. Skilled	2.76	1.75	1.04	2.86	0.04	0.65	1,012
% Decline in barrier	Non-Agriculture					88%	17%	
	Services					119%	12%	
	Unskilled					106%	25%	
	Skilled					86%	10%	
Panel C: SC/ST Caste Group								
2005 (IHDS Wave I)	Non-Agriculture	1.80	1.53	1.35	2.24	0.26	0.55	4,078
	Services	2.13	1.71	1.35	2.67	0.26	0.63	1,670
	1. Unskilled	2.11	1.60	1.41	2.16	0.29	0.54	543
	2. Skilled	2.14	1.77	1.34	2.86	0.25	0.65	1,127
2012 (IHDS Wave II)	Non-Agriculture	1.47	1.31	1.17	2.01	0.15	0.50	6,164
	Services	1.91	1.49	1.12	2.59	0.11	0.61	1,749
	1. Unskilled	1.71	1.30	1.14	1.94	0.12	0.48	687
	2. Skilled	2.06	1.61	1.15	2.79	0.13	0.64	1,062
% Decline in barrier	Non-Agriculture					44%	9%	
	Services					59%	2%	
	Unskilled					58%	10%	
	Skilled					49%	1%	

Note: I estimate the OLS regression equation (14). β_0 gives us values in col(4) and β_1 for col(5).
I do not control for occupations for these estimates.

all sample. This was more prominent for the service sector as the decline was by 95%.[26] If we review the decomposed results for the General and SC/ST caste groups in panels B and C of Table 2, I again observe that over time, the barriers for all sectors decline for both caste groups. However, the decline was larger for the General group than for the marginalized group. For the General group, the model implied barriers for the non agriculture sectors declined by 88% and 44% for the SC/ST group. Specifically, for the SC/ST group, the decline was by 59% in the service sector.[27]

Figure 6 visualizes this decline in barriers under Case 1, estimated in Table 2 over time and by caste group. I observe that these barriers are declining over time. This is true for both caste groups. However, I only observe more workers from the SC/ST groups moving into the service sector. Given India's productivity in services increased during this time, and the data indicates that unobserved innate ability played a role in the declined barriers. Then, it can be a case that those workers belonging to the SC/ST caste groups in non-agriculture might have been more productive or potentially worked harder or upskilled over time. Even though I observe barriers to decline, I do not observe the relative sectoral wage ratios to equalize (=1), indicating that there are still gains in moving to the service sector for the SC/ST group.

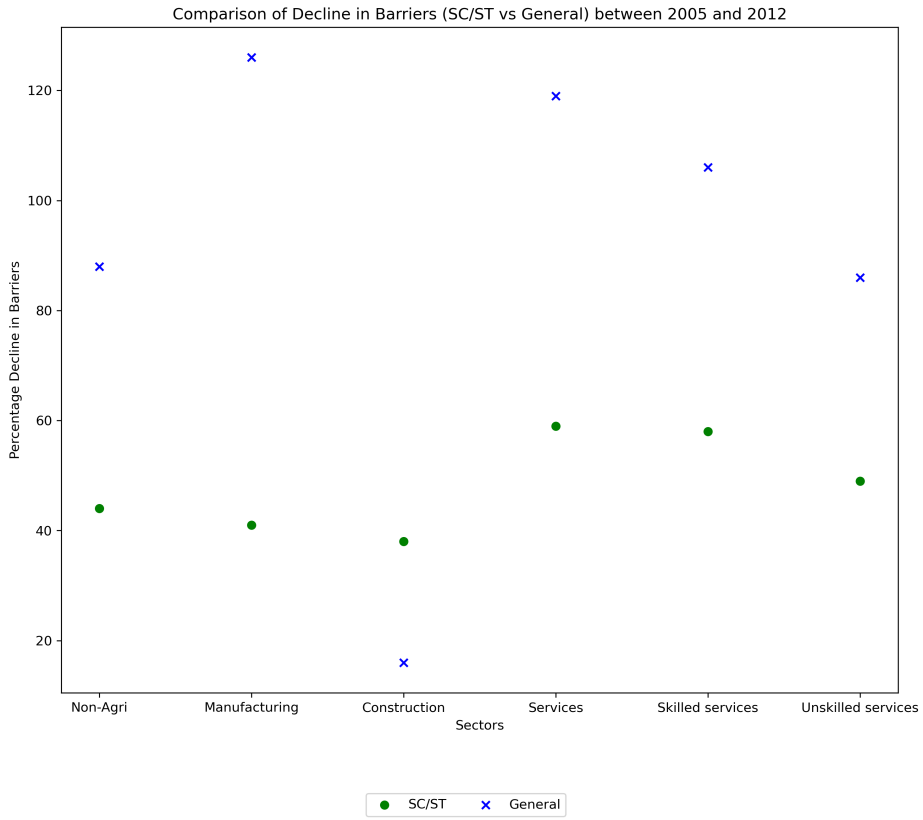


Figure 6: Barriers under case 1 (innate ability) for caste groups over time

[26]Table 2 focuses on the service sector and the aggregate of non agriculture sector (manufacturing, construction, and services). Refer to Table A2 in Appendix A for individual estimations of the remaining sectors.

[27]Negative values of the estimated barriers and estimates of % decline in barriers ranging above 100 implies that the implicitly estimated barriers in the recent waves of IHDS was negative or less than 0. Which can be interpreted as non existence of barriers in the data.

In the model, innate abilities or productivity plays a role via the wages. It is a possibility that firms were able to hire workers from the SC/ST group or more productive group (so they could not discriminate because they needed workers) but could be paying them the same or paying lesser than the workers from the General caste group. This finding echoes the conclusion of chapter 1 of the thesis. The data also indicates that barriers for all sample are converging to the estimated levels for the United States.[28] The findings signal that given the sizable barrier has reduced over time, it could indicate a decline in caste-based barriers over time. The above can be also be interpreted as the fact that the workers from the SC/ST group had a comparative advantage to work in service sector, however, due to limited opportunities and discriminatory barriers they were underrepresented. Decline in such barriers and more opportunities in service sector increased their likelihood of being in the service sector.

Section A.4 in Appendix A provides rough estimates or back-of-the-envelope calculations to answer what the labor shares would be if in 2012 the barriers had remained the same as in 2005 within the model of preferences. The back-of-the-envelope calculation displayed in Table A8 indicate that labor share in the non agriculture sector relative to the agriculture sector would have been lower in 2012 when we use 2005 barrier values than for the estimates using 2012 barriers. For all sample, if the barriers remained the same, the labor share in the service sector (relative to agriculture) would have been 21% lower than what we observe with the decline in the barriers. For the workers in the service sector belonging to the General caste group, would have been 35% lower, whereas for those belonging to the SC/ST caste group in the service sector, the labor share would have been 20% lower. As a future extension, it would be beneficial to perform a series of counterfactual analysis to highlight the impact of ability or productivity in driving structural transformation in India within the model of preferences.

For robustness check, I also estimate the barriers to mobility from switching to non-agriculture industries using NSS-EUS rounds.[29] Referring to results in Table A4 in Appendix A, I observe that, again model implied barriers were larger in 1983 and have declined over time. In 1983, the model implied barriers in non-agriculture sectors were higher for SC/ST compared to the General group. This was also true in 2005, but the size of the barriers under both cases has declined.[30] The decline from 2005 to 2012 is more significant than from 1993 to 2005. The literature suggests that India's growth rate was stagnant after liberalization reforms (1991), though it accelerated from 2004 to 2010. This could be partly due to the delayed impact of the reforms and the increase in trade sector productivity within services post-2004. The decline in demand for unskilled labor-intensive products

[28] Refer to Table A7 for estimated barriers for the United States.

[29] For robustness checks I also control for occupations- refer to Table A6 in Appendix A which quantifies wage gaps and hence barriers after controlling for occupations to account for different occupational and labor market structures. Refer to Table A3 for estimates when I control for ownership of agricultural land.

[30] This is true for the non-agriculture sector- when I club all construction, service and manufacturing sector together.

complemented by (changes in trade patterns) an increase in the export of skilled services, could be the reason behind the significant decrease in barriers from 2005 to 2012 (Erumban et al., 2019; Cravino and Sotelo, 2019; Fan et al., 2023; Sommers, 2024).

Skill development is frequently employed as a strategy to address the challenges of low education levels and high unemployment. Consequently, there is a growing emphasis on development policies and programs in India (Jain et al., 2019; Dar, 2008). The significant barriers implied by the model in 1993 and their subsequent decline over time could potentially be linked to the positive impact of skill-building policies, such as the National Policy on Skill Development, which was implemented to develop employable skills through vocational education. I discuss this linkage in detail in the next section.

5 Role of Vocational Education

The previous section of the chapter quantified the model-implied barriers to structural transformation using wage gains for those transitioning from the agricultural to the non agricultural sector. We observed a decline in these, with sectoral differences in innate abilities played a prominent role in India. However, we also observed a declining trend in the estimates of the model implied barriers for both caste groups, although there was a notable movement of more workers from the SC/ST group who transitioned to the non agriculture sectors. This section examines the potential role of vocational education in enhancing skills and provision of vocational training, which might have led to a decline in barriers and a movement of workers towards more productive sectors. First, I provide a background of policies in India that promote vocational education, followed by establishing a relation between the movement of workers and provision of these policies.

Policies Promoting Vocational Education

In parallel to structural transformation, Indian policies emphasized enhancing skills through the technical and vocational education and training (TVET) sector. The central aim of these initiatives was to notably increase the engagement of young individuals in such programs to train them for the required technical and vocational skills for gainful employment. These programs have a potential to provide marginalized workers the technical know how which can enhance their abilities and hence their likelihood to move towards more productive sectors. The National Skill Development Policy (NSDP) was one such policy which was implemented nationwide during the two IHDS waves in 2009. Though these policies were not targeted only toward SC/ST workers, the literature indicates that there is more take-up of nonformal education by those belonging to lower castes (Vincent and Rajasekhar, 2023; Jambo and Pilz, 2018; Agrawal and Agrawal, 2017). Through this policy, the

government aimed to broaden TVET opportunities via collaborations between the public and private sectors to provide training. In this section, I compare the sample in both IHDS waves to evaluate whether there is a potential correlation of higher take-up of vocational on workers belonging to the marginalized groups in their sectoral job choice.

Correlation of Choice of the Sector with Vocational Education

I show the correlation between sectoral choice and vocational education by estimating the following regression:

$$Industry_{igt} = \beta_0 + \beta_1 Vocational\ \ education_i + \beta_2 Group_{ig} + \beta_3 X_{it} + \epsilon_{it}. \tag{15}$$

In equation (15), $Industry_{igt}$ is the dependent variable which takes a value 0 for the agriculture sector and 1 otherwise. $Group_{ig}$ takes a value 0 if a worker i belongs to the group g category 'General', and 1 if a worker belongs to the category 'SC/ST'. The dependent variable is the variable, which is a dummy variable taking a value 1 if engaged in the non-agriculture sector and 0 otherwise. $Vocational\ \ education_i$ takes a value of 1 if individual has ever taken up vocational education; the remaining control variables include demographic and socio-economic characteristics in X_{it}. The marginal effects of the logit regression results are reported in Table 3.

Table 3: Correlates of Choice of Sector [Logit estimates]

	Dependent variable: Pr(Engaged in Non agri sector)=1
Vocational Education	0.1147**
	(0.0484)
SC/ST	-0.0836***
	(0.0070)
Other Control Variables	Yes
Observations	26,847

Note: The table reports the average marginal effects of a logit regression. The dependent variable takes a value of 1 if the individuals are engaged or employed in non agriculture sectors. The sample consists of both IHDS rounds. Other control variables includes household and socio- economic characteristics such as age, gender, marital status, religion, formal education state and yearly fixed effects. Robust standard errors reported in parentheses. *** p<0.01 **p<0.05 *p<0.1.

The coefficient of β_1 informs us that vocational education is significantly correlated with sectoral choice. The coefficient of the group estimates indicates that relative to workers from the General group, those from the SC/ST group have a lower likelihood of engaging in non-agriculture sectors.

I use the following triple difference-in-difference estimation to establish the relation between

schemes and policies providing vocational education with overtime changes in sectoral choice.

$$\begin{aligned} Industry_{igt} = \beta_0 + \beta_1 Vocational\ \ education_{igt} + \beta_2 Year_t + \beta_3 Group_g + \beta_4 (Year_t^* Group_g) \\ + \beta_5 (Vocational\ \ education_{igt}^* Year_t) + \beta_6 (Vocational\ \ education_{igt}^* Group_g) \\ + \beta_7 (Vocational\ \ education_{igt}^* Year_t^* Group_g) + \beta_8 \mathbf{X}_{it} + \epsilon_{it}. \end{aligned} \tag{16}$$

I estimate the above equation, where the dummy variable $Year_t$ takes a value of 0 for the sample in IHDS wave 1 and 1 for those in IHDS wave 2. Vocational education$_{igt}$ is a dummy variable that takes a value of 1 for those individuals who undertook vocational education and 0 otherwise. The dummy variable $Group_g$ takes a value 1 for those belonging to the SC/ST group and 0 for those from the General group.

Table 4: Relation between the increase in take up of vocational education on Industry choice for the SC/ST group

	Dependent variable: Pr(Engaged in Non agri sector)=1
SC/ST	0.5858***
	(0.003)
Year	0.6528***
	(0.0036)
SC/ST * Vocational edu	0.5865***
	(0.0555)
SC/ST * Vocational edu* 2012	0.5977***
	(0.0758)
Other Control Variables	Yes
Observations	26,710

Note: The Table reports the average marginal effects of a logit regression. The dependent variable takes a value of 1 if the individuals are engaged or employed in non agriculture sectors. The sample consists of both IHDS rounds. Other control variables includes household and socio- economic characteristics such as age, gender, marital status, religion, formal education state fixed effects. Refer to Table A9 in Appendix A for full estimates of the regression. Robust standard errors reported in parentheses. *** p<0.01 **p<0.05 *p<0.1.

The coefficient β_7 of the interaction term $Vocational\ education_{igt}^* Year_t^* Group_g$ is the parameter of interest. It would indicate whether choice of sector significantly differs for those who undertake vocational education from different caste group over time. I estimate the above logit regression and tabulate the marginal effects of the interaction term in Table 4. The marginal effects of the interaction term indicate a significant positive impact of the take-up of vocational education by those workers belonging to the marginalized group in their sectoral choice over time. Taking up vocational education was associated with a higher likelihood of transitioning to non-agricultural sectors over time for workers from the SC/ST group. Based on the analysis, it can be argued that vocational

training has positively affected and enhanced the pool of skilled SC/ST workers which is positively related to transitioning into the non agriculture sectors.

6 Conclusion and Potential Mechanisms

I analyze barriers to structural change via a multi-sectoral model. I examine obstacles primarily arising from channels of human capital (unobserved and observed). I focus on whether these barriers differed for caste groups given the presence of caste based-discrimination in India. The results indicate that wage gains from moving out of agriculture are closer to the sectoral wage differentials or ratios under Case 1, indicating that unobservable innate abilities or productivity play a role. The estimates over time suggest that these model implied barriers declined, though this was true for workers from both caste groups. However, relative to the workers from the upper caste, I observe more workers from the SC/ST groups moving into the service sector. Given that India also observed service-led growth and more workers from the SC/ST group were transitioning to the sector, it can be the case that they were associated with more productive tasks or jobs within the non-agriculture sectors. The results also suggest that vocational education potentially provided skills and upskilling for the workers during this time. Complementing upskilling, more opportunities in the non-agriculture sector in India played a role in the reallocation of labor across sectors in India. The findings also indicate that given an increase in demand for workers, firms could no longer discriminate between workers in terms of hiring but could also be paying less than the workers from the general caste group.

In terms of limitations of the study, it is essential to note the difficulties present in measuring accurate wages in the agriculture sector, given that the income in this sector is often derived from both labor and returns from land ownership. The lock-in effect of land ownership could also be among the factors hindering mobility. Controlling for these factors would enhance the study's robustness and contribute to a more comprehensive understanding of the dynamics at play.

As an extension to the analysis, it will also be important to carefully examine and differentiate the employment status of non-agricultural workers from marginalized groups and those belonging to the upper caste, particularly in terms of casual or contractual work. This analysis will also help understand where the General group workers were transitioning over time.

7 Appendix

A. Figures and Tables

The appendix includes supporting figures and tables for chapter 2. Section A.1. includes supporting figures for stylized facts discussed in the main text of chapter 2. Supporting tables for estimations of barriers through the lens of the model in Section A.2. Additional figures describing the trend of the size of specific industries within the service sector.

A.1. Supporting Figures for Stylized Facts

A.1.1. Distribution of workers with industry divided into manufacturing and construction

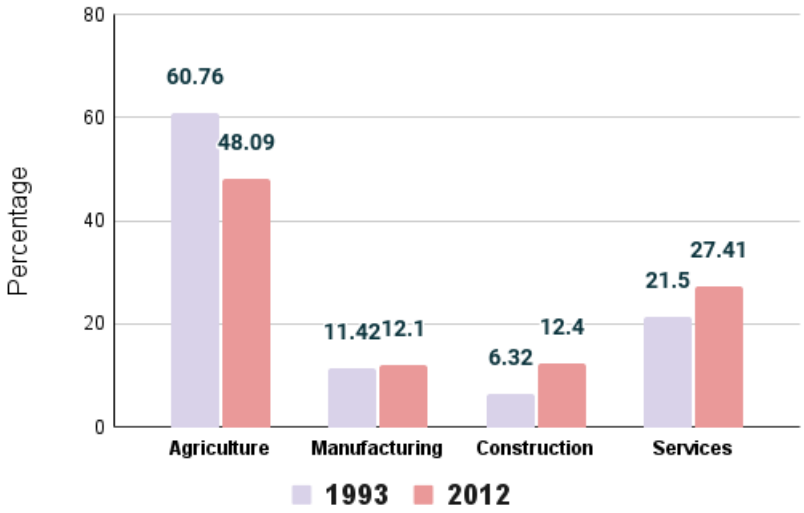


Figure A1: labor re-allocation across sectors over time

A.1.2. Distribution of workers in construction and service sector

Figure A2 displays the changes in distribution of workers within the manufacturing sector. I use NSS-EUS 1993 and 2012 rounds to present the overtime changes in labor distribution by caste and gender groups. I observe over time movement of SC/ST workers into this sector, however, the relative proportion of workers from the General category in this sector declined over time. Similar pattern was observed for the construction sector displayed in Figure A3.

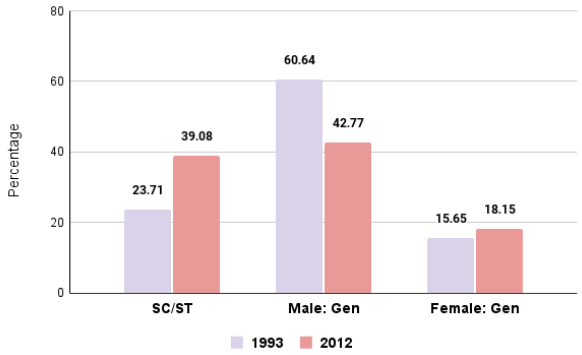


Figure A2: Changes in share of workers in the manufacturing sector over time by caste and gender group

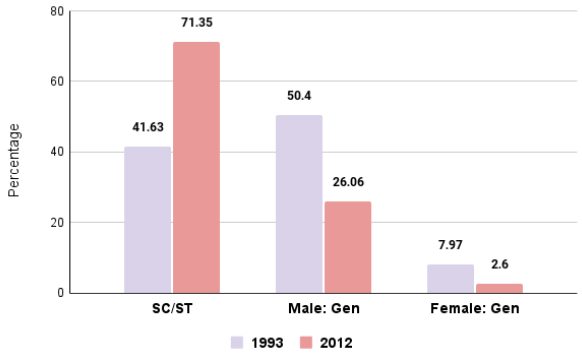


Figure A3: Changes in share of workers in the construction sector over time by caste and gender group

A.1.3. Distribution of workers in skilled and unskilled service sector

I classify workers within the service sector into skilled and unskilled and display the change in distribution of workers over time in each in Figures A4 and A5.

The industry classification into skilled and unskilled services is as below:

- **Skilled Service:** Publishing of books, periodicals and other publishing activities; Financial and insurance activities; Real estate activities; Professional, scientific, and technical activities; Administrative and support service activities; Human health and social work activities; Arts, entertainment, and recreation; Other service activities; Public administration and defence; compulsory social security; Education.
- **Unskilled Service:** Wholesale and retail trade; Transportation and storage; Accommodation and food service activities; Activities of households as employers of domestic personnel.

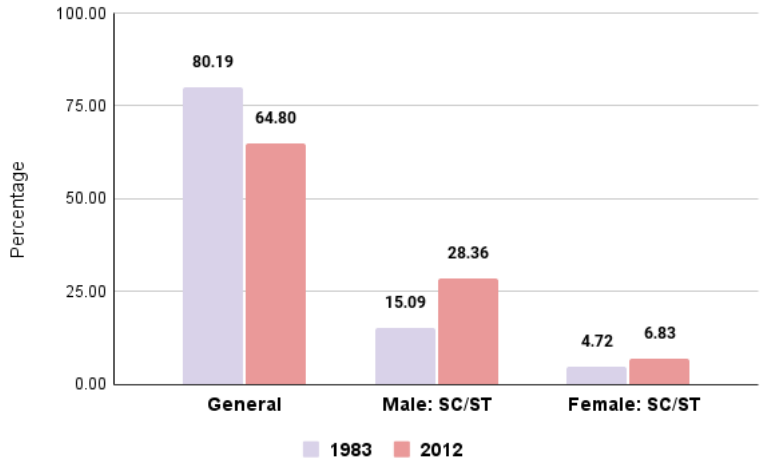


Figure A4: Changes in share of workers in Skilled service sector

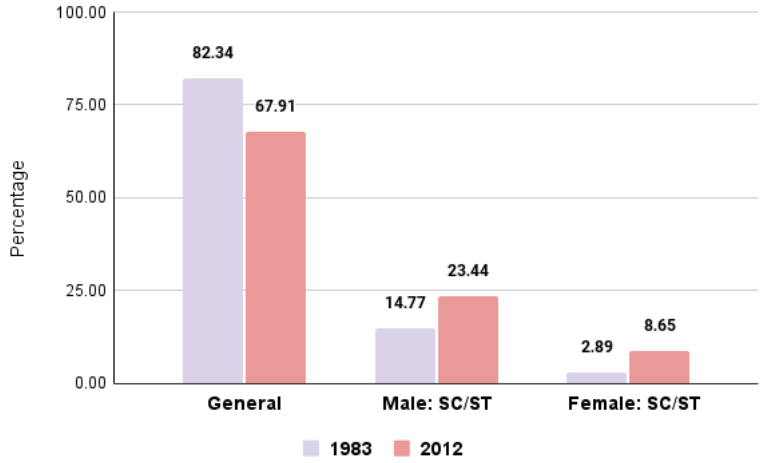


Figure A5: Changes in share of workers in Unskilled service sector

A.1.4. Sectoral Returns (Linear)

Figure A6 and A7 displays sectoral returns for each sectors over time for both caste groups.

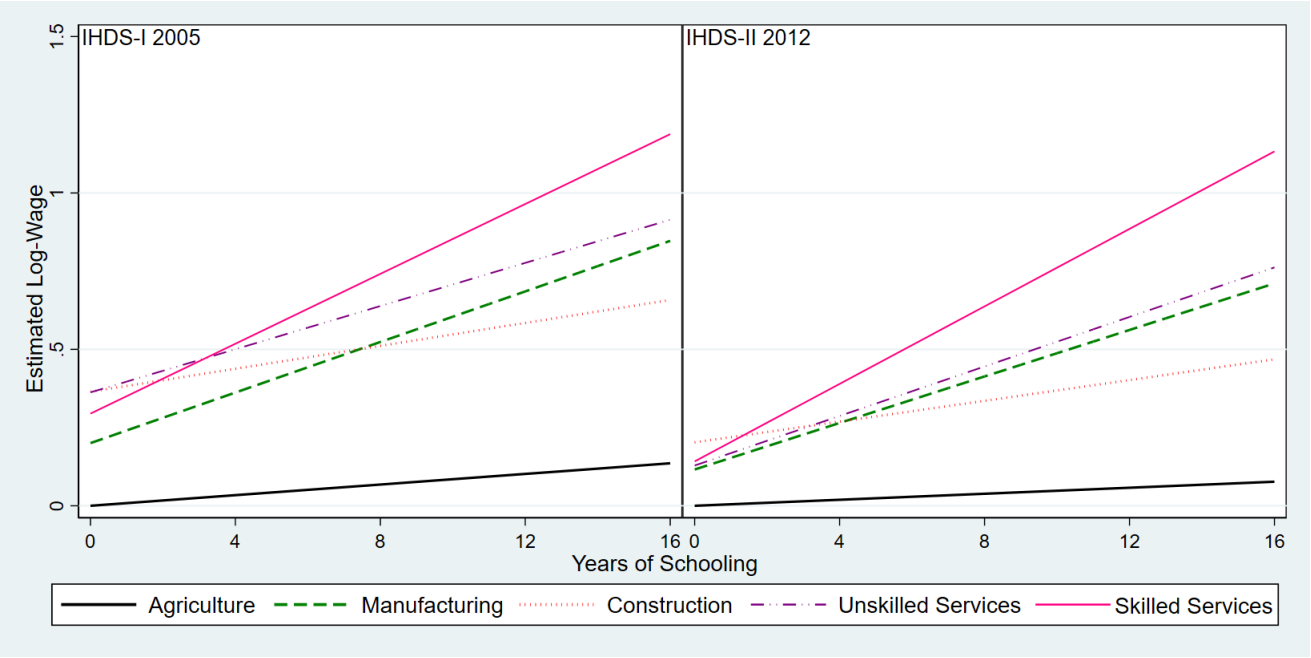


Figure A6: Sectoral wages(log) for SC/ST group

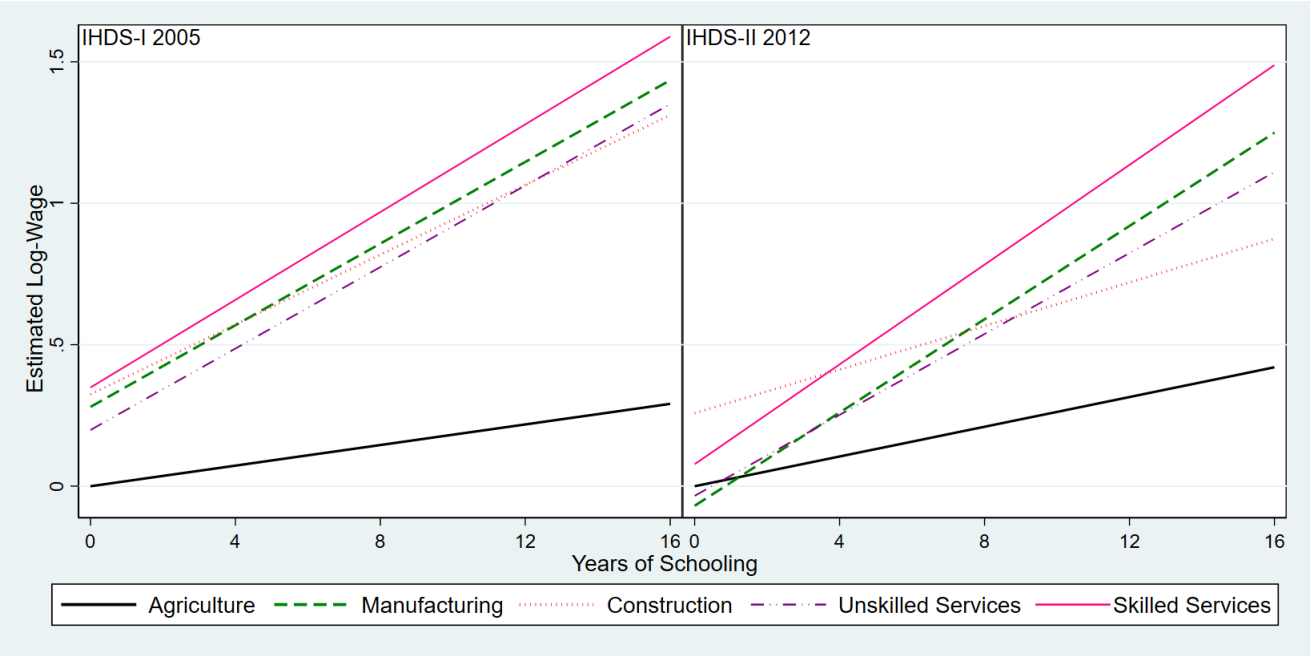
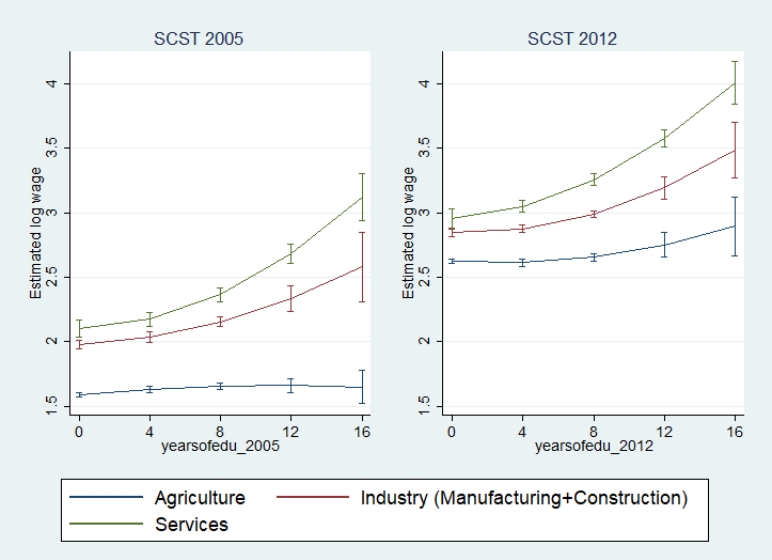
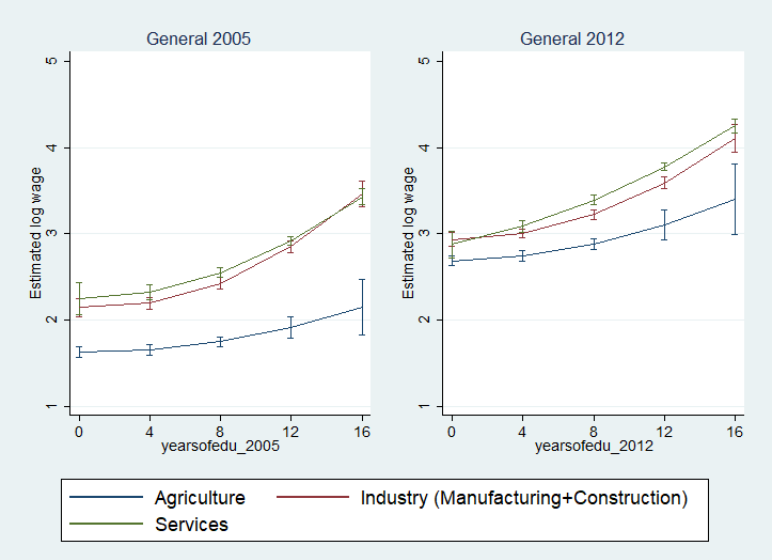


Figure A7: Sectoral wages(log) for General caste group

A.1.5. Sectoral Returns (Quadratic/Non linear)



Panel A: SC/ST group



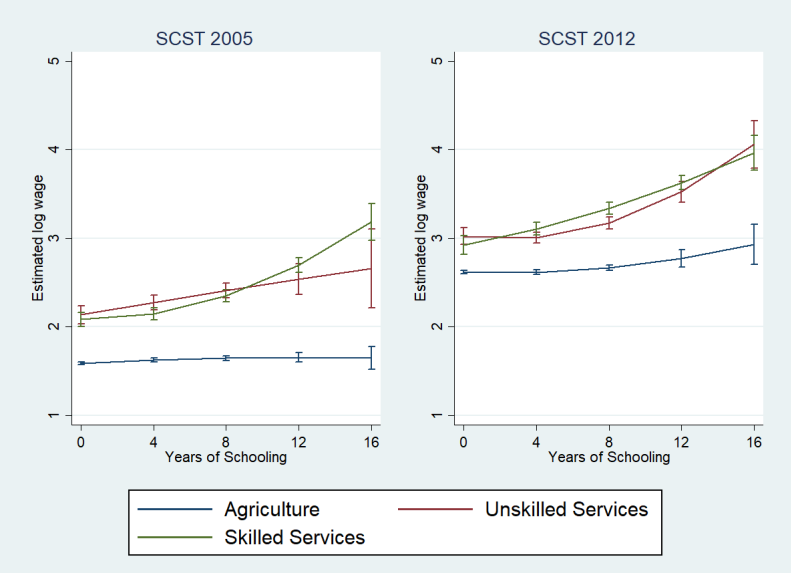
Panel B: General group

Figure A8: Quadratic returns to education by sectors: Agriculture, Industry and Services

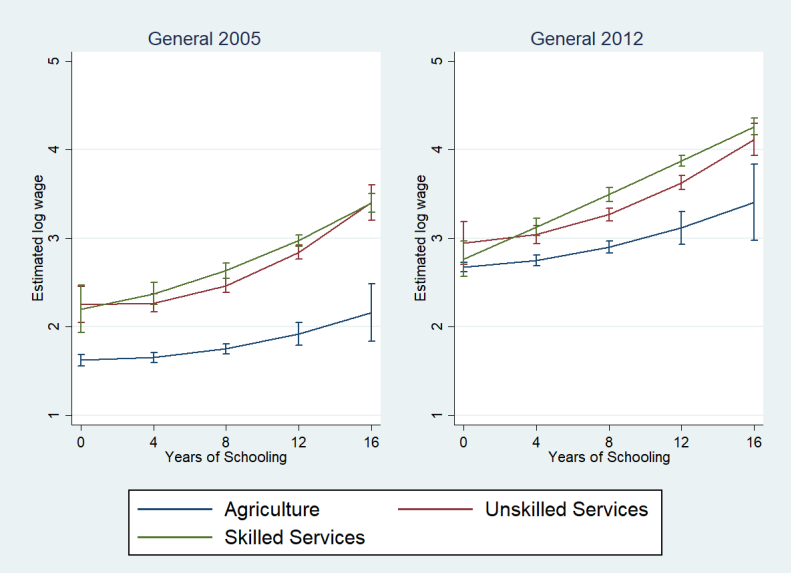
Notes: Panel A presents the quadratic returns to education by sectors for agriculture, industry (manufacturing and construction), and the service sector (skilled and unskilled) for SC/ST workers in both wave IHDS I (2005) and II (2012) and for workers from the General category in Panel B. 95% confidence intervals are constructed and shown as error bars.

In this section, I estimate the non linear returns of attaining higher education. Figure A8 displays quadratic returns of schooling or non linearity while estimating Mincer returns. Convex curves in Figure A9 indicate that in 2005, workers from the General group had increasing returns to education at an increasing rate for both the service sector (skilled and unskilled) and agriculture. This was only true for skilled services for workers from the SC/ST group. There were linear returns to education for SC/ST workers engaged in the unskilled service sector. However, in 2012, for SC/ST workers, I

observe non linear returns to education for those employed in unskilled services and linear returns for the skilled service sector.



Panel A: SC/ST group



Panel B: General group

Figure A9: Quadratic returns to education by sectors: Agriculture, Skilled and Unskilled Service

Notes: Panel A presents the quadratic returns to education by sectors for agriculture and service sector (skilled and unskilled) for SC/ST workers in both wave IHDS I (2005) and II (2012) and for workers from the General category in Panel B. 95% confidence intervals are constructed and shown as error bars.

A.1.6. Tabulation of Sectoral Returns (Linear)

Table A1 tabulate the sectoral returns to schooling displayed in Figures A6 and A7. The table also records whether the returns are significantly different between the caste groups in both years.

Table A1: Sectoral Returns to Schooling by Caste Group

	Returns to education (slope)	
	2005 (1)	2012 (2)
General Caste Group		
1. Agriculture	.018	.026
2. Manufacturing	.072	.082
3. Construction	.062	.039
4. Services		
4.1. Unskilled	.072	.071
4.2. Skilled	.078	.088
SC/ST Caste Group		
1. Agriculture	.008	.005**
2. Manufacturing	.040	.037
3. Construction	.018	.017
4. Services		
4.1. Unskilled	.035	.039
4.2. Skilled	.056	.062
Test of differences of the slopes of the non-agriculture sector: General and SC/ST groups		
General- SC/ST group	0.094**	0.026***

Note: All the above estimates are significant at 1% level of significance. The table records the slope estimates γ: $log(w_{ij}) = \beta_j d_j + \beta_x X_{ij} + \gamma_j s_{ij} d_j + \epsilon_{ij}$. Where X_{ij}= experience(potential), state, gender; s_{ij}= schooling (treated as a continuous variable in the regression) of worker 'i' in sector 'j'; d= sector dummy. For Figure A6 and A7 I plot the above estimates over the scale of years of schooling. Last row gives the coefficient estimates of the interaction term between years of schooling, group and sector. Where we club all the non agriculture sector into one. The F (Wald) test suggests that the returns in the non-agriculture sector were significantly different between the groups in both the years.

A.2. Supporting Tables for Estimations of Barriers Through the Lens of the Model

Table A2 displays wage gaps, and estimates model implied barriers under both cases using the IHDS dataset. Table A3 displays the results post adding a control on agricultural land ownership/cultivation. The results are similar to that discussed in the Section 2.4. Similarly, Table A4 estimates wage gaps using NSS Data corresponding to the barriers in Table A5. NSS data echoes the same results as the IHDS (panel data) waves. Over time, the model implied barriers in the non agriculture sector declined entirely for all samples. The decline in skilled service barriers was the most substantial; this was true for the General group. However, for the SC/ST group, the highest drop was for unskilled services (198%).

I do not control for occupations for the estimates of barriers discussed in Table 2. Thus, implying that individuals move across occupations as well as industries, specifically from the agriculture to the non agriculture sector, to earn higher wages. Table A6 quantifies wage gaps and hence barriers after controlling for occupations to account for different occupational and labor market structures. After controlling for occupations, the extent of barriers (both abilities and human capital) declined compared to the previous case where I did not control for occupations. For barriers under case 1, I observe that the composite barrier was higher for the SC/ST group in 2005 but not for 2012. In 2012, barriers were higher for the General group. Barriers due to observed human capital or case 2 are still larger than barriers under case 1.

Table A2: Barriers to mobility for those switching to non-agriculture industry (IHDS I and II)

	Switched from Agriculture to Sector	Wage gaps				Barriers		Count
		Raw	Adjusted	Case 1 (ability)	Case 2 (human capital)	Case 1 (ability)	Case 2 (human capital)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
Panel A: All Sample								
2005 (IHDS Wave I)	Non-Agriculture	2.04	1.56	1.28	2.62	0.22	0.62	12,713
	Manufacturing	1.78	1.43	1.21	2.37	0.17	0.58	2,948
	Construction	1.75	1.47	1.42	1.88	0.30	0.47	3,715
	Services	2.38	1.69	1.23	2.93	0.19	0.66	6,050
	1. Unskilled	2.16	1.52	1.35	2.17	0.26	0.54	2,271
	2. Skilled	2.53	1.85	1.23	3.28	0.19	0.70	3,779
2012 (IHDS Wave II)	Non-Agriculture	1.61	1.29	1.10	2.25	0.09	0.56	16,586
	Manufacturing	1.44	1.21	1.05	1.99	0.05	0.50	3,782
	Construction	1.34	1.23	1.22	1.48	0.18	0.32	6,756
	Services	2.09	1.48	1.01	2.85	0.01	0.65	6,048
	1. Unskilled	1.77	1.25	1.11	1.91	0.10	0.48	2,547
	2. Skilled	2.36	1.66	1.03	3.16	0.03	0.68	3,501
% Decline in barrier	Non-Agriculture					58%	10%	
	Manufacturing					73%	14%	
	Construction					39%	31%	
	Services					95%	1%	
	Unskilled					62%	12%	
	Skilled					84%	2%	
Panel B: General Caste Group								
2005 (IHDS Wave I)	Non-Agriculture	2.76	1.85	1.31	3.29	0.24	0.70	2,283
	Manufacturing	2.31	1.76	1.33	3.12	0.25	0.68	432
	Construction	2.21	1.72	1.39	2.75	0.28	0.64	374
	Services	3.07	1.96	1.28	3.43	0.22	0.71	1,477
	1. Unskilled	2.53	1.75	1.22	2.88	0.18	0.65	530
	2. Skilled	3.42	2.29	1.39	3.64	0.28	0.73	947
2012 (IHDS Wave II)	Non-Agriculture	2.03	1.35	1.03	2.38	0.03	0.58	2,694
	Manufacturing	1.76	1.26	0.94	2.25	-0.06	0.56	528
	Construction	1.49	1.26	1.31	1.55	0.24	0.35	596
	Services	2.39	1.49	0.96	2.64	-0.04	0.62	1,570
	1. Unskilled	1.84	1.25	0.99	1.96	-0.01	0.49	558
	2. Skilled	2.76	1.75	1.04	2.86	0.04	0.65	1,012
% Decline in barrier	Non-Agriculture					88%	17%	
	Manufacturing					126%	18%	
	Construction					16%	44%	
	Services					119%	12%	
	Unskilled					106%	25%	
	Skilled					86%	10%	
Panel C: SC/ST Caste Group								
2005 (IHDS Wave I)	Non-Agriculture	1.80	1.53	1.35	2.24	0.26	0.55	4,078
	Manufacturing	1.56	1.36	1.22	2.04	0.18	0.51	822
	Construction	1.61	1.46	1.43	1.68	0.30	0.40	1,586
	Services	2.13	1.71	1.35	2.67	0.26	0.63	1,670
	1. Unskilled	2.11	1.60	1.41	2.16	0.29	0.54	543
	2. Skilled	2.14	1.77	1.34	2.86	0.25	0.65	1,127
2012 (IHDS Wave II)	Non-Agriculture	1.47	1.31	1.17	2.01	0.15	0.50	6,164
	Manufacturing	1.37	1.25	1.12	1.88	0.11	0.47	1,200
	Construction	1.31	1.24	1.23	1.47	0.19	0.32	3,215
	Services	1.91	1.49	1.12	2.59	0.11	0.61	1,749
	1. Unskilled	1.71	1.30	1.14	1.94	0.12	0.48	687
	2. Skilled	2.06	1.61	1.15	2.79	0.13	0.64	1,062
% Decline in barrier	Non-Agriculture					44%	9%	
	Manufacturing					41%	8%	
	Construction					38%	21%	
	Services					59%	2%	
	Unskilled					58%	10%	
	Skilled					49%	1%	

Note: I estimate the OLS regression equation (14). β_0 gives us values in col(4) and β_1 for col(5). I do not control for occupations for these estimates.

Table A3: Barriers to mobility for those switching to non-agriculture industry (IHDS I and II)

	Switched from Agriculture to Sector	Wage gaps				Barriers		Count
		Raw	Adjusted	Case 1 (ability)	Case 2 (human capital)	Case 1 (ability)	Case 2 (human capital)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
Panel A: All Sample								
2005 (IHDS Wave I)	Non-Agriculture	2.04	1.71	1.27	2.54	0.21	0.61	12,713
	Manufacturing	1.78	1.56	1.21	2.33	0.17	0.57	2,948
	Construction	1.75	1.52	1.41	1.85	0.29	0.46	3,715
	Services	2.38	1.94	1.22	2.83	0.18	0.65	6,050
	1. Unskilled	2.11	1.62	1.29	2.11	0.22	0.53	2,271
	2. Skilled	2.49	2.12	1.20	3.21	0.17	0.69	3,779
2012 (IHDS Wave II)	Non-Agriculture	1.61	1.42	1.09	2.16	0.07	0.54	16,586
	Manufacturing	1.45	1.29	1.03	1.90	0.03	0.47	3,782
	Construction	1.34	1.26	1.21	1.44	0.17	0.31	6,756
	Services	2.09	1.73	0.97	2.71	0.03	0.63	6,048
	1. Unskilled	1.76	1.35	1.05	1.84	0.05	0.46	2,547
	2. Skilled	2.36	2.03	0.99	3.14	0.01	0.68	3,501
% Decline in barrier	Non-Agriculture					66%	11%	
	Manufacturing					82%	17%	
	Construction					41%	32%	
	Services					83%	3%	
	Unskilled					77%	13%	
	Skilled					94%	1%	
Panel B: General Caste Group								
2005 (IHDS Wave I)	Non-Agriculture	2.76	2.23	1.26	2.98	0.21	0.66	2,283
	Manufacturing	2.31	1.95	1.28	2.79	0.22	0.64	432
	Construction	2.21	1.79	1.36	2.53	0.26	0.60	374
	Services	3.07	2.52	1.20	3.07	0.16	0.67	1,477
	1. Unskilled	2.53	1.86	1.13	2.62	0.11	0.62	530
	2. Skilled	3.42	2.82	1.35	3.32	0.26	0.70	947
2012 (IHDS Wave II)	Non-Agriculture	2.00	1.76	1.01	2.24	0.01	0.55	2,694
	Manufacturing	1.76	1.53	0.92	2.11	-0.08	0.53	528
	Construction	1.48	1.39	1.29	1.49	0.22	0.33	596
	Services	2.33	2.16	0.91	2.49	-0.09	0.59	1,570
	1. Unskilled	1.83	1.47	0.93	1.87	-0.07	0.46	558
	2. Skilled	2.66	2.44	1.00	2.70	0.00	0.63	1,012
% Decline in barrier	Non-Agriculture					95%	17%	
	Manufacturing					136%	17%	
	Construction					15%	45%	
	Services					156%	12%	
	Unskilled					163%	25%	
	Skilled					100%	10%	
Panel C: SC/ST Caste Group								
2005 (IHDS Wave I)	Non-Agriculture	1.80	1.58	1.34	2.19	0.25	0.54	4,078
	Manufacturing	1.56	1.40	1.21	1.98	0.17	0.49	822
	Construction	1.61	1.48	1.43	1.65	0.30	0.39	1,586
	Services	2.13	1.81	1.33	2.60	0.25	0.62	1,670
	1. Unskilled	2.11	1.67	1.41	2.13	0.29	0.53	543
	2. Skilled	2.14	1.88	1.32	2.81	0.24	0.64	1,127
2012 (IHDS Wave II)	Non-Agriculture	1.48	1.36	1.16	1.93	0.14	0.48	6,164
	Manufacturing	1.38	1.29	1.11	1.81	0.09	0.45	1,200
	Construction	1.32	1.26	1.22	1.43	0.18	0.30	3,215
	Services	1.91	1.62	1.09	2.42	0.08	0.59	1,749
	1. Unskilled	1.71	1.38	1.11	1.88	0.09	0.47	687
	2. Skilled	2.06	1.79	1.13	2.76	0.11	0.64	1,062
% Decline in barrier	Non-Agriculture					44%	11%	
	Manufacturing					47%	8%	
	Construction					40%	23%	
	Services					68%	4%	
	Unskilled					68%	11%	
	Skilled					54%	0%	

Note: I estimate the OLS regression equation (14), along with adding a control for agricultural land ownership/cultivation. β_0 gives us values in col(4) and β_1 for col(5). I do not control for occupations for these estimates.

Table A4: Wage differentials for those switching to non-agriculture industry (NSS Rounds)

	Switched from Agriculture to Sector	Wage gaps				Count
		Raw	Adjusted	Case 1 (ability)	Case 2 (human capital)	
	(1)	(2)	(3)	(4)	(5)	
Panel A: All Sample						
1993 (NSS Round: 50^{th})	Non-Agriculture	2.42	1.52	1.29	2.97	39,895
	Services	2.75	1.54	1.33	2.55	22,328
	1. Unskilled	1.87	1.35	1.22	2.18	9,707
	2. Skilled	3.74	2.15	1.43	3.59	12,621
2005 (NSS Round: 61^{st})	Non-Agriculture	2.23	1.43	1.15	3.14	43,672
	Services	2.65	1.51	1.20	2.68	22,419
	1. Unskilled	1.77	1.26	1.09	2.18	11,756
	2. Skilled	3.92	2.35	1.17	4.30	10,663
2012 (NSS Round: 68^{th})	Non-Agriculture	1.81	1.28	1.00	2.67	45,804
	Services	2.22	1.36	0.99	2.28	21,305
	1. Unskilled	1.53	1.12	0.91	2.04	10,335
	2. Skilled	3.18	1.93	0.83	3.75	10,970
Panel B: General Caste Group						
1993 (NSS Round: 50^{th})	Non-Agriculture	2.53	1.49	1.26	2.79	32,450
	Services	2.81	1.49	1.32	2.32	19,299
	1. Unskilled	1.88	1.31	1.21	1.99	8,278
	2. Skilled	3.84	2.12	1.38	3.31	11,021
2005 (NSS Round: 61^{st})	Non-Agriculture	2.84	1.46	1.14	3.52	17,086
	Services	3.19	1.51	1.28	2.66	10,648
	1. Unskilled	2.01	1.32	1.20	2.31	4,839
	2. Skilled	4.56	2.31	1.02	4.42	5,809
2012 (NSS Round: 68^{th})	Non-Agriculture	2.25	1.22	0.89	2.89	15,924
	Services	2.69	1.29	0.98	2.12	9,101
	1. Unskilled	1.69	1.46	0.86	2.09	3,689
	2. Skilled	3.79	3.43	0.74	3.72	5,412
Panel C: SC/ST Caste Group						
1993 (NSS Round: 50^{th})	Non-Agriculture	1.95	1.56	1.38	2.92	8,318
	Services	2.25	1.64	1.36	3.00	3,711
	1. Unskilled	1.65	1.38	1.22	2.61	1,727
	2. Skilled	2.96	2.10	1.55	3.73	1,984
2005 (NSS Round: 61^{st})	Non-Agriculture	1.83	1.42	1.23	2.54	12,019
	Services	2.18	1.53	1.18	2.75	5,099
	1. Unskilled	1.52	1.22	1.06	2.02	2,736
	2. Skilled	3.12	2.19	1.40	3.81	2,363
2012 (NSS Round: 68^{th})	Non-Agriculture	1.54	1.28	1.08	2.21	13,446
	Services	1.86	1.36	0.91	2.57	4,948
	1. Unskilled	1.32	1.07	0.85	2.03	2,604
	2. Skilled	2.63	1.90	1.05	3.48	2,344

Table A5: Barriers to mobility from switching to non-agriculture sector (NSS Rounds)

	Switched from Agriculture to Sector	Barriers		Count
		Case 1 (ability)	Case 2 (human capital)	
	(1)	(2)	(3)	
Panel A: All Sample				
1993 (NSS Round: 50^{th})	Non-Agriculture	0.22	0.66	39,895
	Services	0.25	0.61	22,328
	Unskilled	0.18	0.54	9,707
	Skilled	0.30	0.72	12,621
2005 (NSS Round: 61^{st})	Non-Agriculture	0.13	0.68	43,672
	Services	0.17	0.63	22,419
	Unskilled	0.08	0.54	11,756
	Skilled	0.15	0.77	10,663
2012 (NSS Round: 68^{th})	Non-Agriculture	0.00	0.63	45,804
	Services	-0.01	0.56	21,305
	Unskilled	-0.10	0.51	10,335
	Skilled	-0.20	0.73	10,970
% Decline in barrier (1993-2012)	Non-Agriculture	100%	6%	
	Services	104%	8%	
	Unskilled	155%	6%	
	Skilled	168%	2%	
Panel B: General Caste Group				
1993 (NSS Round: 50^{th})	Non-Agriculture	0.21	0.64	32,450
	Services	0.24	0.57	19,299
	Unskilled	0.17	0.50	8,278
	Skilled	0.28	0.70	11,021
2005 (NSS Round: 61^{st})	Non-Agriculture	0.12	0.72	17,086
	Services	0.22	0.62	10,648
	Unskilled	0.17	0.57	4,839
	Skilled	0.02	0.77	5,809
2012 (NSS Round: 68^{th})	Non-Agriculture	-0.12	0.65	15,924
	Services	-0.02	0.53	9,101
	Unskilled	-0.16	0.52	3,689
	Skilled	-0.35	0.73	5,412
% Decline in barrier(1993-2012)	Non-Agriculture	160%	-2%	
	Services	108%	7%	
	Unskilled	194%	-5%	
	Skilled	228%	-5%	
Panel C: SC/ST Caste Group				
1993 (NSS Round: 50^{th})	Non-Agriculture	0.28	0.66	8,318
	Services	0.26	0.67	3,711
	Unskilled	0.18	0.62	1,727
	Skilled	0.35	0.73	1,984
2005 (NSS Round: 61^{st})	Non-Agriculture	0.19	0.61	12,019
	Services	0.15	0.64	5,099
	Unskilled	0.06	0.50	2,736
	Skilled	0.29	0.74	2,363
2012 (NSS Round: 68^{th})	Non-Agriculture	0.07	0.55	13,446
	Services	-0.10	0.61	4,948
	Unskilled	-0.18	0.51	2,604
	Skilled	0.05	0.71	2,344
% Decline in barrier	Non-Agriculture	73%	17%	
	Services	137%	8%	
	Unskilled	198%	18%	
	Skilled	87%	3%	

Table A6: Barriers to mobility from switching to non-agriculture sector

	Switched from Agriculture to Sector	Wage gaps				Barriers		Count
		Raw	Adjusted	Case 1 (ability)	Case 2 (human capital)	Case 1 (ability)	Case 2 (human capital)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
Panel A: General Caste Group								
2005 (IHDS Wave I)	Non-Agriculture	2.75	1.49	1.21	2.3	0.17	0.57	2,283
	Services	3.06	1.53	1.21	2.33	0.17	0.57	1477
	1. Unskilled	2.53	1.51	1.17	2.35	0.15	0.57	530
	2. Skilled	3.42	1.55	1.25	2.35	0.20	0.57	947
2012 (IHDS Wave II)	Non-Agriculture	2.02	1.33	1.09	2.02	0.08	0.50	2,694
	Services	2.39	1.39	1.05	2.25	0.05	0.56	1,570
	1. Unskilled	1.84	1.27	1.05	1.94	0.05	0.48	558
	2. Skilled	2.76	1.56	1.14	2.45	0.12	0.59	1012
% Decline in barrier	Non-Agriculture					52%	11%	
	Services					73%	3%	
	Unskilled					67%	16%	
	Skilled					39%	3%	
Panel B: SC/ST Caste Group								
2005 (IHDS Wave I)	Non-Agriculture	1.8	1.29	1.22	1.68	0.18	0.40	4,072
	Services	2.13	1.35	1.19	1.92	0.16	0.48	1,670
	1. Unskilled	2.11	1.43	1.36	1.83	0.26	0.45	543
	2. Skilled	2.14	1.28	1.10	1.89	0.09	0.47	1,127
2012 (IHDS Wave II)	Non-Agriculture	1.48	1.10	1.03	1.44	0.03	0.31	6,164
	Services	1.91	1.15	0.99	1.68	-0.01	0.40	1,749
	1. Unskilled	1.71	1.10	1.01	1.49	0.01	0.33	687
	2. Skilled	2.06	1.23	1.01	1.81	0.01	0.45	1,062
% Decline in barrier	Non-Agriculture					84%	25%	
	Services					106%	16%	
	Unskilled					96%	27%	
	Skilled					89%	5%	

Note: I estimate the OLS regression equation (14) using IHDS waves. β_0 gives us values in col(4) and β_1 for col(5). I also control for occupations for these estimates.

Table A7: Wage differentials from switching to non-agriculture sector (Other Nations)

	Wage gaps		Model Implied Barriers		Wage gains of switchers
	Raw	Adjusted	Selection view	Technology view	
United States 1990 Herrendorf and Schoellman (2018)	1.48	1.31	1.00	1.47	1.06
Brazil 2000 Alvarez (2020)	2.29	1.28	1.07	2.02	1.01-1.12
Indonesia 1995 Hamory et al. (2021)	1.81	1.12	1.00	1.74	1.05

Notes: The table presents estimated barriers for the United States, Indonesia and Brazil. The table is from Herrendorf and Schoellman (2018).

A.3. Additional Figures Describing the Trend of the Size of Specific Industries Within the Service Sector

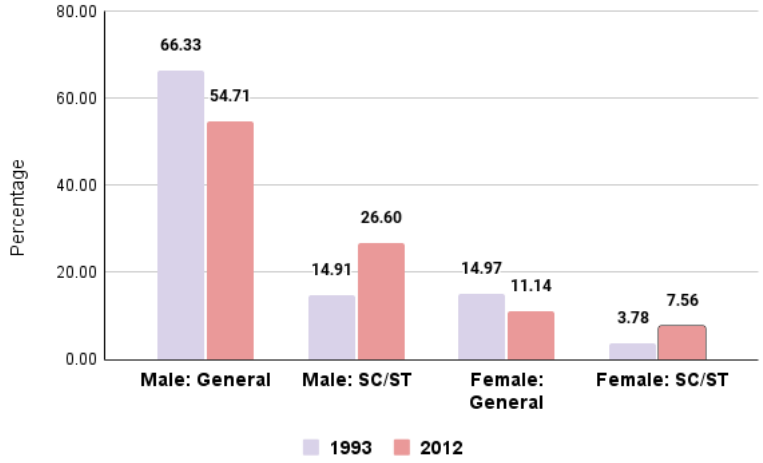


Figure A10: Changes in share of workers in service sector over time by caste and gender group

Note: We use NSS-EUS 1993 and 2012 rounds to present the overtime changes in labor distribution by caste and gender groups.

Figure A11 and A12 displays the trend of the size of specific services.

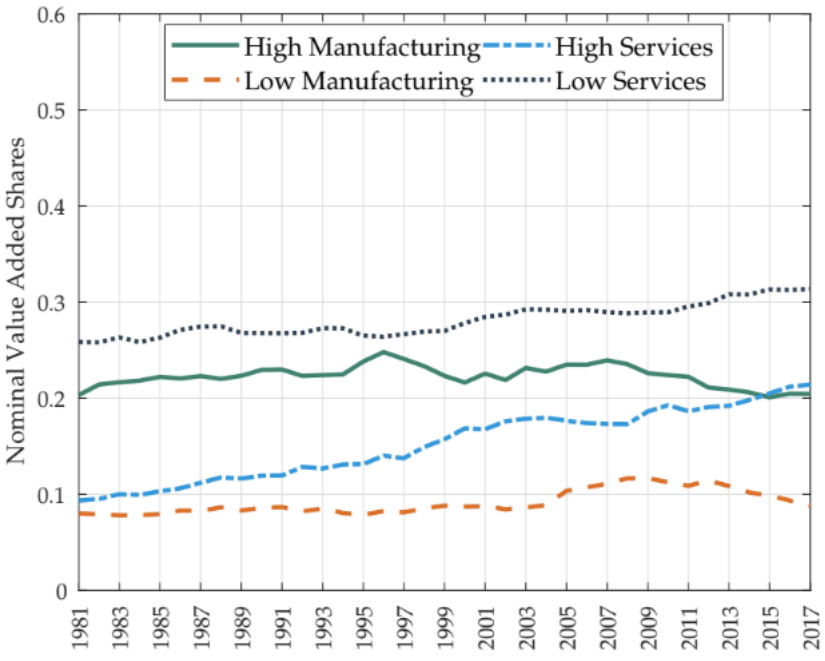


Figure A11: Nominal value added shares

Note: The above Figure is from Serrano-Quintero (2022). The Figure presents the nominal value added shares of sectors. Our focus is on the service sector, where, high service includes transportation, public administration, real estate, financial and business service. Wholesale and retail trade, hotels/restaurants, education, health work and private household services are categorised in low services. The shares are calculated using India's KLEMS data.

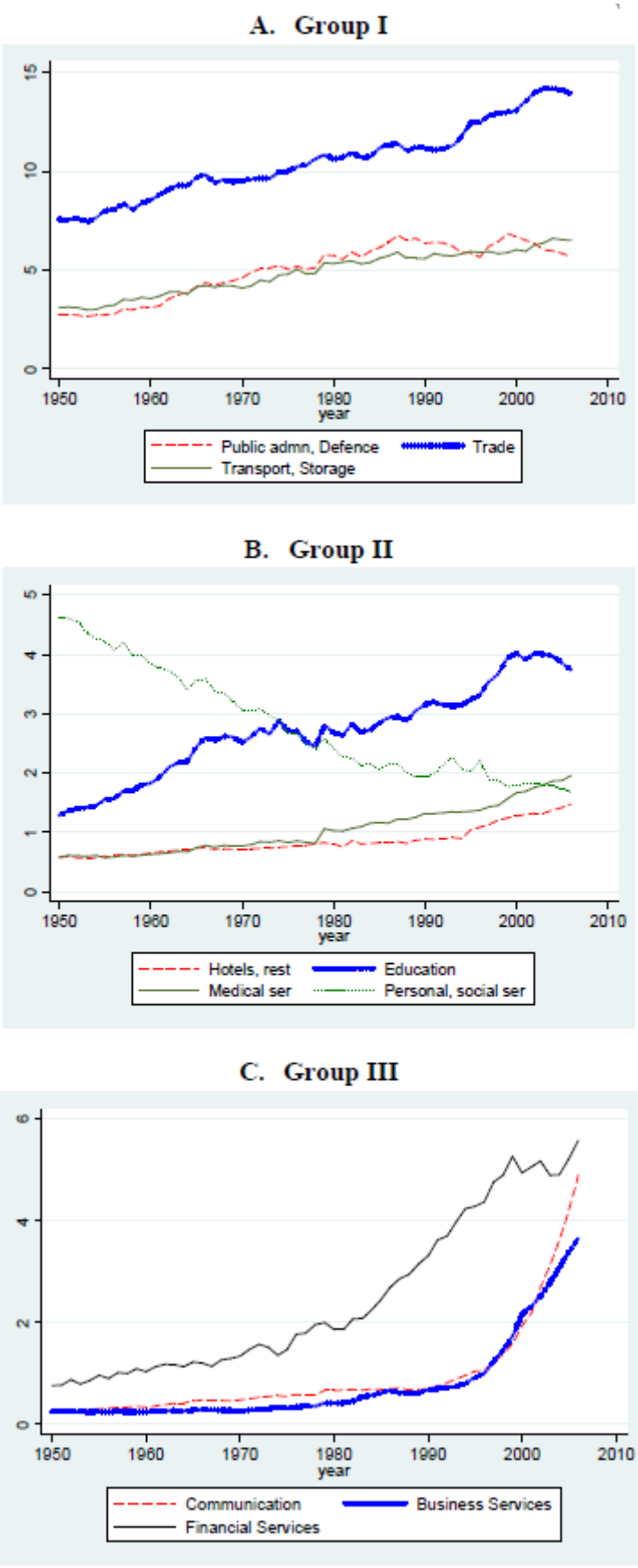


Figure A12: Size of specific service sectors (as a % of GDP)

Note: The above Figure is from Eichengreen and Gupta (2013) and its earlier version (Eichengreen and Gupta, 2011). The Figure presents the size of sectors within the service sector as % of GDP over time. The shares are calculated using the data provided by Central Statistical Office (CSO).

A.4. Back of the Envelope Calculations

In this section I provide back-of-the-envelope calculations to answer what would have happened to labor shares if the barriers would have stayed the same (keeping everything else constant) in the discussed model. To do this, I rewrite equation (10) as below to estimate labor shares for 2012 keeping the barriers same as 1993:[31]

$$\left\{\frac{1}{1-\tau_{na}}\right\}_{1993} = \left\{\frac{W_{na}/L_{na}}{W_a/L_a}\right\}_{2012},$$

$$\left\{\frac{L_{na}}{L_a}\right\}_{2012} = \{1-\tau_{na}\}_{1993}\left\{\frac{W_{na}}{W_a}\right\}_{2012}.$$

For values of barriers, I use estimates in column (6) and for $\left\{\frac{W_{na}}{W_a}\right\}_{2012}$ I use estimates in column (3) of Table 2. Table A8 displays the back-of-the-envelope estimates in column (1) using 2005 barriers and column (2) provides using 2012 barriers.

Table A8: Estimates of Labor Share (Back of the Envelope Estimates)

	Labor Share $\left\{\frac{L_{na}}{L_a}\right\}_{2012}$	
	Using τ_{2005} (1)	Using τ_{2012} (2)
Panel A: All Sample		
Non-Agriculture	0.61	0.70
Services	0.55	0.67
1. Unskilled	0.59	0.72
2. Skilled	0.49	0.58
Panel B: General Caste Group		
Non-Agriculture	0.57	0.72
Services	0.51	0.69
1. Unskilled	0.66	0.81
2. Skilled	0.42	0.55
Panel C: SC/ST Caste Group		
Non-Agriculture	0.56	0.65
Services	0.49	0.59
1. Unskilled	0.55	0.68
2. Skilled	0.46	0.54

[31] For case when $\frac{W_{na}/L_{na}}{W_a/L_a} > 1$

A.5. Supporting Tables for Relation between Choice of Sector and Vocational Education

Table A9: Relation between the increase in take up of vocational education on Industry choice for the SC/ST group (full estimates)

	Dependent variable: Pr(Engaged in Non agri sector)=1
SC/ST	0.5858***
	(0.003)
No Vocational edu	0.6014***
	(0.0025)
Year	
1983	0.5460***
	(0.0039)
2012	0.6528***
	(0.0036)
Interaction: Group *Year	
SC/ST * 1983	0.5272***
	(0.0045)
SC/ST * 2012	0.6401***
	(0.0041)
Interaction: Group *Vocational edu	
General*No Vocational edu	0.6678***
	(0.006)
SC/ST * No Vocational edu	0.5858***
	(0.0030)
SC/ST * Vocational edu	0.5865***
	(0.0555)
Interaction: Year *Vocational edu	
1983*No Vocational edu	0.5459***
	(0.0039)
2012*No Vocational edu	0.6529***
	(0.0036)
Interaction: Group*Year *Vocational edu	
General*1983*No Vocational edu	0.6220***
	(0.0089)
General*2012*No Vocational edu	0.7106***
	(.0083)
SC/ST*1983*No Vocational edu	0.5270***
	(0.0046)
SC/ST*1983*Vocational edu	0.5745***
	(0.0812)
SC/ST*2012*No Vocational edu	0.6402***
	(0.0041)
SC/ST*2012*Vocational edu	0.5977***
	(0.0758)
Other Control Variables	Yes
Observations	26,710

Note: The Table reports the average marginal effects of a logit regression. The dependent variable takes a value of 1 if the individuals are engaged or employed in non agriculture sectors. The sample consists of both IHDS rounds. Other control variables includes household and socio- economic characteristics such as age, gender, marital status, religion, formal education state fixed effects. Robust standard errors reported in parentheses. *** p<0.01 **p<0.05 *p<0.1.

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