ESSAYS IN THE ECONOMICS OF CASTE AND RELIGION

By

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ABSTRACT

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Through my dissertation, I aim to uncover the processes that govern the relationship between social or ethnic identity and economic outcomes such as employment and education. I focus in particular on studying outcomes for Muslim women in India who have remained on the fringes of economic enquiry. A majority of the literature on economic exclusion in India has focused on caste based discrimination, which is warranted given the acute poverty and deprivation faced by lower caste communities in the country. However, despite being comparable on measures of economic, social and educational deprivation, Indian Muslims have remained absent from the development discourse in the country. I hope my research will contribute to filling this lacuna in the literature.

The ***first chapter*** examines the evolution of labor force participation rate (LFPR) differences between women from the Hindu, Schedule Caste/Schedule Tribe (SC/ST) and Muslim communities in India. I find that affirmative action policies have led to convergence in the education levels of Hindus and SC/ST which has consequently led to a narrowing of the LFPR gap of the two groups, however, the Hindu-Muslim gap in female labor participation remains persistently high. I find that part of the religious gap is explained due to Muslim women being trapped in enclaves of low economic development due to a combination of Muslim ghettoization and relatively localized marriage markets. Contrary to popular rhetoric, I find that culture does not play a big role in explaining the absence of Muslim women from the labor force.

In the ***second chapter*** my coauthor Dr Maitreyi Bordia Das and I, study the causes for large differences in female labor force participation between West Bengal and Bangladesh. Despite historical and cultural commonalities, both regions exhibit very different levels of socio-economic development, one

of which is the wide disparity in female labor force participation. We find that observable covariates do not play a major role in explaining the wide gap in female LFPR between the two regions. This is driven by the fact that in West Bengal, much like the rest of India, higher levels of education and improvements in social status leads to withdrawal of women from the labor force. On the other hand, we find the opposite to be true in Bangladesh. In comparing Muslims on either side of the border, our results remain qualitatively similar to the aggregate results. We conclude that the differing political trajectories followed by the two regions have created widely varying economic structures which have in turn led to divergent demands for female labor in the two countries- the most obvious of which is the decline of agriculture in West Bengal and the continued flourishing of both agriculture and manufacturing in Bangladesh.

The ***third chapter*** aims to study the impact of communal violence in India on the schooling and education decisions of Muslims in India. The causes and consequences of violent conflict, particularly civil war, mass violence and ethnic conflict, has attracted considerable scholarly attention across disciplines. However, there is much less research on the how small isolated and geographically dispersed incidences of violence can lead to long term deficit in human capital accumulation for entire communities. This effect could be driven by the immediate loss of life and livelihood following conflict. However, repeated conflict also ingrains a culture of fear in the minds of the victimized community that implicitly determines economic behavior in the long-run. My paper deals with one such group, namely Indian Muslim. I use data on religious violence from 1950-2006 combined with data on education from several consecutive rounds of the National Sample Survey (NSS) on Employment and Unemployment (Schedule 10) and Participation in Education (Schedule 25.2) covering the period between 1983 and 2014. My results suggest that both contemporaneous and cumulative violence has no effect on the educational outcomes and dropout decision of Muslim girls and boys.

To all the strong women in my life. Thank you for blazing the trail on which I wander.

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Caste, Religion and Economic Participation of Women in India

1 Introduction

This paper aims to study gaps in labor force participation rates (LFPR) for women from the Hindu, Schedule Caste/Schedule Tribe (SC/ST) and Muslim communities in India. The motivation behind such a comparison is twofold: firstly, SC/ST and Muslims are the most deprived communities in India, and the status of women from these communities merits in-depth analysis. Secondly, summary statistics show that despite similarity on many indicators of economic development, the labor market participation behavior of women from these communities is markedly different. My data spans over two decades (1983/84 to 2011/12), and covers a period of remarkable growth in the Indian economy, boosted by widespread economic reforms in the early 1990s. Have the benefits of this growth trickled down to these marginalized communities? How have women from these communities responded to this period of rapid growth[1]? Is lack of education or poverty holding back women from these communities from fully participating in the economy? These are some of the questions this paper will attempt to answer.

Female labor force participation has received widespread attention in economic literature (Blau & Kahn, 2013). While some studies have looked at how changes in fertility affect the decision of women to enter or exit the labor force (Bloom et al. 2009; Hotz & Miller, 1988; Rosenzweig & Wolpin, 1980), others have studied the effect of female labor supply on children's cognitive development and health (Blau & Grossberg, 1992; Brooks-Gunn et al. 2002; Ruhm, 2004). Of particular interest to us is the growing literature that looks at the effect of culture on economic outcomes, particularly female labor supply

[1] Munshi & Rosenzweig (2006) use survey data from Bombay spread over 20 years to show that lower caste girls are exploiting opportunities presented by the new economy to enroll in English schools as a means of upward mobility, in contrast to boys who are constrained by caste networks that restrict them to traditional occupation and local language schools.

(Antecol, 2003; Fernandez, 2007). This paper attempts to not only study religion and caste based gaps in female LFPR, but also examine how much of these gaps are attributable to differences in observable covariates such as education, and how much can be attributed to unobservable components such as culture and discrimination. I am also interested in knowing how this gap in female LFPR has evolved over time, particularly when the Indian economy has gone through rapid structures changes and there have been marked improvements in income levels and human capital development. This issue has come into renewed focus with recent data suggesting that female LFPR in India has been declining over the last decade. Klansen and Pieters (2015) study the phenomenon of stagnating female LFPR in urban India and conclude that this trend is being driven by rising income and education of men coupled with low growth in sectors that employ women[2].

I use data from seven rounds of the National Sample Survey (NSS) on Employment and Unemployment in India and find that there is considerable gap between the LFPR of Hindu women in comparison to SC/ST and Muslim women. Despite being similar on various indicators of development, SC/ST women have the highest LFPR and Muslim women have the lowest LFPR across all socio-religious categories in India. While the Hindu-SC/ST gap has been narrowing over time, the Hindu-Muslim gap remains high. Moreover, I find that observable characteristics such as education, poverty and household size explain a large part of the Hindu-SC/ST gap, whereas very little of the Hindu-Muslim gap is explained by these covariates. My findings are consistent with recent research on caste and religion based disparities in India. Hnatkovska et al. (2012) find that between 1983/84 and 2004/05, there has been significant convergence in wages and consumption levels between SC/STs and non-SC/STs, and this is driven largely by convergence in levels of education. For both wage and consumption convergence they find that SC/STs in lower percentiles have benefited more compared to the relatively better off. Bhalotra et al. (2010) study gaps in infant mortality rates between Hindus, Muslims and SC/STs and find that despite low indicators of socio-economic status, children born to Muslim mothers have, and continue

[2] This finding is consistent with other cross-country studies that find economic growth and female LFPR follow a U-shape pattern, where initial economic growth is accompanied by declining female participation. However as incomes continue to grow, female LFPR also rises (see Mammen & Paxson, 2000)

to exhibit, higher survival rates. This paradoxical result is consistent with my finding that shows the inability of background characteristics in explaining outcomes for Muslim women. I find that Muslim women's absence from the labor force is explained in large part due to their concentration in areas of low economic activity. I use the second wave of India Human Development Survey to test the role of culture and find that it plays only a small part in explaining Muslim women's low LFP.

The paper is divided in the following way: The second section provides a brief introduction to the caste system in India, section 3 reviews the literature on caste and religious inequality in India, and section 4 outlines the methodology while section 5 explains the data and summary statistics. Sections 6 and 7 explore the role of background characteristics in explaining the LFPR gaps, while section 8 provides avenues for future research and concludes.

2 System of Caste in India

India has been and continues to be deeply stratified on the basis of caste and religion. Even today, caste status plays an important role in determining opportunities and outcomes for the people of the country. While there are thousands of castes in India, they are divided between five main religions, namely, Hinduism, Islam, Christianity, Sikhism and Buddhism. Efforts to remove caste based inequality led some monarchs and British colonials to recognize most of the lower caste and religious populations as historically marginalized. Consequently, in independent India, the constitution went to great length in formulating affirmative action for marginalized populations, namely, Dalits, Adivasis, and to a lesser extent Shudras, and Muslims. In official lexicon Dalits are identified as Scheduled Castes (SCs), Adivasis as Schedule Tribes (STs), Shudras as Other Backward Class (OBCs) and Muslims as Muslims. Together, these four groups are identified to be placed lower in the caste and religious hierarchy while the Hindu Upper Castes are understood to be placed higher.

The Hindu caste system can be divided into four hierarchical groups as follows: Brahmin (the priestly caste), Kshatriyas (the warrior caste), Vaishyas (the trading caste), Shudras (the service caste such as farmers, craftsmen and shepherds) and Ati-Shudras. The Ati-Shudras, now called Dalits, have been designated the work of menial labor including manual scavenging and were segregated from the village and main areas of the cities owing to their subordinate caste status (Omvedt, 2004; Thorat, 2002). While most of them are still Hindus many converted to other religions such as Buddhism, Christianity, Islam and Sikhism, to escape caste based oppression. According to the Indian constitution, Ati-Shudras who converted to Islam or Christianity are no longer recognized as SC for the purpose of affirmative action policies. According to the 2011 Census Ati-Shudras form 16.2% of the Indian population and in our analysis they are referred to as Schedule Caste.

The next group is Adivasi, which translates to original inhabitants. Over a period of time some Adivasis have been co-opted into the caste system alongside Dalits while others have continued to move further away from the fertile plains and into forests (Fürer-Haimendorf, 1982). The social status of Adivasis is found to be similar to that of the Dalits. Apart from their own tribal religions, which are grouped under the larger category of Hinduism, they follow Christianity and to a much smaller extent, Islam. Their current population as per the 2011 Census is 8.2%, which makes them smallest of the population groups. In this paper they are referred to as Schedule Tribe.

Shudras or Other Backward Caste are the largest of the population group. Their main occupations were farming, rearing cattle and other forms of skilled labor (Ambedkar, 1970), that were counted as service to the castes above them in social hierarchy. Like Dalits, most of them are Hindu though many converted to other religions for a chance at upward mobility. The Indian census does not ask persons whether they identify as OBCs and there is significant heterogeneity across states in which caste is officially defined as OBC. In fact, the National Sample Survey (NSS) did not include OBCs as a caste group till 1999-00, and for this purpose OBCs are included with 'Hindus' in our analysis[3].

[3] Along with a smaller central OBC list, each state is allowed discretion in whom to include or exclude from the state OBC list. For this reason, the definition of OBC varies from state to state, and it is not uncommon to find the same caste defined as OBC in one state and upper caste in a neighboring state. Because of the inconsistent definition of OBC across time and states, we decide to include OBCs under 'Hindu' category. Unlike SC/ST, OBC are eligible for affirmative action policies only if they meet certain income criterion.

As indicated above, a large number of Muslims in modern India are former Shudras, Dalits and Adivasis who converted to Islam. Apart from the caste baggage that the community carried over after conversion, they face religion based marginalization. The dominant Hindu-nationalist rhetoric defines Islam and Christianity as foreign religions (Rauf, 2011) and this contributes to their persecution. Their right to freedom of religion is enshrined in the Indian constitution, which recognizes Muslims primarily as 'minorities'. In this paper they are referred to as Muslims.

3 Review of Existing Literature

3.1 Economic exclusion and caste in India

Much of the literature on economic discrimination in India has been centered on caste based discrimination. Indeed, Scheduled Caste and Scheduled Tribes continue to be one of the most deprived social groups in the country and still lag behind upper caste Hindus and other religions on indicators of social and economic development. The relative as well as absolute deprivation of SC/ST is widely documented (Hanna & Linden, 2012; Ito, 2009; Zacharias & Vakulabharanam, 2011). According to Planning Commission statistics for 2009-10, in urban areas, ST and SC have a poverty rate of 30.4% and 34.1% respectively compared to 12.4% for Hindus and 21% for India as a whole. Similarly in rural areas, compared to an overall poverty rate of 33.8%, ST and SC have a head count ratio (HCR) of 47.4% and 42.3% respectively (Government of India, 2012). Borooah (2005) decomposes the differences between Hindu and SC/ST households on income levels, incidence of poverty and levels of poverty into a residual effect which accounts for the difference between the 'income generating'[4] profile of the SC/ST and Hindu households, and a discrimination effect. He finds that at the minimum, one-third of the difference in income across households is attributable to discrimination or 'unequal treatment' of the SC/ST households.

Discrimination and exclusion in the Indian context comes from a multitude of institutions which 'discriminate, isolate, shame, and deprive subordinate groups on the basis of identities like caste, religion

[4] Income generating profile refers to the household's ownership of land, regional location, non-land assets, number of adult workers and household head's education level

and gender' (Thorat & Newman, 2010). Based on a field study which involved sending out three applications in an upper caste Hindu, Dalit and Muslim name for advertised private sector jobs, Thorat and Attwell (2007) find that Muslims elicited the least favorable response from potential employers, followed by Dalits. On the other hand, in a similar experiment Banerjee et al.(2009) find no conclusive evidence of caste or religion having an effect on the callback decision of software and call-center firms in and around New Delhi, India. Deshpande (2011), in perhaps one of the most comprehensive analyses of economic discrimination experienced by Dalits in recent times, shows that caste discrimination cuts across all levels of employment, right from the market for unskilled labor to the market for graduates from elite education institutions (ibid., p190). The book covers a gamut of issues from occupational distribution, wages, education, asset ownership and landholding, and develops a CDI (Caste Development Index) using various rounds of the National Family Health Survey, on the lines of the Human Development Index developed by the UNDP. The analysis shows that in almost all the states and across all three rounds of the NFHS, the CDI for SCs is consistently lower than that for non-SC/ST and the same is the case for STs, though they fare marginally better than SCs. She finds considerable variation across states both within and across rounds, and finds that the CDI for SCs is positively correlated with per capita real State Domestic Product (NSDP), indicating their better performance in economically better performing states. However, she finds that the level of inequality between groups is not correlated with state income. She also finds no clear relationship between SC-CDI disparity and real NSDP growth rate. In a very telling analysis of the relationship between caste and gender in labor markets, Deshpande (ibid.) finds that the GCDI (Gender Caste Development Index), follows a pattern similar to the CDI. However, it does not have any correlation with per capita real NSDP, indicating that the better economic performance of a state does not necessarily translate to increased well-being for Dalit women.

Wage disparity between different groups is perhaps one of the most widely used measures of economic discrimination. In India, the method of wage decomposition has been used to estimate the wage gap between various caste groups, and more recently, religions as well (Bhaumik & Chakrabarty, 2006). Banerjee and Knight (1985) find that the wage gap between SC and non-SC in their sample is almost 17%, and of this they estimate, more than half is on account of discrimination. A more recent study by Madheswaran and Attwell (2007), arrives at slightly different results. They estimate that a major part of the difference in wages between SC/ST and non-SC/ST is due to differences in endowments, while 15% is due to pure discrimination. They argue that the gap in wages is primarily due to differences in the kinds of occupations that SC/ST and others hold, rather than pure wage discrimination. They however find that returns to education for SC/ST are considerably lower than for other groups and that wage discrimination exists in both public and private sector, and is much higher in the private sector.

3.2 Indian Muslims

The status of Indian Muslims has been a subject of historical (Hardy, 1972), sociological (Fazalbhoy, 1997; Robinson, 2004), political (Brass, 2005; Rauf, 2011) and economic (Khalidi, 2006) enquiry for many decades. Until very recently, the discussion on Indian Muslims revolved around issues of terrorism, communal violence and personal law, while the economic and social deprivation of the community was rarely discussed. The setting up of the Prime Minister's High Level Committee on Social, Economic and Educational Status of the Muslim Community of India (more commonly known as the Sachar Committee) in 2005, was perhaps the first official attempt at recognizing and studying the existence and extent of the backward status of the Muslim community in India. The committee submitted its report in November 2006 and became the reference for studying the various dimensions that define Muslim existence in modern India, from violence, exclusion and education to employment, health and poverty. In addition, recently released official poverty estimates of the Planning Commission indicate that Muslims are by far the most economically deprived religious community in India, across rural and urban areas. In rural Assam, West Bengal and Uttar Pradesh, the headcount ratio (HCR) for Muslims stands at 53.6 (39.9), 34.4 (28.8) and 44.4 (39.6)[5]. Similarly in urban areas, Muslims have a high HCR in states such as Gujarat- 42.4 (17.7), Bihar- 56.5 (39.4) and Uttar Pradesh- 49.5 (31.7) (Government of India, 2012). That these figures are high, even when using the controversially low poverty lines defined by the Planning Commission, highlights not only the relative, but also the absolute deprivation faced by Indian Muslims.

[5] Figures in parenthesis indicate overall state HCR

Bhaumik and Chakrabarty (2006) examine the difference in wages for Hindus and Muslims over the period between 1987 and 2005 using NSS data. Similar to studies on Dalits, they find that differences in education are the primary cause for differences in wages between the two groups. A large part of this is due to the difference in the proportion of wage earners in the two groups with tertiary education. It will be seen later in this research that this is not only due to the fact that a relatively lower proportion of Muslims have tertiary education, but also because only a small proportion of them are engaged in higher paying regular/salaried employment. This is corroborated in a study (Borooah et al. 2007) of the 55th round of NSS which finds that compared to upper caste Hindus, Muslim workers have a significantly lower probability of being in regular salaried employment. It will be shown in this paper that this is even more the case for Muslim women than for Muslim men.

Muslim women have largely been absent from realm of economic enquiry. Hasan and Menon (2005), best sum up the treatment of Muslim women in academic literature (p.3), *'the literature on Indian women in general is characterized by three broad tendencies: it ignores Muslim women, considers their status a product of personal laws, and assumes sameness in the status and forms of oppression, cross-community'*[6]. The assumption of sameness of women across groups, religions and communities, has received considerable attention in the works of the so-called 'feminist economists' who developed the Gender and Development (GAD) approach to development as a response to the WID (Women in Development) approach championed by Esther Boserup (1970). The GAD framework for the first time accepted the heterogeneity among women, and recognized that patriarchy operates both within and across class and other divisions to oppress women.

The assumption of homogeneity of Indian women and the over-emphasis on personal law and issues of religious identity in the context of Muslim women has meant that their socioeconomic, educational and political status remained understudied in India. A survey, called the Muslim Women Survey (MWS), by

[6] The Indian constitution allows religious minorities to follow their own religious laws concerning issues of marriage, divorce, division of property and succession. Indian Muslims come under a version of Sharia law that is governed by the All-India Muslim Personal Law board. While several successive governments have proposed the creation of a Uniform Civil Law Code, it remains a matter of considerable political contention.

Hasan and Menon (2004), spread over 9541 households over 12 states was conducted to study the situation of Muslim women in India, covering a gamut of issues such as: education, work, socio-economic status, marriage, mobility, access to media, political participation, domestic violence and decision-making. The findings of the MWS are largely consistent with the trend observed at the national level in the NSS data, particularly in the area of education and employment. The study finds evidence of high drop-out rates and very low participation in higher education. Moreover, it shows that southern and western states perform better on indicators of education than northern and eastern states, and this is consistent with the findings of this research. The study finds very low levels of work participation and a concentration of women in self-employment and low-skill sectors. In an analysis of the 1993-94 round of the NSS, Bordia-Das (2005) corroborates the findings of the MWS, by concluding that the major reasons for low work participation of Muslim women is their limited engagement in agriculture in rural areas, and their 'exclusion from professional, technical and clerical jobs' in urban areas. The concentration of Muslims in certain sectors, areas, and kinds of work is corroborated in another recent study (Bordia Das, 2008) which found clear evidence of the presence of ethnic economic enclaves for Muslim men.

4 Methodology

My primary outcome of interest is the mean female labor force participation rate across the three caste-religion groups in India and its evolution over the last 25 years. The aim of this paper is to explore the contribution of observable background characteristics in explaining the LFPR gaps between the three groups. My methodology is twofold- I first examine the combined role of all covariates in explaining the LFPR gaps and this gives the total, predicted and unexplained gap. I then look at the role of individual characteristics in explaining the total and the predicted gap. I use two methods for the overall decomposition analysis- DFL method based on DiNardo, Fortin and Lemieux (1996) and the OB method based on Oaxaca (1973) and Blinder (1973). For assessing the role of individual characteristics I use an extension of the OB method. Observable covariates include age, marital status, level of education, rural residence indicator, number of children below the age of 5, household size, household head characteristics, and controls for local economic conditions. In addition, the model also includes a full set of controls for state of residence to capture regional variations in the economic participation of women.

4.1 DFL method

Reweighting methods continue to be a popular tool in economics to study gender, ethnicity and race based gaps in various health and labor market outcomes[7]. The intuition behind reweighting is simple- if we want to study outcome differences between group L and M, we reweight group L so that its distribution of observables closely matches that of M, while retaining its own mapping from observables to outcome. Essentially, we give more weight to those Ls whose observables are similar to the Ms in our sample and progressively less weight to the Ls whose background characteristics are different from the Ms. In our sample, the L signifies Hindu women while M refers to SC/ST or Muslim women.

To begin, define the probability density for outcome y of caste/religion group c with background characteristics X as:

$$F(y|c) = \int_x F(y|c,X)dF(X|c) \tag{1}$$

From here it is easy to construct a valid counterfactual density of the following form:

$$F\left(y\middle|c_{y|X} = L, c_X = M\right) = \int_X F(y|c = L,X)dF(X|c = M) \tag{2}$$

This counterfactual density is valid only when the changing the marginal distribution function from $dF(X|c = L)$ to $dF(X|c = M)$ leaves the conditional distribution $F(y|c = L,X)$ unchanged. Using weights of the form $\varphi_{L\to M}(X)$ the counterfactual density in (2) can be written as

$$F\left(y\middle|c_{y|X} = L, c_X = M\right) = \int_X F(y|c = L,X)\varphi_{L\to M}(X)dF(X|c = L) \tag{3}$$

Where using Bayes' rule, we can write $\varphi_{L\to M}(X)$ as

$$\frac{dF(X|c = M)}{dF(X|c = L)} \equiv \frac{\Pr(c=M\,|X)}{\Pr(c=L|X)} * \frac{\Pr(c=L)}{\Pr(c=M)} \tag{4}$$

I use logit (any binary model can be used) to calculate $\Pr(c = i\,|X)$, which is the probability of being from caste/religion group i as a function of background characteristics X. The second part, that is

[7] For a comprehensive review of decomposition methods in economics see Fortin et al. (2010). For an application of DFL method to studying racial gaps in IMR see Elder et al. (2011)

$\Pr(c = i)$, is simply the unconditional proportion of population in group i. In constructing the counterfactual weights, I use data for Hindu women pooled with the corresponding comparison group (SC/ST or Muslims), and then obtain three set of means: mean Hindu LFPR (H), mean SC/ST or Muslim LFPR (C) and mean counterfactual Hindu LFPR (H'). The gaps in labor force participation are calculated as follows: Total Gap (T) = H - C, Explained Gap (E) = H - H' and Unexplained Gap (U) = H' - C.

4.2 Oaxaca-Blinder method

The Oaxaca-Blinder (OB) method for wage decomposition is the first and one of the most well-known decomposition techniques in economics. The original model used differences in means to break down male-female wage gaps into an explained component that can be attributed to differences in endowments such as education and experience and a residual component that is attributed to discrimination (and other unobservable characteristics).

In keeping with the notation developed in the previous section, let the groups be denoted by L and M. I am interested in knowing how much of the total gap T can be explained by the covariates X and how much remains unexplained.

$$T = E(y_L) - E(y_M)$$

Where $y_c = F(X'_c\beta_c)$ and F is a mapping of X to y. In our case, the mapping is linear, that is, $y_c = (X'_c\beta_c)$. According to the OB model, we can estimate T by using the sample differences in mean values of y_L and y_M. More formally

$$T = \overline{y_L} - \overline{y_M} = \left[\overline{(X'_L\beta_L)} - \overline{(X'_M\beta_L)}\right] + \left[\overline{(X'_M\beta_L)} - \overline{(X'_M\beta_{M)}}\right] = E + U \tag{5}$$

Here the first part is explained due to differences in characteristics, whereas the second part is unexplained or due to differences in coefficients or returns to characteristics. An extension of the OB also allows us to calculate the role of individual covariates (or group of covariates) in predicting the explained gap. These estimates are calculated as $\left[\overline{(Z'_L\beta_L^Z)} - \overline{(Z'_M\beta_L^Z)}\right]$ where Z_i is a subset of the variables from X and $\beta_L^Z$is the corresponding coefficient from regressing y on X for group L.

5 Data and Summary Statistics

I use data from the 38th (1983-84), 43rd (1988), 50th (1993-94), 55th (1999-00), 61st (2004-05), 66th (2009-10)[8] and 68th (2011-12) rounds of the National Sample Survey on Employment and Unemployment in India. These nationally representative surveys are usually conducted every five years to provide a comprehensive assessment of the labor market situation in the country. Each round covers between 100,000-120000 households and 450,000-600,000 individuals.

My working sample is comprised of women between the ages of 15-59 belonging to 3 mutually exclusive categories- Hindu, Schedule Caste/Schedule Tribe and Muslim. The Hindu category consists of all those who report being Hindu but not SC/ST. The Muslim category contains all Muslims regardless of caste. And finally, SC/ST includes all non-Muslim SC/ST persons. I drop all observations who are non-SC/ST or non-Hindu/Muslim[9]. My measure of labor force participation rate is based on a one-year reference period and includes work in a subsidiary status[10]. I drop observations for which information on caste or religion is missing[11].

To account for regional variation, I include a full set of state dummies. I restrict the sample to 15 major states of India that cover roughly 92-95% of India's population. Three new states of Jharkhand, Uttaranchal and Chhattisgarh were carved out of the states of Bihar, Uttar Pradesh and Madhya Pradesh respectively, in 2000. To ensure comparability across rounds, I treat the new states as a part of the old state resulting in a total of 15 states[12]. I also include controls for local economic conditions by controlling

[8] Significant changes have been undertaken in designing the surveys beginning with the 66th round (2009-10). One of the most important changes was a marked reduction in the sample size as well as reclassification of rural and urban areas. Moreover, 66th round was conducted in a year when many areas of the country experienced acute drought, which may affect labor market outcomes. We thus need to proceed with caution when comparing results of the 66th round with previous rounds.

[9] This group includes non-SC/ST members of religious minorities such as Sikhs, Christians, Jains, Buddhists and Others. They represent roughly 4.9 percent of our sample.

[10] The NSS defines this as usual status. This includes the work done as primary status in the last 365 days as well as work done in a subsidiary status for at least 30 days in the last year. Women who reported the following activities were counted as being in the labor force: worked in HH enterprise (self-employed) as own account worker or employer, worked as helper in HH enterprise (unpaid family worker), worked as regular salaried/ wage employee, worked as casual wage labor in public works or in other types of work, sought work, did not seek but was available for work

[11] We drop 21/120909 households in 38th round, none in 50th and 55th round (115409 and 120386 households respectively), 96/124680 households in 61st Round and 87/100957 households in 66th round for missing data on caste and/or religion.

[12] The states included in our analysis are Uttar Pradesh, Bihar, Maharashtra, Madhya Pradesh, West Bengal, Andhra Pradesh, Tamil Nadu, Karnataka, Gujarat, Rajasthan, Orissa, Kerala, Assam, Punjab and Jammu & Kashmir.

for adult male unemployment rate and the proportion of men with a secondary school education or higher in the respondent's region. I also drop all observations that are missing information on any of the covariates such as monthly per capita income, age, years of education, household size[13]. The final sample consists of 140,000 to 180,000 women per round.

I control for level of education by dividing it into five mutually exclusive categories based on highest level of completed schooling-no education, incomplete primary school, complete primary school, middle school and secondary and higher[14]. Controls for household head's education are similarly constructed. Controls for age of respondent and age of head are also added.

Concurrent with recent literature, household income and wealth is believed to be an important component driving the decision of women to participate in the labor force. The NSS does not report measures of income but does provide monthly household per capita consumption expenditure. However, controlling for consumption directly would create endogeneity. I work around this problem using two solutions. I first control for characteristics of the household head and male household members that I believe proxy for some measure of permanent household income. In the second specification, I also add predicted consumption expenditure rather than actual expenditure to more directly control for measures of income.

A caveat of the NSS data is that each of the respondent is asked her/his relationship to the household head only, hence, unless the adult female in the house is the head or spouse of the household head it is impossible to determine exactly how many children in the household are her own. This is particularly problematic in the case of joint families which are very prevalent in India, where children live in the same household with the mother, grandmother and aunts. One solution to that would have been to include only

[13] Less than 1 percent of our sample is dropped by excluding observations with missing data on any of our covariates.

[14] This method does not account for technical education because technical education is reported by a very small proportion of the population. Moreover, the technical education question has changed over the rounds making it inconsistent across all our sample years. We do however try an alternative specification that converts level of education (general and technical) into years of education and it only reinforces our main finding that covariates explain a sizeable portion of the Hindu-SC/ST gap, but very little of the Hindu-Muslim Gap. Results available on request.

those women who report themselves to be heads or spouses of the head. They represent between 60-61% of our working sample. However, this would have led to excluding a vast number of women who live in joint families and whose labor market behavior may be quite different from women living in nuclear families. To control for the effect of fertility decisions on labor market behavior, I include as a covariate, the total number of children below 5 in the household. This is reasonable since child rearing responsibilities in India are often shared among all women of the household when living in joint families.

The premise of the paper is that there are substantial differences in the LFPR of women from different communities, and this is very evident from Figure 1. While on the one hand, SC/ST women have the lowest indicators of human capital, they have the highest LFPR. On the other hand, Muslim women, who fare similarly on indicators of education and income, have the lowest LFPR. As Figure 1 shows, this disparity between groups is particular to women, since men have similar levels of LFPR across all the three groups. Until the 61st round, the LFPR of women was steadily increasing, however it has gone down substantially in the last two rounds. Some of this has been attributed to the fact that younger women are staying in school/college longer, which does seem to be true. However, there has also been a disproportionate increase in the number of women who are withdrawing from the labor force in favor of domestic work, and this is a secular trend across all groups.

Historically Muslims have been involved in crafts and artisanal trade and this is mirrored in the fact that a majority of working Muslim women are 'self-employed', most of them in home based micro-manufacturing units. On the other hand, SC/ST women are disproportionately represented in casual labor, most of which is in the rural agriculture sector. These clear trends in occupational distribution are reflective of the fact that landholding in India has been concentrated in the hands of the upper caste, which in the absence of substantive land reforms, has led to persistent ethnic employment enclaves. While Muslim women have lowest LFPR, they also have the highest rate of unemployment, which incidentally is the highest across all groups and genders. In our sample, Hindu and SC/ST women had an unemployment rate of 4% in 2009-10, whereas the same for Muslim women was 7%.

The persistently low levels of education of women in India has been a major concern for policymakers. However, our data shows that there is considerable heterogeneity across the three groups of women as well. Descriptive statistics in Table 1.9-1.11 show that Hindu women continue to have the highest levels of education. On the other hand, while SC/ST women have made remarkable improvements over the years, they still have the lowest levels of education and high rates on illiteracy. Finally, Muslim women who were previously performing significantly better than SC/ST women are now placed only marginally better on indicators of education. According to the 66th Round, Hindu women had an average of 5.85 years, Muslim women had 4 years and SC/ST women had 3.5 years of education.

Household level statistics also show considerable heterogeneity across groups. Between 83-86 percent of SC/ST households live in rural areas, whereas Muslims are the most urbanized community. Muslim households have the most members and have the highest number of children under 5, which is indicative of the community's higher fertility rate and lower child and infant mortality (Bhalotra, 2009). Muslim tend to live in areas where male unemployment rate is higher, and more than 80% Muslim and SC/ST women live in households with no adult male engaged in regular salaried employment.

6 Role of All Covariates

For analysis based on the DFL method, I construct a counterfactual Hindu distribution that has the characteristics of SC/ST and Muslims respectively, but retains its own mapping from background characteristics to labor force participation behavior. Figures A1-A4 show that the reweighted Hindu population looks quite similar to its corresponding reference group in terms of the distribution of covariates. The counterfactual (CF) Hindu distribution is marginally younger than the SC/ST sample. In both cases the CF population has slightly higher years of education, and smaller HH size compared to the reference group. On all other indicators, our CF, on average, looks almost identical to the corresponding comparison group. The gap between actual Hindus and the counterfactual Hindus is what I call predicted or explained gap, whereas the gap between counterfactual Hindus and the comparison group is called the unexplained gap. Point estimates based on DFL method are shown in Tables 1 and 2, and point estimates based on OB method are shown in Tables 3 and 4. As is evident, both the DFL and OB method give similar results for both groups. I report OB results with an alternative specification that includes predicted income along with other proxy controls for household wealth. The results of this alternative specification are in Tables 5 and 6. The alternative specification gives us results that are qualitatively similar to the main specification.

Gap by Caste: Between 46-57 % percent of the gap in LFPR between SC/ST and Hindu women can be explained by differences in covariates. What this means is that if Hindu women had the same distribution of characteristics as SC/ST women, their LFPR would be between 5 to 8.7 percentage points higher than it is. As an example, column 1 of Table 1 shows that the Hindu counterfactual LFPR is 51.5 percent, which is the Hindu LFPR if they had the SC/ST characteristics on average. Compared to this, the actual Hindu LFPR is 42.9%. This means that the gap in Hindu-SC/ST LFPR which can be predicted by differences in observables is 8.6% compared to the overall gap of 18.1%. Table 2 shows that the results using the OB method are also quite similar. Roughly 8.5% of the total gap between Hindu and SC/ST in 1983-84 is explained by differences in observables.

Lower caste women are overwhelmingly concentrated in rural areas, where opportunities to be employed as unskilled marginal and casual labor are abundant. This is the sector that employs the highest proportion of SC/ST women, and if they are increasingly getting pushed into low paying casual labor, then the higher labor force participation of lower caste women could be a sign of economic distress rather than economic empowerment. As Figure 2 shows, relative to total gap, the explained component of the SC/ST gap has also been steadily, albeit slowly, increasing over the years, and this underscores the importance of social and human capital indicators in predicting economic outcomes for lower caste women.

The absolute gap in LFP between Hindu and SC/ST women has also been declining quite significantly over the years. In 1983 the LFPR of SC/ST women was 18% higher than Hindu women, however by 2009-10 this had dropped to only 10%. When I include measures for predicted consumption expenditure, the explained portion of the Hindu-SC/ST gap rises to almost 85% in 1999-00. Household income seems to have a significant positive association with female labor force participation for SC/ST women, an argument I will revisit in the next section.

Gaps by Religion: Muslims fare similarly to SC/ST on indicators of human development and poverty, however the labor market response of Muslim women to these indicators is markedly different. If Muslim women's labor market behavior was similar to SC/ST women, we would expect Muslim LFPR to be higher than Hindu LFPR, however the gap between Hindu and Muslim women is large and positive, the opposite of what was seen between Hindu and SC/ST women. Also in contrast to lower caste women, observables explain a very small part of the LFPR gap between Muslim and Hindu women, and this explained component has been declining over the years from 18% in 1983 to 8% in 2009. Again, using 1983-84 as an example, column 1 of Table 2 shows that the Hindu counterfactual LFPR is 39.1% compared to the actual Hindu LFPR of 42.9%. This implies that of the total gap of 16.8%, only 3.9% is explained by differences in observables between Hindu and Muslim women. Table 4 reports the results using the OB method and gives similar results, 3% of the Hindu-Muslim gap is explained.

The absolute gap between Hindu-Muslim LFPR has fluctuated significantly over the years, rising to its highest level of 18 percentage points in 2004-05. If Hindus in our sample had the Muslim distribution of characteristics, their LFPR would have been 0.5 to 4 percentage points lower than it is. As we will see in the next section, almost the entire explained portion of the Hindu-Muslim gap can be attributed to regional concentration of Muslims in low female LFPR states.

If low human capital indicators and economic deprivation predict high LFPR for SC/ST women, why do these same characteristics have little to no power in explaining the low LFPR of Muslim women? One reason for this paradox could perhaps be attributed to the presence of ethnic economic enclaves. Many Muslims, particularly in rural areas, are involved in craft and artisanal trade, and traditionally the 'skill' of the craft is passed on to sons and other male family members rather than to daughters. Low levels of education, combined with little to no specific 'skills', severely restrict the employment options available to Muslim women. Moreover, there is some evidence to suggest that women working in home based enterprises systematically under report their economic activity because they themselves don't place economic value on their work. Women working as a part of their husband's or father's small business may consider such work to be part of their domestic duties, particularly because home based work does not involve a fixed wage or salary. Finally, religious traditions and customs could also explain Muslim women's absence from the labor force. I explore each of these hypotheses in the next section.

7 Role of Individual Covariates

The results from the previous section show that despite similar levels of economic and human capital development, Muslim and SC/ST women exhibit vastly different labor market behavior. Given these paradoxical results that emerge when looking at the role of all covariates combined, it becomes important to see what contribution individual covariates have in explaining LFPR gaps between the different groups. I use an extension of the Oaxaca-Blinder method to examine the role of individual covariates. For an easier and more intuitive interpretation of results, I group the covariates intro 3 categories: personal, household and regional characteristics. The personal category includes age, level of education, and marital status, household category includes household size, number of children under the age of five in the household, indicator for adult household male characteristics and household head's characteristics and the regional category includes rural residence indicator, regional adult male outcomes as well as state fixed effects.

Gaps by Caste: Together personal and household characteristics account for 80-90% of the explained gap for Hindus and SC/ST, whereas regional variables play a smaller role. As an example, if Hindu women had the personal characteristics of SC/ST women in 2004-05, their LFPR would have been higher by 3.2

percentage points. Overall personal and household characteristics, respectively, explained 48% of the total gap in 2004-05, whereas this was 38% in 1983-94. This shows that personal and household characteristics are increasingly playing a larger role in explaining the labor market behavior of SC/ST women. This could be, at least in part, due to the rapid convergence in levels of education between SC/STs and Hindus. While SC/ST levels of education are still the lowest among all groups, they have been the fastest to increase over the period under study. This convergence has been aided by affirmative action policies that guarantee 22.5% seats in higher education and public employment for SC/STs at the state and federal level.

On the other hand, given that a vast majority of SC/ST women continued to be employed in the agriculture sector, it become imperative to examine whether female LFPR among SC/ST and Hindus is being driven by economic opportunities or economic distress. To this effect, I examine how female LFPR for the three groups is associated with change in income. If the decision to enter the labor force is indeed driven by economic need, then we would expect LFPR to fall as incomes increase. Moreover, the decline will be sharper for those groups for which the relationship is stronger. To test this, I divide real income[15] into 250 quantiles and aggregate female LFPR for the three groups within each quantile. Figure 4 shows that both SC/ST and Hindu women's LFPR has a strong negative correlation with income whereas for Muslim women the relationship is relatively flat. The relationship has become more pronounced over the years. Descriptive statistics showed that female LFPR in India has been declining in recent years. The graph suggests two reasons why that may be happening- female LFPR is becoming more strongly associated with increases in income, and real incomes themselves are rising- both of which are correlated with lower rate of female employment.

Gaps by Religion: In contrast to SC/ST, the role of personal and household characteristics is almost negligible in explaining the Hindu-Muslim gap in LFPR. Regional characteristics more than account for

[15] We use household monthly per capita expenditure as a proxy for household income. Nominal values are converted to real values using publically available poverty lines. We use 1983 rural Maharashtra as the base. The method of calculating these poverty lines changed significantly in 2009-10, hence we restrict our analysis from the 38th to the 61st round to maintain consistency.

the entire explained gap between the two groups. On closer examination of the sample, the reason for this becomes clearer. More than half of the Muslim women in the sample come from the states of Bihar, Uttar Pradesh and West Bengal, whereas only 30% of Hindu women live in these states. However, it is in these three states that Hindu women have the lowest LFPR, hence when I give more weight to the Hindu women from these states, I close some of the gap between Hindus and Muslims. Figure 5 offers suggestive evidence for this hypothesis. I plot female LFPR for the two groups as a function of the proportion of Muslims in the region[16]. If female LFPR is depressed in areas where concentration of Muslims is high, we would expect LFPR to be negatively correlated with concentration of Muslims. Figure 5 confirms that areas with higher concentration of Muslims exhibit lower levels of female participation for all groups, not just Muslims. Descriptive statistics show that along with exhibiting higher rates of unemployment, Muslim women are also more likely to live in areas with higher male unemployment rate compared to the other two groups. This suggests that Muslim women are more likely to live in areas where opportunities for employment are low for both women and men. According to the Indian census, a majority of women in India move within the same district or state at the time of marriage. Such localized marriage markets could mean that Muslim women remain trapped in enclaves of low economic activity.

Without this regional heterogeneity, the gap between these two groups would have remained the same and would even have widened in some cases. For example, according to the 38th Round, if Hindus had the personal characteristics of Muslims, their LFPR would have been 1.2 percentage points higher than it was. This is similar to the result I saw in the Hindu-SC/ST comparison, where less educated and poorer Hindu and SC/ST women are more likely to participate in the labor force. Thus covariates, excluding spatial distribution, explain little to none of the reason behind the significantly lower LFPR of Muslim women in India.

[16] Each circle represents a sector-state-year combination and the size of each circle is proportional to the corresponding population weights. There are 2 sectors- rural and urban, 15 states and 7 years of data available.

8 Extensions

8.1 How does culture influence participation gaps?

In this section, I examine the role of culture in explaining the persistence or absence of Muslim women from the labor force. Das (2005) presents some anecdotal evidence from the Muslim Women's Survey that points to the practice of *purdah* or veiling among Muslim women as a factor in restricting their mobility for purpose of employment. She does however conclude that there is considerable heterogeneity across class divisions in the practice of purdah, and that lack of jobs (particularly agriculture based) outside the house contribute to Muslim women's concentration in home-based work. While most of the evidence on the role of culture remains anecdotal and descriptive, I try to offer some empirical evidence on this issue. The NSS does not collect any information on intra-household decision making, mobility or violence, so for this section I use data from the India Human Development Survey. The IHDS is a two panel nationally representative survey and I use the second wave (2011-12) of the survey. I am able to construct almost all the controls used in the main analysis, along with some controls for "culture". An advantage of this dataset is that it asks for measures of more permanent household wealth (such as ownership of durables and assets), along with flow variables such as income and consumption. I use a composite "asset" measure to control for HH wealth. This variable takes values from 0 to 33 and is a simple sum of assets owned by the household. I construct various measures for the culture variable using the "gender relations" part of the women's questionnaire. I divide gender relations this into 3 parts- mobility (0-4), attitude towards violence (0-6) and decision making (0-6). Each of these is constructed using answers to questions about these variables (higher is better)[17]. I also control for whether the woman observes covering of head/face and whether the woman says work decision is made by self or husband/someone else. In total, I have 5 controls for culture. Decomposition results from Table 7 show that while culture does play a small role in explaining the LFPR gap between Hindus and Muslims, the role of culture is not large enough to explain the persistently low LFPR for Muslim women. For example, column 2 of Table 7 shows that of the total Hindu-Muslim gap of 15.5 percentage points, culture explains only 1.8 percentage points. Much

[17] As an example, the question on mobility asks- Can you go to health clinic by your self- YES (1) or NO (0). There are 4 such questions. If a woman answers YES for all 4 she gets a mobility score of 4, if she answers YES for two NO for two her mobility score is 2.

of the Hindu-Muslim gap is explained by regional variables, as was seen in the main analysis using NSS data. For Muslim women, culture explains 28% of the explained and 11% of the overall Hindu-Muslim gap in female labor force participation.

8.2 Do alternative mappings change the results?

In the main analysis, for both DFL and Oaxaca-Blinder, I have reweighted Hindus to look take on the individual characteristics of Muslims or SC/STs. However, decomposition methods can be sensitive to the choice of the reference category or group. To test the generalizability of my results, I can use alternative reweighting methods and see how the results change with the alternative reference groups. In this section, I present two alternative reference categories. In the first case, I use SC/ST (or Muslims) as the reference category to compare with Hindus. In the second case, I use a pooled sample of the two groups to create a composite reference category. The results using SC/STs and Muslims as the reference category are reported in Tables A4 and A5 respectively, whereas the results using the pooled sample of Hindu-SC/ST and Hindu-Muslim is reported in Tables A6 and A7.

The results show that for SC/STs, the predicted gaps are quite similar across the different reference category choices, including when comparing with the predicted gaps obtained using DFL. On the other hand, the results for Muslims are slightly sensitive to the choice of reference category. For Muslims, all methodologies follow a similar pattern across the seven rounds of data, however they differ slightly in the magnitude of the predicted gap based on which reference category is used. This is not unexpected since we know that Muslim women's participation rate is less sensitive to background characteristics, and is also different in magnitude, compared to the other two groups. For example, figure 5 shows that while Hindu and SC/ST women's LFPR has a strong negative association with increases in income, Muslim women's participation rate is quite flat with respect to changes in real income.

The role of individual covariates is also largely similar for the different reference category choices. Personal and household characteristics accounts for majority of the explained gap between Hindus and

SC/STs, whereas regional variation does not play a major role. On the other hand, for Muslims both personal and household characteristics predict a negative gap, whereas regional variation account for more than the entire predicted gap. As an example, whether we use the Hindus or Muslims as a reference category, convergence in regional variation would reduce the Hindu-Muslim gap in 1983 by 4.9 percentage points. On the other hand, if we used the pooled reference category, convergence in regional heterogeneity would reduce the Hindu-Muslim gap by 5.7 percentage points.

8.3 How do results differ in rural and urban areas?

There has been considerable recent debate and discussion about the causes and consequences of stagnation of female participation in India's urban areas (Klasen & Pieters, 2015), and sharp decline in participation in rural areas (Chatterjee, Murgai, & Rama, 2015; Eswaran, Ramaswami, & Wadhwa, 2013). Given these differing trends in rural and urban areas, accompanied by the fact that SC/STs are concentrated in rural areas whereas Muslims are a more urban community relative to the average, it may be insightful to look at how results vary when considering these geographic differences separately.

In rural areas, the gap in LFPR between Hindus and SC/STs has been steadily narrowing over time- from 15% in 1983 to 8.9% in 2011. Unlike the aggregated sample, a smaller proportion of this gap is explained by differences in observable characteristics. This is predominantly because, while personal and household characteristics continue to explain much of the gap between the two groups, regional characteristics predict a negative, but statistically insignificant, gap. On the other hand, the LFPR gap between Hindus and Muslims in rural areas is higher than for the aggregate sample and continued to rise, before declining in recent years. Like before, all the explained gap is due to regional variation, while personal and household characteristics predict that the gap should be lower by 2.5-3 percentage points.

In urban areas as well, the gap between Hindus and SC/STs has been steadily narrowing from 12.4% in 1983 to 3.3% in 2011. Depending on the round, between 35-75% of this gap can be explained by differences in observable covariates, with household level variables accounting for much of this explained gap. Notably, while the Hindu LFPR has remained stagnant around 21%, the urban SC/ST participation rate has declined significantly over the years from 34% in 1983 to 24% in 2011. Like Hindus, the urban Muslim LFPR has also been stagnant around 18-14%. The gap between the two groups has also remained consistently between 4-6 percentage points. However, covariates predict a negative gap between the two groups. That is, if Hindus had the characteristics of urban Muslim women, their LFPR would have been 2-5 percentage points higher than it is. This is because urban Muslim women have household level characteristics that are strong predictors of female participation among Hindus, and this strong negative isn't offset by regional characteristics that only explain a small, and statistically insignificant, portion of the gap.

8.4 Has the predictive power of covariates declined?

The main results show that not only has the gap in LFPR between Hindus and Muslims remained consistently high, the explained portion of the gap has also declined over time. This could either be due to convergence in the level of covariates between the two groups, such as equalizing levels of income and education, or it could be due to a decline in the ability of the covariates to predict participation rates. To see which of these could explain the declining explained gap between Hindus and Muslims, I run the decomposition using a fixed Hindu mapping for all the rounds. In Table 1.20, the Hindu mapping from 1983-84 is used as the reference category and in Table 1.21 the 2009-10 Hindu mapping is used as the reference category. By fixing the mapping to a specific group/year, we are holding constant the explanatory power of the covariates (from the reference category), while allowing the level of the covariates to change over time. The results for both the mappings are quite similar in magnitude to the main results and show a similar declining trend in the explained Hindu-Muslim gap. This indicates that the results are not driven by the declining predictive power of covariates, but by convergence in covariate levels.

9 Discussion and Conclusion

I use data from 7 rounds of the NSS survey on employment in India to estimate the gaps in labor force participation rates between women from 3 different caste/religion groups, namely Hindus, Schedule Caste/Schedule Tribe and Muslims. I use two different decomposition methods to decompose the gap into a part explainable by differences in background characteristics and an unexplained component. Additionally, I also examined the role of individual covariates in explaining the predicted gap.

Several findings emerge from these results that can serve as input into formulating better targeted redistribution policies, as well as input into future research on the economics of inequality in the Indian context. My analysis showed that the gap in LFPR between Hindu and SC/ST women has been steadily narrowing over the years, however the gap between Hindu and Muslim women has remained consistently high. Moreover, while background characteristics explain over half of the Hindi-SC/ST gap, they explain very little of the Hindu-Muslim gap. My results show that the higher LFPR of SC/ST and Hindu women seems to be driven in large part due to poverty and economic distress and this is especially true for SC/ST women. It is hence not surprising that rising incomes are associated with withdrawal of women from the labor force in recent years across all groups.

Recognizing the need for looking at the role of culture and religion in explaining economic outcomes for women, particularly from multi-ethnic and diverse countries such as India, I examine the role of culture in explaining the persistently low LFPR of Muslim women. I find that culture plays a small but significant role. It is important to recognize that while culture may operate in conjunction with background characteristics to reinforce conventional economic relationships, it could also represent behaviors and unobservables that lead to outcomes that are contrary to what economic models predict.

Based on personal and household characteristics we would expect Muslims to exhibit significantly higher LFPR compared to their own current levels and compared to Hindus. However, I find that Muslim women's absence from the labor force cannot be explained by their low levels of education and income.

Moreover, contrary to popular rhetoric, culture does not seem to be an important predictor of the low Muslim female LFPR either. Overall my results show that while personal and household characteristics, such as low levels of education and income, play a critical role in explaining the high SC/ST female LFPR, they provide little to no insight into the persistently low rates of labor force participation of Muslim women. Finally, I find that geographic location plays an important role in explaining economic outcomes for women. I find that Muslim women's low LFPR is being driven largely by their concentration in areas of low economic activity which is also reflected in their high rates of unemployment. If avenues for mobility outside such areas are restricted by both lack of economic opportunities and cultural restrictions, then women can become trapped in a cycle of deprivation. These findings highlight not only the markedly different experiences of deprivation faced by women from minority communities in India, but also their widely varying response to this deprivation, thus underscoring the need for specifically targeted policies and intervention that address these needs.

APPENDICES

APPENDIX A

MAIN TABLES AND FIGURES

Table 1.1: Decomposition of Hindu-SC/ST LFPR Gap (DFL Method)

		38th 1983-84	43rd 1988-89	50th 1993-94	55th 1999-00	61st 2004-05	66th 2009-10	68th 2011-12
LFPR	Hindu	0.429	0.424	0.412	0.379	0.432	0.317	0.302
		(0.0438)***	(0.0496)***	(0.0503)***	(0.0458)***	(0.0426)***	(0.0387)***	(0.0364)***
	SC/ST	0.610	0.599	0.586	0.542	0.560	0.416	0.399
		(0.0463)***	(0.0449)***	(0.0480)***	(0.0456)***	(0.0430)***	(0.0422)***	(0.0363)***
	Hindu CF	0.515	0.503***	0.495***	0.460***	0.505***	0.369***	0.351***
		(0.0484)***	(0.0532)***	(0.0523)***	(0.0523)***	(0.0460)***	(0.0447)***	(0.0407)***
Gap	Total	-0.181	-0.175	-0.174	-0.162	-0.128	-0.0986	-0.0965
		(0.0309)	(0.0282)	(0.0293)	(0.0223)	(0.0247)	(0.0201)	(0.0167)
	Predicted	-0.0861	-0.0798	-0.0835	-0.0808	-0.0727	-0.0518	-0.0484
		(0.0181)	(0.0158)	(0.0161)	(0.0155)	(0.0149)	(0.0126)	(0.0122)
	Unexplained	-0.0950	-0.0955	-0.0910	-0.0815	-0.0551	-0.0469	-0.0481
		(0.0232)	(0.0219)	(0.0224)	(0.0187)	(0.0180)	(0.0133)	(0.0132)

Note: Hindu CF is the Hindu population reweighted to look like SC/ST population, Standard errors are reported in parenthesis. *p-value≤0.10, ** p-value≤0.05, *** p-value≤0.01

Table 1.2: Decomposition of Hindu-Muslim LFPR Gap (DFL Method)

		38th 1983-84	43rd 1988-89	50th 1993-94	55th 1999-00	61st 2004-05	66th 2009-10	68th 2011-12
LFPR	Hindu	0.429	0.424	0.412	0.379	0.432	0.317	0.302
		(0.0438)***	(0.0496)***	(0.0503)***	(0.0458)***	(0.0426)***	(0.0387)***	(0.0364)***
	Muslim	0.262	0.273	0.232	0.228	0.253	0.184	0.203
		(0.0237)***	(0.0279)***	(0.0213)***	(0.0167)***	(0.0180)***	(0.0174)***	(0.0210)***
	Hindu CF	0.391	0.374	0.362	0.335	0.393	0.305	0.292
		(0.0355)***	(0.0404)***	(0.0394)***	(0.0411)***	(0.0363)***	(0.0353)***	(0.0302)***
Gap	Total	0.168	0.151	0.180	0.151	0.179	0.133	0.0996
		(0.0318)	(0.0356)	(0.0345)	(0.0388)	(0.0320)	(0.0273)	(0.0272)
	Predicted	0.0388	0.0498	0.0499	0.0448	0.0390	0.0119	0.0101
		(0.0138)	(0.0157)	(0.0132)	(0.0232)	(0.0158)	(0.0158)	(0.0131)
	Unexplained	0.129	0.101	0.130	0.106	0.140	0.121	0.0894
		(0.0212)	(0.0218)	(0.0238)	(0.0363)	(0.0256)	(0.0244)	(0.0240)

Note: Hindu CF is the Hindu population reweighted to look like Muslim population, Standard errors are reported in parenthesis. *p-value≤0.10, ** p-value≤0.05, *** p-value≤0.01

Table 1.3: Decomposition of Hindu-SC/ST LFPR Gap (Oaxaca-Blinder Method)

		38th 1983-84	43rd 1988-89	50th 1993-94	55th 1999-00	61st 2004-05	66th 2009-10	68th 2011-12
LFPR	Hindu	0.4294	0.4236	0.4120	0.3794	0.4324	0.3174	0.3025
		(0.0409)***	(0.0462)***	(0.0460)***	(0.0421)***	(0.0399)***	(0.0358)***	(0.0334)***
	SC/ST	0.6104	0.5989	0.5864	0.5416	0.5601	0.4160	0.3989
		(0.0433)***	(0.0434)***	(0.0452)***	(0.0424)***	(0.0405)***	(0.0396)***	(0.0339)***
Gap	Difference	-0.1811	-0.1753	-0.1745	-0.1622	-0.1278	-0.0986	-0.0965
		(0.0305)***	(0.0282)***	(0.0278)***	(0.0231)***	(0.0248)***	(0.0204)***	(0.0173)***
	Predicted	-0.0867	-0.0803	-0.0870	-0.0799	-0.0758	-0.0475	-0.0481
		(0.0182)***	(0.0192)***	(0.0173)***	(0.0149)***	(0.0149)***	(0.0136)***	(0.0119)***
	Unexplained	-0.0944	-0.0950	-0.0875	-0.0823	-0.0520	-0.0511	-0.0484
		(0.0270)***	(0.0226)***	(0.0228)***	(0.0197)***	(0.0195)***	(0.0195)***	(0.0157)***
Predicted Gap	Personal	-0.0301	-0.0299	-0.0429	-0.0326	-0.0331	-0.0280	-0.0238
		(0.0057)***	(0.0057)***	(0.0062)***	(0.0052)***	(0.0049)***	(0.0068)***	(0.0054)***
	Household	-0.0408	-0.0451	-0.0408	-0.0357	-0.0308	-0.0157	-0.0166
		(0.0061)***	(0.0051)***	(0.0043)***	(0.0039)***	(0.0049)***	(0.0043)***	(0.0040)***
	Regional	-0.0159	-0.0053	-0.0033	-0.0116	-0.0118	-0.0039	-0.0077
		(0.0134)	(0.0153)	(0.0143)	(0.0117)	(0.0108)	(0.0094)	(0.0094)
N		110,851	119,416	106,574	112,356	111,815	87,764	87,346
Explained (% of total)		47.87	45.81	49.86	49.26	59.31	48.17	49.84

Note: Standard errors are reported in parenthesis. *p-value≤0.10, ** p-value≤0.05, *** p-value≤0.01

Table 1.4: Decomposition of Hindu-Muslim LFPR Gap (Oaxaca-Blinder Method)

		38th 1983-84	43rd 1988-89	50th 1993-94	55th 1999-00	61st 2004-05	66th 2009-10	68th 2011-12
LFPR	Hindu	0.4294	0.4236	0.4120	0.3794	0.4324	0.3174	0.3025
		(0.0409)***	(0.0462)***	(0.0460)***	(0.0421)***	(0.0399)***	(0.0358)***	(0.0334)***
	Muslim	0.2618	0.2730	0.2323	0.2285	0.2529	0.1840	0.2029
		(0.0241)***	(0.0272)***	(0.0219)***	(0.0182)***	(0.0189)***	(0.0175)***	(0.0223)***
Gap	Difference	0.1675	0.1507	0.1797	0.1510	0.1795	0.1334	0.0996
		(0.0315)***	(0.0336)***	(0.0339)***	(0.0368)***	(0.0314)***	(0.0261)***	(0.0268)***
	Predicted	0.0206	0.0281	0.0295	0.0269	0.0122	-0.0014	-0.0019
		(0.0305)	(0.0305)	(0.0286)	(0.0287)	(0.0259)	(0.0225)	(0.0206)
	Unexplained	0.1470	0.1225	0.1502	0.1240	0.1673	0.1348	0.1015
		(0.0214)***	(0.0201)***	(0.0205)***	(0.0272)***	(0.0194)***	(0.0213)***	(0.0199)***
Predicted Gap	Personal	-0.0127	-0.0102	-0.0158	-0.0086	-0.0094	-0.0141	-0.0081
		(0.0044)***	(0.0052)*	(0.0065)**	(0.0061)	(0.0061)	(0.0058)**	(0.0045)*
	Household	-0.0159	-0.0188	-0.0196	-0.0175	-0.0192	-0.0087	-0.0135
		(0.0059)***	(0.0061)***	(0.0055)***	(0.0061)***	(0.0061)***	(0.0039)**	(0.0039)***
	Regional	0.0493	0.0572	0.0648	0.0529	0.0408	0.0214	0.0197
		(0.0259)*	(0.0253)**	(0.0223)***	(0.0245)**	(0.0213)*	(0.0198)	(0.0189)
N		99,524	108,986	93,522	99,432	98,912	78,311	80,085
Explained (% of total)		12.30	18.65	16.42	17.81	6.80	-1.05	-1.91

Note: Standard errors are reported in parenthesis. *p-value≤0.10, ** p-value≤0.05, *** p-value≤0.01

Table 1.5: Decomposition of Hindu-SC/ST LFPR Gap (Oaxaca-Blinder Method including Predicted Income)

		38th 1983-84	43rd 1988-89	50th 1993-94	55th 1999-00	61st 2004-05	66th 2009-10	68th 2011-12
LFPR	Hindu	0.429	0.424	0.412	0.379	0.432	0.317	0.302
		(0.0409)***	(0.0462)***	(0.0461)***	(0.0425)***	(0.0400)***	(0.0359)***	(0.0334)***
	SC/ST	0.610	0.599	0.586	0.542	0.560	0.416	0.399
		(0.0433)***	(0.0434)***	(0.0452)***	(0.0427)***	(0.0407)***	(0.0397)***	(0.0340)***
Gap	Difference	-0.1811	-0.1753	-0.1745	-0.1622	-0.1278	-0.0986	-0.0965
		(0.0305)***	(0.0282)***	(0.0278)***	(0.0229)***	(0.0248)***	(0.0204)***	(0.0174)***
	Predicted	-0.0854	-0.0870	-0.1096	-0.1395	-0.1144	-0.0592	-0.0544
		(0.0255)***	(0.0256)***	(0.0190)***	(0.0233)***	(0.0166)***	(0.0152)***	(0.0158)***
	Unexplained	-0.0957	-0.0883	-0.0649	-0.0227	-0.0134	-0.0394	-0.0421
		(0.0325)***	(0.0278)***	(0.0244)***	(0.0264)	(0.0217)	(0.0207)*	(0.0187)**
Predicted Gap	Personal	-0.0301	-0.0298	-0.0427	-0.0323	-0.0327	-0.0280	-0.0237
		(0.0057)***	(0.0057)***	(0.0062)***	(0.0049)***	(0.0048)***	(0.0067)***	(0.0054)***
	Household	-0.0415	-0.0416	-0.0257	0.0023	-0.0064	-0.0075	-0.0127
		(0.0068)***	(0.0089)***	(0.0079)***	(0.0133)	(0.0074)	(0.0098)	(0.0092)
	Regional	-0.0160	-0.0040	0.0010	0.0050	-0.0016	0.0009	-0.0054
		(0.0136)	(0.0157)	(0.0144)	(0.0134)	(0.0107)	(0.0113)	(0.0109)
	Predicted Inc.	0.0021	-0.0116	-0.0422	-0.1145	-0.0738	-0.0247	-0.0125
		(0.0241)	(0.0284)	(0.0200)**	(0.0377)***	(0.0188)***	(0.0217)	(0.0261)
N		110,851	119,416	106,574	112,356	111,815	87,764	87,346
Explained (% of total)		47.16	49.63	62.81	86.00	89.51	60.04	56.37

Note: Standard errors are reported in parenthesis. *p-value≤0.10, ** p-value≤0.05, *** p-value≤0.01

Table 1.6: Decomposition of Hindu-Muslim LFPR Gap (Oaxaca-Blinder Method including Predicted Income)

		38th 1983-84	43rd 1988-89	50th 1993-94	55th 1999-00	61st 2004-05	66th 2009-10	68th 2011-12
LFPR	Hindu	0.429	0.424	0.412	0.379	0.432	0.317	0.302
		(0.0409)***	(0.0462)***	(0.0461)***	(0.0425)***	(0.0400)***	(0.0359)***	(0.0334)***
	Muslim	0.262	0.273	0.232	0.228	0.253	0.184	0.203
		(0.0240)***	(0.0273)***	(0.0216)***	(0.0179)***	(0.0188)***	(0.0176)***	(0.0224)***
Gap	Difference	0.1675	0.1507	0.1797	0.1510	0.1795	0.1334	0.0996
		(0.0315)***	(0.0336)***	(0.0339)***	(0.0371)***	(0.0317)***	(0.0263)***	(0.0267)***
	Predicted	0.0210	0.0273	0.0226	-0.0005	-0.0024	-0.0059	-0.0031
		(0.0311)	(0.0305)	(0.0285)	(0.0303)	(0.0262)	(0.0228)	(0.0207)
	Unexplained	0.1465	0.1234	0.1570	0.1515	0.1819	0.1392	0.1026
		(0.0220)***	(0.0201)***	(0.0206)***	(0.0292)***	(0.0205)***	(0.0218)***	(0.0203)***
Predicted Gap	Personal	-0.0127	-0.0102	-0.0156	-0.0084	-0.0092	-0.0141	-0.0080
		(0.0044)***	(0.0052)*	(0.0065)**	(0.0060)	(0.0060)	(0.0058)**	(0.0046)*
	Household	-0.0164	-0.0158	-0.0058	0.0241	0.0079	0.0006	-0.0085
		(0.0077)**	(0.0091)*	(0.0077)	(0.0137)*	(0.0071)	(0.0101)	(0.0108)
	Regional	0.0493	0.0570	0.0637	0.0412	0.0321	0.0208	0.0194
		(0.0259)*	(0.0254)**	(0.0216)***	(0.0276)	(0.0215)	(0.0202)	(0.0191)
	Predicted Inc.	0.0009	-0.0037	-0.0197	-0.0575	-0.0332	-0.0132	-0.0059
		(0.0107)	(0.0091)	(0.0097)**	(0.0236)**	(0.0116)***	(0.0118)	(0.0125)
N		99,524	108,986	93,522	99,432	98,912	78,311	80,085
Explained (% of total)		12.54	18.12	12.58	-0.33	-1.34	-4.42	-3.11

Note: Standard errors are reported in parenthesis. *p-value≤0.10, ** p-value≤0.05, *** p-value≤0.01

Table 1.7: Measuring Role of Culture-IHDS II (Oaxaca Blinder Method)

		Hindu-SC/ST	Hindu-Muslim
LFPR	Hindu	0.389	0.389
		(.005)***	(0.005)***
	SC/ST or Muslim	0.510	0.233
		(.008)***	(0.009)***
	Difference	-0.122	0.155
		(.009)***	(0.010)***
	Predicted	-0.081	0.063
		(.005)***	(0.007)***
	Unexplained	-0.040	0.092
		(.009)***	(0.011)***
Explained	Personal	-0.008	-0.001
		(.003)***	(0.003)
	Household	-0.016	-0.008
		(.003)***	(0.003)***
	Regional	-0.001	0.071
		(.003)	(0.004)***
	Assets/Wealth	-0.042	-0.017
		(.004)***	(0.002)***
	Culture	-0.014	0.018
		(.002)**	(0.004)***
N		26,208	20,955

Note: Standard errors are reported in parenthesis. *p-value≤0.10, ** p-value≤0.05, *** p-value≤0.01

Table 1.8: Summary of Culture Variable- IHDS

	Hindu	Muslim	SC/ST
Mobility (0-4)	2.65	2.56	2.70
Decision making (0-6)	1.46	1.39	1.51
Violence (0-6)	2.97	2.85	2.91
Woman decides whether to work (0/1)	0.35	0.30	0.45
Observe head/face covering (0/1)	0.56	0.87	0.57

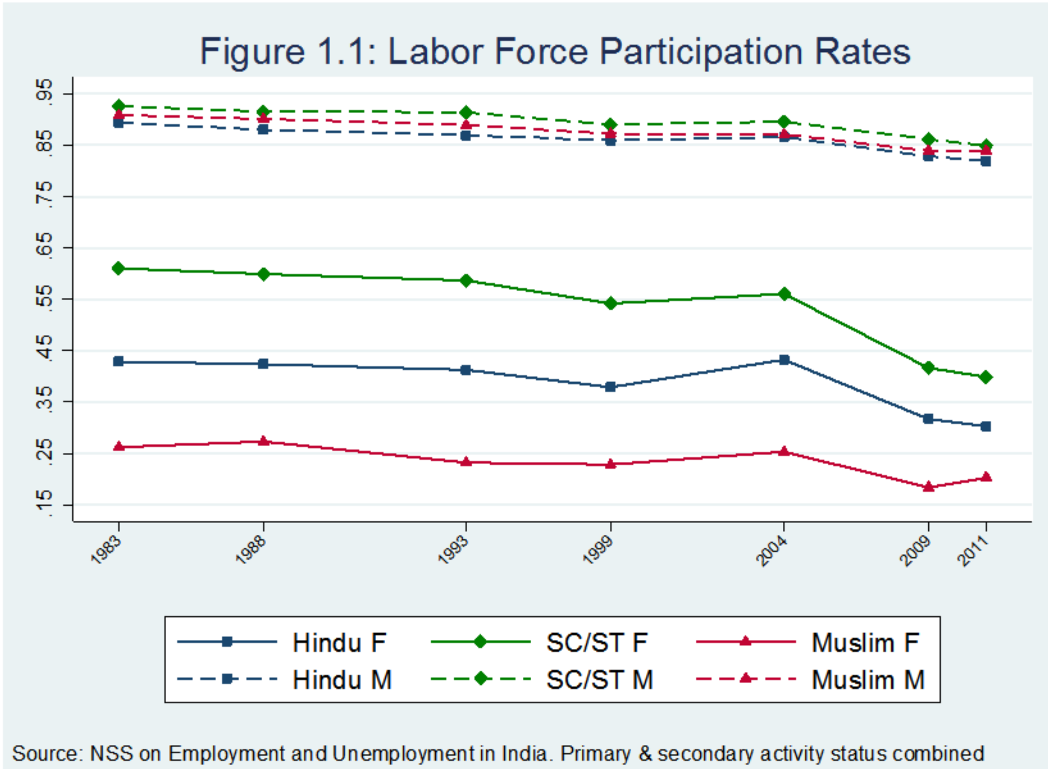


Figure 1.1: Labor Force Participation Rates
.15
.25
.35
.45
.55
.65
.75
.85
.95
1983
1988
1993
1999
2004
2009
2011
Hindu F
SC/ST F
Muslim F
Hindu M
SC/ST M
Muslim M
Source: NSS on Employment and Unemployment in India. Primary & secondary activity status combined

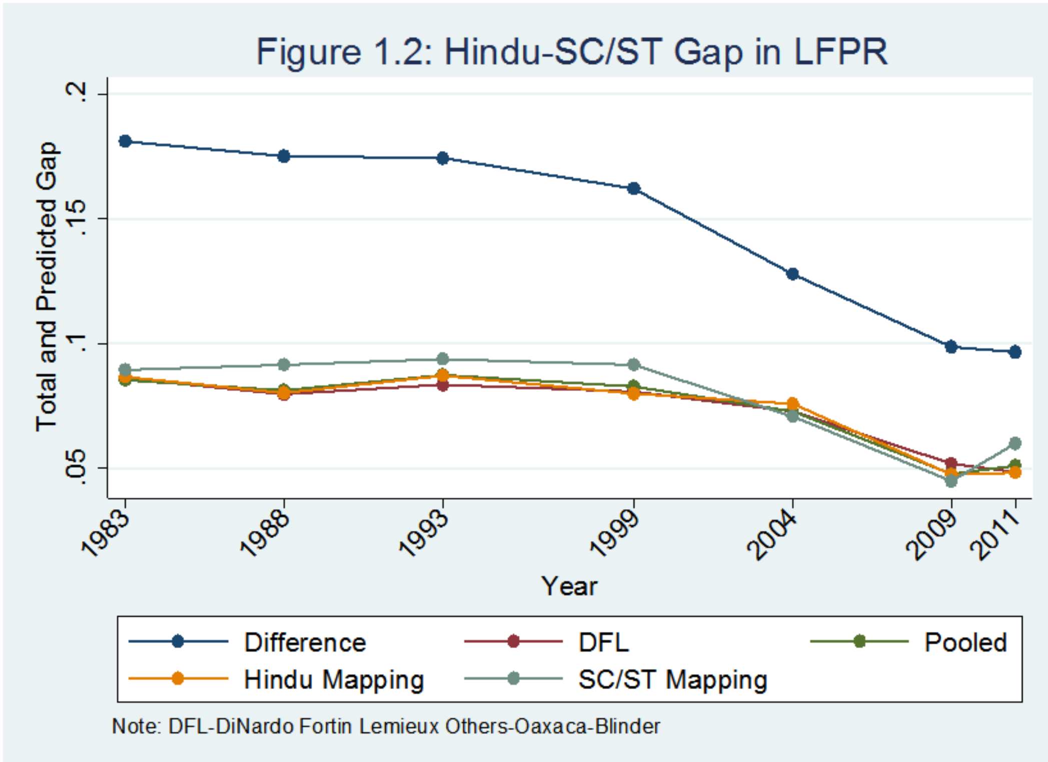


Figure 1.2: Hindu-SC/ST Gap in LFPR
Total and Predicted Gap
.05
.1
.15
.2
1983
1988
1993
1999
2004
2009
2011
Year
Difference
DFL
Pooled
Hindu Mapping
SC/ST Mapping
Note: DFL-DiNardo Fortin Lemieux Others-Oaxaca-Blinder

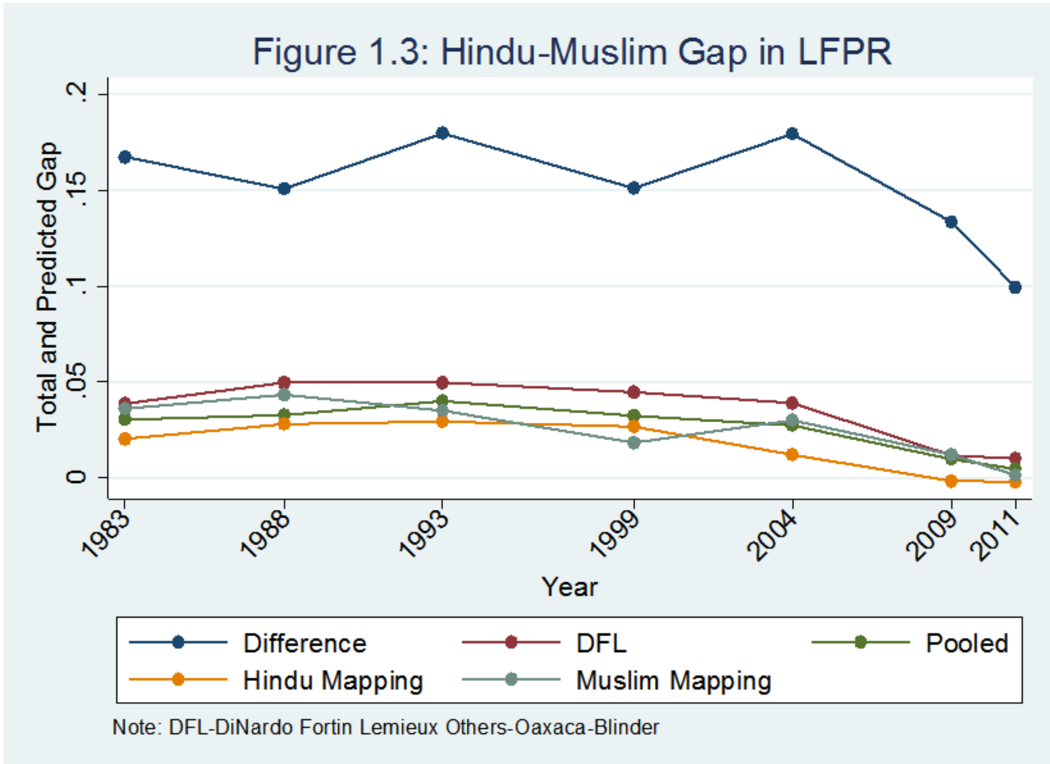


Figure 1.3: Hindu-Muslim Gap in LFPR
Total and Predicted Gap
0
.05
.1
.15
.2
1983
1988
1993
1999
2004
2009
2011
Year
Difference
DFL
Pooled
Hindu Mapping
Muslim Mapping
Note: DFL-DiNardo Fortin Lemieux Others-Oaxaca-Blinder

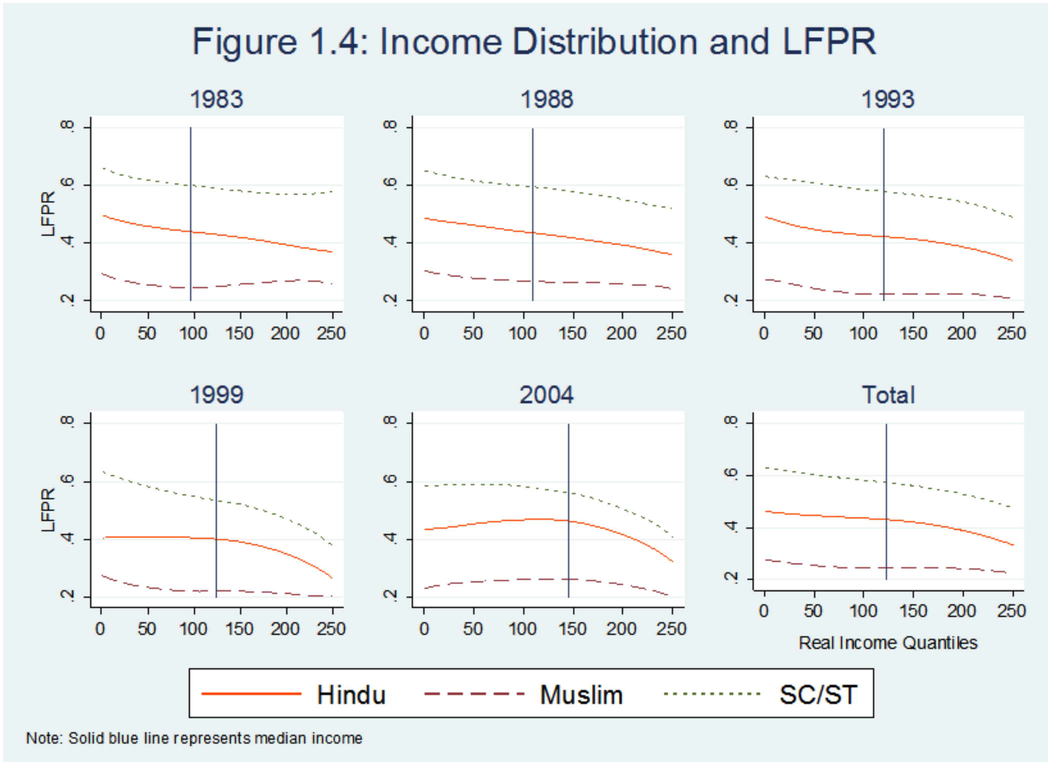


Figure 1.4: Income Distribution and LFPR
1983
1988
1993
1999
2004
Total
LFPR
.2
.4
.6
.8
0
50
100
150
200
250
Real Income Quantiles
Hindu
Muslim
SC/ST
Note: Solid blue line represents median income

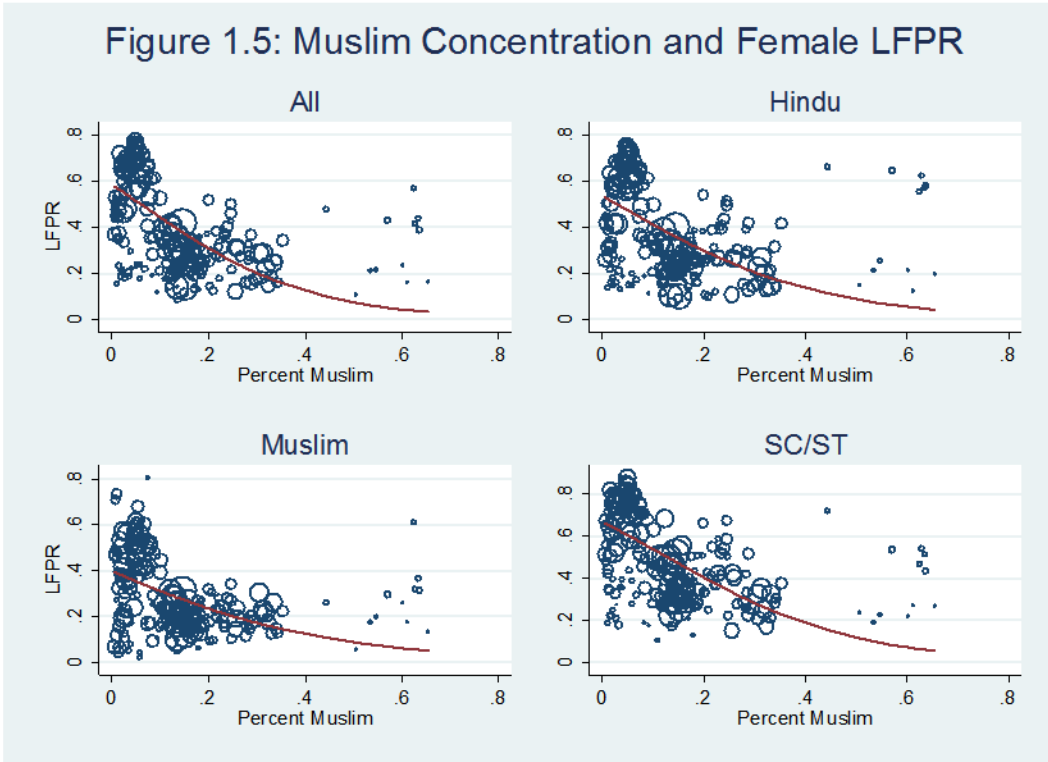


Figure 1.5: Muslim Concentration and Female LFPR
All
Hindu
Muslim
SC/ST
LFPR
Percent Muslim
0
.2
.4
.6
.8

APPENDIX B

SUPPLEMENTARY TABLES AND FIGURES

Table 1.9: Descriptive Statistics- Hindus

		38		43		50		55		61		66		68	
		Mean	*SE*	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Age Group	15-24	35.29	0.201	34.66	0.195	33.44	0.208	31.79	0.227	31.12	0.241	28.93	0.338	28.72	0.328
	25-39	37.07	0.203	37.98	0.2	38.84	0.217	40.47	0.243	39.98	0.255	40.76	0.37	40.81	0.356
	40-49	16.35	0.154	16.27	0.15	16.57	0.163	16.62	0.182	17.64	0.195	18.6	0.29	18.56	0.276
	50-59	11.29	0.137	11.09	0.127	11.15	0.139	11.13	0.149	11.26	0.159	11.71	0.245	11.92	0.229
Education	No Education	63.39	0.199	59.56	0.197	52.28	0.221	46.07	0.245	40.17	0.256	31.93	0.368	29.77	0.353
	Below Primary	7.86	0.108	8.94	0.114	9.36	0.128	8.81	0.134	8.72	0.145	8.35	0.222	8.6	0.208
	Primary	11.7	0.13	11.87	0.127	11.23	0.141	10.87	0.156	12.2	0.17	12.12	0.252	10.92	0.226
	Middle	9.02	0.112	9.29	0.112	11.97	0.138	14.58	0.171	16.23	0.189	16.83	0.27	16.61	0.258
	Secondary & higher	8.04	0.112	10.34	0.112	15.15	0.151	19.67	0.196	22.68	0.21	30.77	0.324	34.1	0.326
Head Age Group	0-30	15.85	0.159	15.18	0.151	13.44	0.157	11.51	0.166	9.85	0.166	8.63	0.22	8.79	0.22
	30-45	35.46	0.199	36.46	0.2	37.21	0.214	38.13	0.24	38.2	0.255	37.95	0.364	38.61	0.357
	45-60	35.82	0.202	35.99	0.195	37.27	0.213	36.68	0.235	37.62	0.247	39.4	0.369	38.67	0.347
	60-99	12.86	0.141	12.38	0.13	12.08	0.143	13.69	0.159	14.34	0.172	14.02	0.245	13.93	0.23
Head Education	No Education	41.72	0.207	38.88	0.205	34.67	0.214	32.59	0.231	29.99	0.242	25.8	0.35	25.03	0.338
	Below Primary	16.33	0.167	17.33	0.154	15.98	0.162	14.35	0.168	12.59	0.166	10.67	0.237	11.64	0.24
	Primary	16.4	0.15	16.1	0.146	14.36	0.154	13.11	0.176	14.43	0.182	14.2	0.266	12.17	0.231
	Middle	11.69	0.131	11.22	0.123	13.58	0.151	14.77	0.17	15.95	0.186	16.37	0.271	16.54	0.261
	Secondary & higher	13.87	0.146	16.46	0.144	21.41	0.175	25.18	0.211	27.03	0.23	32.95	0.338	34.61	0.329
Rural		74.39	0.174	75.18	0.161	72.62	0.18	71.58	0.221	71.61	0.236	68.82	0.31	68.38	0.302
Married		80.44	0.164	80.31	0.159	79.19	0.176	79.11	0.194	78.76	0.209	78.3	0.3	78.19	0.29
Salaried Men in HH		23.06	0.176	24.73	0.178	24.02	0.185	23.26	0.215	22.86	0.216	22.86	0.283	23.64	0.274
Female Headed		3.86	0.087	3.86	0.078	3.86	0.082	4.63	0.097	4.75	0.106	5.07	0.154	5.16	0.147
Children Below 5		1	0.005	0.94	0.005	0.81	0.005	0.78	0.005	0.72	0.005	0.61	0.007	0.51	0.006
HH Size		6.54	0.013	6.33	0.012	5.95	0.011	6.06	0.014	5.8	0.014	5.43	0.018	5.3	0.017
Unemployment Rate in Region		2.1	0.007	2.62	0.007	2.03	0.006	2.04	0.008	1.81	0.007	1.34	0.007	1.56	0.008
Secondary Education Rate in Region		14.99	0.045	17.59	0.044	23.14	0.053	27.11	0.065	28.86	0.072	36.65	0.108	38.21	0.101

Table 1.9 (cont'd)

Log MPCE	4.69	*0.004*	4.99	*0.005*	5.71	*0.002*	6.2	*0.003*	6.44	*0.003*	6.93	*0.004*	7.22	*0.004*
N	*80,369*		*88,261*		*78,794*		*80,154*		*79,067*		*61,829*		*62,090*	

Table 1.10: Descriptive Statistics- Muslims

		38		43		50		55		61		66		68	
		Mean	*SE*	Mean	*SE*	Mean	*SE*	Mean	*SE*	Mean	*SE*	Mean	*SE*	Mean	*SE*
Age Group	15-24	37.26	*0.447*	37.31	*0.455*	36.23	*0.481*	37.4	*0.582*	37.67	*0.52*	36.87	*0.731*	35.72	*0.674*
	25-39	37.45	*0.47*	37.82	*0.462*	39.59	*0.49*	39.38	*0.558*	37.29	*0.512*	38.39	*0.744*	38.53	*0.692*
	40-49	15.54	*0.33*	14.77	*0.326*	14.58	*0.347*	14.6	*0.413*	15.74	*0.391*	16.08	*0.546*	16.44	*0.517*
	50-59	9.75	*0.269*	10.1	*0.283*	9.59	*0.292*	8.62	*0.278*	9.31	*0.309*	8.66	*0.437*	9.31	*0.396*
Education	No Education	72.03	*0.441*	69.29	*0.408*	61.84	*0.475*	54.92	*0.563*	48.81	*0.535*	41.92	*0.768*	37.88	*0.708*
	Below Primary	9.81	*0.341*	10.96	*0.275*	11.9	*0.317*	11.03	*0.311*	11.85	*0.33*	11.13	*0.473*	11.43	*0.478*
	Primary	9.48	*0.264*	9.76	*0.254*	10.21	*0.291*	11.73	*0.319*	13.33	*0.345*	14.91	*0.545*	14.48	*0.499*
	Middle	5.28	*0.213*	5.94	*0.189*	9.38	*0.275*	12.19	*0.352*	13.54	*0.331*	15.1	*0.496*	15.6	*0.473*
	Secondary & higher	3.39	*0.156*	4.05	*0.155*	6.68	*0.215*	10.13	*0.273*	12.46	*0.364*	16.95	*0.518*	20.62	*0.507*
Head Age Group	0-30	17.63	*0.364*	18.3	*0.39*	17.07	*0.391*	14.74	*0.511*	11.87	*0.365*	11.57	*0.527*	10.38	*0.444*
	30-45	37.53	*0.467*	36.01	*0.454*	38.6	*0.487*	39.82	*0.57*	38.21	*0.517*	38.3	*0.733*	37.21	*0.694*
	45-60	33.64	*0.435*	34.08	*0.443*	33.8	*0.464*	34.45	*0.531*	37.74	*0.522*	37.01	*0.724*	39.85	*0.685*
	60-99	11.2	*0.274*	11.62	*0.275*	10.52	*0.32*	11	*0.295*	12.18	*0.312*	13.13	*0.548*	12.56	*0.436*
Head Education	No Education	53.43	*0.472*	51.19	*0.47*	48.63	*0.501*	44.79	*0.591*	44.05	*0.536*	40.04	*0.755*	39.25	*0.718*
	Below Primary	16.87	*0.393*	17.61	*0.344*	17.51	*0.374*	17.26	*0.436*	15.5	*0.365*	13	*0.506*	14.29	*0.49*
	Primary	13.81	*0.305*	14.7	*0.309*	13.04	*0.333*	12.65	*0.326*	15.57	*0.364*	16.3	*0.568*	15.74	*0.495*
	Middle	8.22	*0.24*	8.11	*0.236*	9.79	*0.282*	11.35	*0.31*	11.32	*0.309*	13.83	*0.496*	14.13	*0.468*
	Secondary & higher	7.67	*0.251*	8.39	*0.228*	11.03	*0.289*	13.95	*0.372*	13.57	*0.381*	16.82	*0.549*	16.6	*0.438*
Rural		65.31	*0.438*	68.55	*0.401*	65.18	*0.441*	65.02	*0.484*	66.48	*0.506*	65.7	*0.641*	63.05	*0.632*
Married		78.5	*0.373*	78.92	*0.374*	78.47	*0.398*	76.2	*0.453*	74.08	*0.471*	74.4	*0.642*	73.53	*0.613*
Salaried Men in HH		19.33	*0.35*	18.57	*0.332*	17.56	*0.357*	18.61	*0.38*	17.71	*0.398*	18.66	*0.516*	18.74	*0.494*
Female Headed		4.52	*0.183*	4.69	*0.175*	4.95	*0.209*	5.67	*0.22*	6.21	*0.237*	6.03	*0.311*	7.07	*0.349*
Children Below 5		1.23	*0.012*	1.18	*0.01*	1.06	*0.011*	1.05	*0.013*	0.92	*0.012*	0.75	*0.017*	0.73	*0.014*
HH Size		7	*0.03*	6.83	*0.028*	6.44	*0.028*	6.81	*0.039*	6.57	*0.031*	6	*0.039*	6.09	*0.035*
Unemployment Rate in Region		2.47	*0.017*	2.81	*0.018*	2.29	*0.015*	2.5	*0.015*	1.98	*0.015*	1.57	*0.014*	1.8	*0.018*
Secondary Education Rate in Region		17.26	*0.11*	19.41	*0.1*	24.9	*0.126*	28.66	*0.158*	29.45	*0.147*	36.16	*0.242*	38.32	*0.216*

Table 1.10 (cont'd)

Log MPCE	4.55	*0.009*	4.88	*0.011*	5.58	*0.005*	6.06	*0.008*	6.3	*0.005*	6.76	*0.007*	7.07	*0.007*
N	19,155		20,726		14,728		19,278		19,845		16,482		17,995	

Table 1.11: Descriptive Statistics- SC/ST

		38		43		50		55		61		66		68	
		Mean	*SE*	Mean	*SE*	Mean	*SE*	Mean	*SE*	Mean	*SE*	Mean	*SE*	Mean	*SE*
Age Group	15-24	34.41	*0.314*	35.16	*0.308*	32.46	*0.32*	32.77	*0.34*	33.03	*0.362*	32.21	*0.532*	31.69	*0.511*
	25-39	38.01	*0.324*	38.27	*0.316*	40.17	*0.335*	40.51	*0.347*	40.09	*0.379*	40.45	*0.555*	40.93	*0.546*
	40-49	17.02	*0.287*	15.73	*0.235*	16.49	*0.259*	16.53	*0.269*	16.83	*0.289*	17.16	*0.428*	16.8	*0.406*
	50-59	10.56	*0.199*	10.83	*0.2*	10.88	*0.212*	10.19	*0.212*	10.05	*0.229*	10.19	*0.338*	10.59	*0.357*
Education	No Education	86.96	*0.224*	85.16	*0.218*	78.89	*0.273*	70.16	*0.338*	62.87	*0.366*	50.22	*0.566*	47.62	*0.556*
	Below Primary	4.31	*0.13*	4.55	*0.128*	6.71	*0.169*	7.34	*0.182*	8.33	*0.207*	9.53	*0.347*	9.89	*0.339*
	Primary	4.62	*0.145*	4.95	*0.132*	5.76	*0.154*	7.59	*0.207*	9.88	*0.221*	12.52	*0.369*	11.92	*0.358*
	Middle	2.88	*0.111*	3.34	*0.112*	5.07	*0.145*	8.21	*0.186*	10.5	*0.231*	13.14	*0.377*	14.58	*0.377*
	Secondary & higher	1.23	*0.071*	2	*0.079*	3.58	*0.12*	6.7	*0.217*	8.41	*0.201*	14.59	*0.352*	15.99	*0.361*
Head Age Group	0-30	21.47	*0.268*	22.52	*0.277*	19.64	*0.275*	16.46	*0.259*	14.42	*0.275*	13.37	*0.39*	12.84	*0.377*
	30-45	38.13	*0.324*	37.65	*0.314*	39.69	*0.335*	41.22	*0.357*	41.18	*0.381*	41.61	*0.56*	41.76	*0.548*
	45-60	32.44	*0.328*	32.12	*0.299*	33.29	*0.322*	33.63	*0.331*	35.29	*0.366*	36.67	*0.545*	36.29	*0.529*
	60-99	7.96	*0.17*	7.71	*0.167*	7.38	*0.175*	8.69	*0.185*	9.11	*0.217*	8.36	*0.292*	9.12	*0.314*
Head Education	No Education	67.57	*0.323*	66.42	*0.302*	62.27	*0.33*	57.01	*0.355*	51.76	*0.385*	45.31	*0.568*	43.1	*0.557*
	Below Primary	14.08	*0.258*	13.65	*0.217*	14.54	*0.242*	13.7	*0.233*	14.16	*0.273*	12.8	*0.391*	14.53	*0.391*
	Primary	9.86	*0.198*	10.16	*0.198*	9.79	*0.199*	10.01	*0.203*	12.39	*0.246*	14.01	*0.391*	13.7	*0.38*
	Middle	5.19	*0.138*	5.63	*0.139*	6.97	*0.172*	9.27	*0.197*	11.09	*0.235*	13.03	*0.362*	13.26	*0.358*
	Secondary & higher	3.29	*0.132*	4.14	*0.124*	6.43	*0.161*	10.01	*0.262*	10.6	*0.232*	14.85	*0.36*	15.41	*0.353*
Rural		86.57	*0.227*	87.46	*0.185*	86.49	*0.199*	84.13	*0.226*	83.72	*0.275*	83.6	*0.314*	81.52	*0.346*
Married		83.95	*0.235*	83.78	*0.233*	83.08	*0.252*	80.88	*0.291*	79.67	*0.304*	78.35	*0.461*	78.48	*0.445*
Salaried Men in HH		16.34	*0.242*	16.74	*0.231*	14.26	*0.226*	15.11	*0.293*	15.96	*0.274*	15.52	*0.342*	16.83	*0.369*
Female Headed		2.7	*0.1*	3.06	*0.11*	3.21	*0.119*	3.44	*0.119*	4.66	*0.155*	4.95	*0.239*	5.48	*0.244*
Children Below 5		1	*0.008*	1.01	*0.007*	0.88	*0.007*	0.83	*0.007*	0.8	*0.008*	0.65	*0.01*	0.58	*0.01*
HH Size		5.99	*0.02*	5.82	*0.016*	5.54	*0.016*	5.78	*0.017*	5.66	*0.019*	5.37	*0.025*	5.25	*0.024*
Unemployment Rate in Region		1.65	*0.01*	2.11	*0.01*	1.72	*0.009*	1.75	*0.009*	1.61	*0.01*	1.21	*0.01*	1.38	*0.011*
Secondary Education Rate in Region		11.45	*0.062*	13.78	*0.054*	18.37	*0.065*	22.68	*0.075*	24.45	*0.088*	31.36	*0.128*	33.11	*0.134*

Table 1.11 (cont'd)

Log MPCE	4.39	*0.007*	4.65	*0.009*	5.42	*0.003*	5.94	*0.003*	6.13	*0.003*	6.62	*0.005*	6.9	*0.005*
N	30,482		31,156		27,780		32,202		32,748		25,935		25,256	

Table 1.12: Decomposition of Hindu-SC/ST LFPR Gap (Oaxaca-Blinder Method- SC/ST Mapping)

		38th 1983-84	43rd 1988-89	50th 1993-94	55th 1999-00	61st 2004-05	66th 2009-10	68th 2011-12
LFPR	Hindu	0.4294	0.4236	0.4120	0.3794	0.4324	0.3174	0.3025
		(0.0409)***	(0.0462)***	(0.0460)***	(0.0421)***	(0.0399)***	(0.0358)***	(0.0334)***
	SC/ST	0.6104	0.5989	0.5864	0.5416	0.5601	0.4160	0.3989
		(0.0433)***	(0.0434)***	(0.0452)***	(0.0424)***	(0.0405)***	(0.0396)***	(0.0339)***
Gap	Difference	-0.1811	-0.1753	-0.1745	-0.1622	-0.1278	-0.0986	-0.0965
		(0.0305)***	(0.0282)***	(0.0278)***	(0.0231)***	(0.0248)***	(0.0204)***	(0.0173)***
	Predicted	-0.0894	-0.0914	-0.0938	-0.0915	-0.0707	-0.0448	-0.0600
		(0.0223)***	(0.0234)***	(0.0223)***	(0.0177)***	(0.0187)***	(0.0162)***	(0.0135)***
	Unexplained	-0.0917	-0.0839	-0.0806	-0.0707	-0.0571	-0.0538	-0.0365
		(0.0236)***	(0.0197)***	(0.0177)***	(0.0157)***	(0.0159)***	(0.0130)***	(0.0140)***
Predicted Gap	Personal	-0.0267	-0.0295	-0.0327	-0.0365	-0.0325	-0.0284	-0.0265
		(0.0056)***	(0.0052)***	(0.0053)***	(0.0062)***	(0.0061)***	(0.0067)***	(0.0061)***
	Household	-0.0385	-0.0456	-0.0453	-0.0365	-0.0246	-0.0158	-0.0195
		(0.0055)***	(0.0060)***	(0.0065)***	(0.0045)***	(0.0046)***	(0.0045)***	(0.0035)***
	Regional	-0.0242	-0.0163	-0.0158	-0.0186	-0.0136	-0.0006	-0.0140
		(0.0182)	(0.0189)	(0.0179)	(0.0146)	(0.0152)	(0.0141)	(0.0104)
N		110,851	119,416	106,574	112,356	111,815	87,764	87,346
Explained (% of total)		49.36	52.14	53.75	56.41	55.32	45.44	62.18

Note: Standard errors are reported in parenthesis. *p-value≤0.10, ** p-value≤0.05, *** p-value≤0.01

Table 1.13: Decomposition of Hindu-Muslim LFPR Gap (Oaxaca-Blinder Method-Muslim Mapping)

		38th 1983-84	43rd 1988-89	50th 1993-94	55th 1999-00	61st 2004-05	66th 2009-10	68th 2011-12
LFPR	Hindu	0.4294	0.4236	0.4120	0.3794	0.4324	0.3174	0.3025
		(0.0409)***	(0.0462)***	(0.0460)***	(0.0421)***	(0.0399)***	(0.0358)***	(0.0334)***
	Muslim	0.2618	0.2730	0.2323	0.2285	0.2529	0.1840	0.2029
		(0.0241)***	(0.0272)***	(0.0219)***	(0.0182)***	(0.0189)***	(0.0175)***	(0.0223)***
Gap	Difference	0.1675	0.1507	0.1797	0.1510	0.1795	0.1334	0.0996
		(0.0315)***	(0.0336)***	(0.0339)***	(0.0368)***	(0.0314)***	(0.0261)***	(0.0268)***
	Predicted	0.0362	0.0434	0.0353	0.0185	0.0301	0.0122	0.0015
		(0.0220)*	(0.0255)*	(0.0192)*	(0.0184)	(0.0186)	(0.0142)	(0.0186)
	Unexplained	0.1314	0.1073	0.1444	0.1325	0.1493	0.1211	0.0981
		(0.0181)***	(0.0185)***	(0.0215)***	(0.0262)***	(0.0230)***	(0.0210)***	(0.0170)***
Predicted Gap	Personal	-0.0030	-0.0029	-0.0034	-0.0051	-0.0011	-0.0005	-0.0138
		(0.0027)	(0.0039)	(0.0035)	(0.0053)	(0.0038)	(0.0030)	(0.0056)**
	Household	-0.0097	-0.0062	-0.0135	-0.0089	-0.0106	-0.0118	-0.0007
		(0.0045)**	(0.0045)	(0.0045)***	(0.0054)*	(0.0049)**	(0.0053)**	(0.0037)
	Regional	0.0490	0.0525	0.0521	0.0325	0.0418	0.0246	0.0159
		(0.0203)**	(0.0231)**	(0.0171)***	(0.0147)**	(0.0155)***	(0.0119)**	(0.0167)
N		99,524	108,986	93,522	99,432	98,912	78,311	80,085
Explained (% of total)		21.61	28.80	19.64	12.25	16.77	9.15	1.51

Note: Standard errors are reported in parenthesis. *p-value≤0.10, ** p-value≤0.05, *** p-value≤0.01

Table 1.14: Decomposition of Hindu-SC/ST LFPR Gap (Oaxaca-Blinder Method-Pooled Mapping)

		38th 1983-84	43rd 1988-89	50th 1993-94	55th 1999-00	61st 2004-05	66th 2009-10	68th 2011-12
LFPR	Hindu	0.4294	0.4236	0.4120	0.3794	0.4324	0.3174	0.3025
		(0.0409)***	(0.0462)***	(0.0460)***	(0.0421)***	(0.0399)***	(0.0358)***	(0.0334)***
	SC/ST	0.6104	0.5989	0.5864	0.5416	0.5601	0.4160	0.3989
		(0.0433)***	(0.0434)***	(0.0452)***	(0.0424)***	(0.0405)***	(0.0396)***	(0.0339)***
Gap	Difference	-0.1811	-0.1753	-0.1745	-0.1622	-0.1278	-0.0986	-0.0965
		(0.0305)***	(0.0282)***	(0.0278)***	(0.0231)***	(0.0248)***	(0.0204)***	(0.0173)***
	Predicted	-0.0854	-0.0812	-0.0874	-0.0828	-0.0727	-0.0478	-0.0511
		(0.0191)***	(0.0200)***	(0.0188)***	(0.0159)***	(0.0161)***	(0.0140)***	(0.0121)***
	Unexplained	-0.0957	-0.0941	-0.0871	-0.0795	-0.0551	-0.0508	-0.0454
		(0.0252)***	(0.0210)***	(0.0203)***	(0.0176)***	(0.0176)***	(0.0156)***	(0.0144)***
Predicted Gap	Personal	-0.0275	-0.0286	-0.0384	-0.0323	-0.0320	-0.0281	-0.0243
		(0.0057)***	(0.0054)***	(0.0058)***	(0.0054)***	(0.0049)***	(0.0064)***	(0.0053)***
	Household	-0.0403	-0.0449	-0.0420	-0.0362	-0.0291	-0.0144	-0.0168
		(0.0058)***	(0.0050)***	(0.0045)***	(0.0035)***	(0.0044)***	(0.0037)***	(0.0033)***
	Regional	-0.0176	-0.0077	-0.0070	-0.0142	-0.0116	-0.0053	-0.0099
		(0.0149)	(0.0162)	(0.0153)	(0.0129)	(0.0124)	(0.0112)	(0.0094)
N		110,851	119,416	106,574	112,356	111,815	87,764	87,346
Explained (% of total)		47.16	46.32	50.09	51.05	56.89	48.48	52.95

Note: Standard errors are reported in parenthesis. *p-value≤0.10, ** p-value≤0.05, *** p-value≤0.01

Table 1.15: Decomposition of Hindu-Muslim LFPR Gap (Oaxaca-Blinder Method-Pooled Mapping)

		38th 1983-84	43rd 1988-89	50th 1993-94	55th 1999-00	61st 2004-05	66th 2009-10	68th 2011-12
LFPR	Hindu	0.4294	0.4236	0.4120	0.3794	0.4324	0.3174	0.3025
		(0.0409)***	(0.0462)***	(0.0460)***	(0.0421)***	(0.0399)***	(0.0358)***	(0.0334)***
	Muslim	0.2618	0.2730	0.2323	0.2285	0.2529	0.1840	0.2029
		(0.0241)***	(0.0272)***	(0.0219)***	(0.0182)***	(0.0189)***	(0.0175)***	(0.0223)***
Gap	Difference	0.1675	0.1507	0.1797	0.1510	0.1795	0.1334	0.0996
		(0.0315)***	(0.0336)***	(0.0339)***	(0.0368)***	(0.0314)***	(0.0261)***	(0.0268)***
	Predicted	0.0304	0.0327	0.0403	0.0325	0.0275	0.0099	0.0047
		(0.0289)	(0.0302)	(0.0290)	(0.0276)	(0.0257)	(0.0206)	(0.0204)
	Unexplained	0.1371	0.1180	0.1394	0.1185	0.1520	0.1235	0.0949
		(0.0195)***	(0.0185)***	(0.0206)***	(0.0253)***	(0.0184)***	(0.0187)***	(0.0170)***
Predicted Gap	Personal	-0.0119	-0.0096	-0.0144	-0.0086	-0.0089	-0.0127	-0.0099
		(0.0041)***	(0.0049)*	(0.0060)**	(0.0057)	(0.0055)	(0.0053)**	(0.0045)**
	Household	-0.0151	-0.0168	-0.0187	-0.0166	-0.0177	-0.0092	-0.0112
		(0.0055)***	(0.0058)***	(0.0053)***	(0.0058)***	(0.0056)***	(0.0039)**	(0.0032)***
	Regional	0.0575	0.0591	0.0734	0.0577	0.0541	0.0317	0.0258
		(0.0247)**	(0.0255)**	(0.0237)***	(0.0231)**	(0.0212)**	(0.0173)*	(0.0179)
N		99,524	108,986	93,522	99,432	98,912	78,311	80,085
Explained (% of total)		18.15	21.70	22.43	21.52	15.32	7.42	4.72

Note: Standard errors are reported in parenthesis. *p-value≤0.10, ** p-value≤0.05, *** p-value≤0.01

Table 1.16: Decomposition of Rural Hindu-SC/ST LFPR Gap (Oaxaca-Blinder Method)

		38th 1983-84	43rd 1988-89	50th 1993-94	55th 1999-00	61st 2004-05	66th 2009-10	68th 2011-12
LFPR	Hindu	0.5024	0.4888	0.4827	0.4525	0.5051	0.3738	0.3457
		(0.0538)***	(0.0637)***	(0.0663)***	(0.0599)***	(0.0544)***	(0.0540)***	(0.0530)***
	SC/ST	0.6522	0.6342	0.6267	0.5899	0.6083	0.4468	0.4345
		(0.0517)***	(0.0509)***	(0.0545)***	(0.0519)***	(0.0485)***	(0.0506)***	(0.0440)***
Gap	Difference	-0.1498	-0.1453	-0.1440	-0.1374	-0.1032	-0.0729	-0.0889
		(0.0366)***	(0.0354)***	(0.0375)***	(0.0291)***	(0.0318)***	(0.0245)***	(0.0238)***
	Predicted	-0.0468	-0.0429	-0.0406	-0.0450	-0.0365	-0.0165	-0.0266
		(0.0186)**	(0.0197)**	(0.0221)*	(0.0199)**	(0.0180)**	(0.0185)	(0.0197)
	Unexplained	-0.1030	-0.1025	-0.1034	-0.0924	-0.0667	-0.0564	-0.0622
		(0.0312)***	(0.0248)***	(0.0264)***	(0.0224)***	(0.0198)***	(0.0189)***	(0.0169)***
Predicted Gap	Personal	-0.0258	-0.0274	-0.0373	-0.0296	-0.0270	-0.0233	-0.0208
		(0.0051)***	(0.0053)***	(0.0055)***	(0.0053)***	(0.0045)***	(0.0070)***	(0.0058)***
	Household	-0.0315	-0.0343	-0.0311	-0.0263	-0.0242	-0.0092	-0.0123
		(0.0052)***	(0.0039)***	(0.0031)***	(0.0033)***	(0.0048)***	(0.0045)**	(0.0041)***
	Regional	0.0106	0.0188	0.0278	0.0109	0.0147	0.0160	0.0065
		(0.0178)	(0.0197)	(0.0211)	(0.0179)	(0.0157)	(0.0150)	(0.0188)
N		75,109	80,973	68,669	71,579	74,452	54,902	55,137
Explained (% of total)		31.24	29.53	28.19	32.75	35.37	22.63	29.92

Note: Standard errors are reported in parenthesis. *p-value≤0.10, ** p-value≤0.05, *** p-value≤0.01

Table 1.17: Decomposition of Rural Hindu-Muslim LFPR Gap (Oaxaca-Blinder Method)

		38th 1983-84	43rd 1988-89	50th 1993-94	55th 1999-00	61st 2004-05	66th 2009-10	68th 2011-12
LFPR	Hindu	0.5024	0.4888	0.4827	0.4525	0.5051	0.3738	0.3457
		(0.0538)***	(0.0637)***	(0.0663)***	(0.0599)***	(0.0544)***	(0.0540)***	(0.0530)***
	Muslim	0.3087	0.3165	0.2576	0.2683	0.2889	0.2055	0.2317
		(0.0324)***	(0.0413)***	(0.0349)***	(0.0217)***	(0.0280)***	(0.0275)***	(0.0328)***
Gap	Difference	0.1937	0.1723	0.2250	0.1843	0.2162	0.1683	0.1140
		(0.0364)***	(0.0419)***	(0.0429)***	(0.0483)***	(0.0404)***	(0.0343)***	(0.0350)***
	Predicted	0.0408	0.0545	0.0785	0.0774	0.0546	0.0371	0.0324
		(0.0324)	(0.0364)	(0.0355)**	(0.0478)	(0.0356)	(0.0376)	(0.0324)
	Unexplained	0.1529	0.1178	0.1465	0.1068	0.1617	0.1312	0.0816
		(0.0268)***	(0.0257)***	(0.0218)***	(0.0496)**	(0.0253)***	(0.0361)***	(0.0368)**
Predicted Gap	Personal	-0.0109	-0.0093	-0.0144	-0.0095	-0.0068	-0.0145	-0.0070
		(0.0047)**	(0.0066)	(0.0082)*	(0.0083)	(0.0076)	(0.0076)*	(0.0057)
	Household	-0.0144	-0.0153	-0.0160	-0.0152	-0.0175	-0.0069	-0.0096
		(0.0055)***	(0.0058)***	(0.0055)***	(0.0057)***	(0.0061)***	(0.0040)*	(0.0039)**
	Regional	0.0661	0.0790	0.1090	0.1022	0.0788	0.0585	0.0491
		(0.0308)**	(0.0330)**	(0.0291)***	(0.0458)**	(0.0344)**	(0.0352)*	(0.0332)
N		61,166	68,389	54,654	57,652	61,828	45,034	47,021
Explained (% of total)		21.06	31.63	34.89	42.00	25.25	22.04	28.42

Note: Standard errors are reported in parenthesis. *p-value≤0.10, ** p-value≤0.05, *** p-value≤0.01

Table 1.18: Decomposition of Urban Hindu-SC/ST LFPR Gap (Oaxaca-Blinder Method)

		38th 1983-84	43rd 1988-89	50th 1993-94	55th 1999-00	61st 2004-05	66th 2009-10	68th 2011-12
LFPR	Hindu	0.2171	0.2261	0.2244	0.1953	0.2488	0.1927	0.2090
		(0.0197)***	(0.0249)***	(0.0219)***	(0.0208)***	(0.0231)***	(0.0217)***	(0.0174)***
	SC/ST	0.3411	0.3528	0.3286	0.2855	0.3125	0.2589	0.2419
		(0.0194)***	(0.0276)***	(0.0240)***	(0.0192)***	(0.0230)***	(0.0193)***	(0.0161)***
Gap	Difference	-0.1239	-0.1267	-0.1041	-0.0903	-0.0636	-0.0662	-0.0329
		(0.0136)***	(0.0149)***	(0.0106)***	(0.0143)***	(0.0151)***	(0.0096)***	(0.0082)***
	Predicted	-0.0534	-0.0556	-0.0535	-0.0367	-0.0468	-0.0235	-0.0173
		(0.0095)***	(0.0131)***	(0.0097)***	(0.0115)***	(0.0111)***	(0.0090)***	(0.0063)***
	Unexplained	-0.0706	-0.0711	-0.0506	-0.0536	-0.0168	-0.0427	-0.0156
		(0.0140)***	(0.0191)***	(0.0127)***	(0.0142)***	(0.0155)	(0.0114)***	(0.0088)*
Predicted Gap	Personal	-0.0189	-0.0112	-0.0169	-0.0077	-0.0174	-0.0057	-0.0056
		(0.0056)***	(0.0054)**	(0.0036)***	(0.0052)	(0.0059)***	(0.0040)	(0.0050)
	Household	-0.0448	-0.0562	-0.0442	-0.0388	-0.0291	-0.0246	-0.0171
		(0.0058)***	(0.0074)***	(0.0069)***	(0.0058)***	(0.0071)***	(0.0045)***	(0.0045)***
	Regional	0.0103	0.0117	0.0076	0.0098	-0.0003	0.0068	0.0053
		(0.0050)**	(0.0050)**	(0.0034)**	(0.0060)	(0.0054)	(0.0060)	(0.0036)
N		35,742	38,443	37,905	40,777	37,363	32,862	32,209
Explained (% of total)		43.10	43.88	51.39	40.64	73.58	35.50	52.58

Note: Standard errors are reported in parenthesis. *p-value≤0.10, ** p-value≤0.05, *** p-value≤0.01

Table 1.19: Decomposition of Urban Hindu-Muslim LFPR Gap (Oaxaca-Blinder Method)

		38th 1983-84	43rd 1988-89	50th 1993-94	55th 1999-00	61st 2004-05	66th 2009-10	68th 2011-12
LFPR	Hindu	0.2171	0.2261	0.2244	0.1953	0.2488	0.1927	0.2090
		(0.0197)***	(0.0249)***	(0.0219)***	(0.0208)***	(0.0231)***	(0.0217)***	(0.0174)***
	Muslim	0.1735	0.1780	0.1849	0.1545	0.1815	0.1428	0.1538
		(0.0172)***	(0.0218)***	(0.0147)***	(0.0119)***	(0.0092)***	(0.0105)***	(0.0118)***
Gap	Difference	0.0436	0.0481	0.0395	0.0408	0.0674	0.0499	0.0553
		(0.0125)***	(0.0172)***	(0.0213)*	(0.0220)*	(0.0281)**	(0.0273)*	(0.0217)**
	Predicted	-0.0468	-0.0456	-0.0406	-0.0312	-0.0379	-0.0201	-0.0231
		(0.0113)***	(0.0170)***	(0.0128)***	(0.0125)**	(0.0148)**	(0.0124)	(0.0108)**
	Unexplained	0.0904	0.0937	0.0802	0.0720	0.1052	0.0700	0.0783
		(0.0119)***	(0.0189)***	(0.0164)***	(0.0175)***	(0.0247)***	(0.0246)***	(0.0223)***
Predicted Gap	Personal	-0.0176	-0.0081	-0.0101	-0.0014	-0.0131	-0.0045	-0.0029
		(0.0060)***	(0.0055)	(0.0058)*	(0.0058)	(0.0076)*	(0.0047)	(0.0067)
	Household	-0.0438	-0.0493	-0.0440	-0.0335	-0.0297	-0.0179	-0.0260
		(0.0093)***	(0.0118)***	(0.0102)***	(0.0097)***	(0.0108)***	(0.0082)**	(0.0077)***
	Regional	0.0146	0.0119	0.0135	0.0037	0.0049	0.0023	0.0058
		(0.0133)	(0.0106)	(0.0104)	(0.0106)	(0.0129)	(0.0118)	(0.0112)
N		38,358	40,597	38,868	41,780	37,084	33,277	33,064
Explained (% of total)		-107.34	-94.80	-102.78	-76.47	-56.23	-40.28	-41.77

Note: Standard errors are reported in parenthesis. *p-value≤0.10, ** p-value≤0.05, *** p-value≤0.01

Table 1.20: Decomposition of Hindu-Muslim LFPR Gap (Oaxaca-Blinder Method-Hindu 38th Round Mapping)

		38th 1983-84	43rd 1988-89	50th 1993-94	55th 1999-00	61st 2004-05	66th 2009-10	68th 2011-12
LFPR	Hindu	0.4294	0.4236	0.4120	0.3794	0.4324	0.3174	0.3025
		(0.0409)***	(0.0462)***	(0.0460)***	(0.0421)***	(0.0399)***	(0.0358)***	(0.0334)***
	Muslim	0.2618	0.2730	0.2323	0.2285	0.2529	0.1840	0.2029
		(0.0241)***	(0.0272)***	(0.0219)***	(0.0182)***	(0.0189)***	(0.0175)***	(0.0223)***
Gap	Difference	0.1675	0.1507	0.1797	0.1510	0.1795	0.1334	0.0996
		(0.0315)***	(0.0336)***	(0.0339)***	(0.0368)***	(0.0314)***	(0.0261)***	(0.0268)***
	Predicted	0.0206	0.0160	0.0222	0.0154	0.0062	-0.0058	-0.0001
		(0.0305)	(0.0293)	(0.0322)	(0.0338)	(0.0323)	(0.0297)	(0.0308)
	Unexplained	0.1470	0.1346	0.1574	0.1356	0.1733	0.1391	0.0997
		(0.0214)***	(0.0218)***	(0.0268)***	(0.0250)***	(0.0253)***	(0.0248)***	(0.0188)***
Predicted Gap	Personal	-0.0127	-0.0118	-0.0106	-0.0083	-0.0074	-0.0065	-0.0044
		(0.0044)***	(0.0052)**	(0.0055)*	(0.0058)	(0.0056)	(0.0051)	(0.0052)
	Household	-0.0159	-0.0188	-0.0229	-0.0196	-0.0231	-0.0249	-0.0248
		(0.0059)***	(0.0059)***	(0.0065)***	(0.0072)***	(0.0073)***	(0.0061)***	(0.0067)***
	Regional	0.0493	0.0466	0.0558	0.0432	0.0366	0.0257	0.0290
		(0.0259)*	(0.0243)*	(0.0262)**	(0.0270)	(0.0263)	(0.0260)	(0.0260)
N		99,524	108,986	93,522	99,432	98,912	78,311	80,085
Explained (% of total)		12.30	10.62	12.35	10.20	3.45	-4.35	-0.10

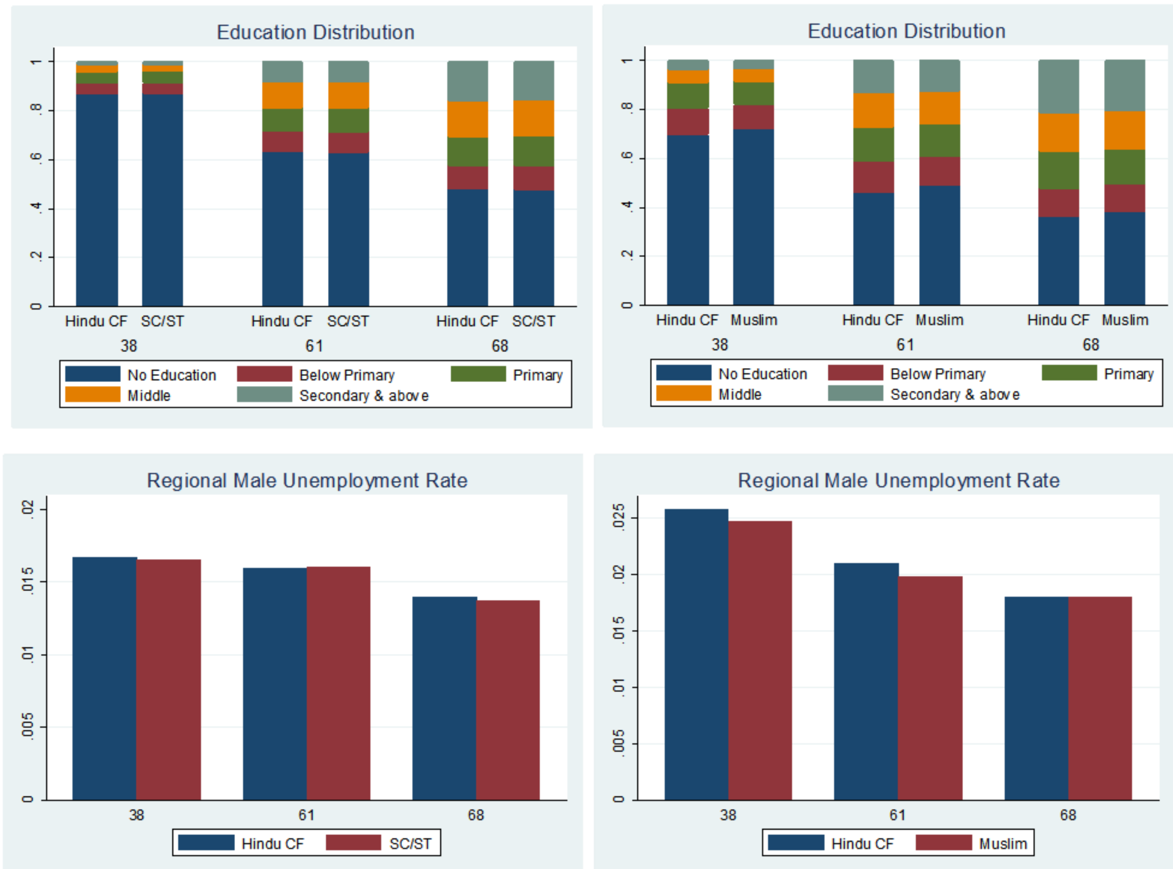
Note: Standard errors are reported in parenthesis. *p-value≤0.10, ** p-value≤0.05, *** p-value≤0.01

Table 1.21: Decomposition of Hindu-Muslim LFPR Gap (Oaxaca-Blinder Method-Hindu 68th Round Mapping)

		38th 1983-84	43rd 1988-89	50th 1993-94	55th 1999-00	61st 2004-05	66th 2009-10	68th 2011-12
LFPR	Hindu	0.4294	0.4236	0.4120	0.3794	0.4324	0.3174	0.3025
		(0.0409)***	(0.0462)***	(0.0460)***	(0.0421)***	(0.0399)***	(0.0358)***	(0.0334)***
	Muslim	0.2618	0.2730	0.2323	0.2285	0.2529	0.1840	0.2029
		(0.0241)***	(0.0272)***	(0.0219)***	(0.0182)***	(0.0189)***	(0.0175)***	(0.0223)***
Gap	Difference	0.1675	0.1507	0.1797	0.1510	0.1795	0.1334	0.0996
		(0.0315)***	(0.0336)***	(0.0339)***	(0.0368)***	(0.0314)***	(0.0261)***	(0.0268)***
	Predicted	0.0147	0.0177	0.0257	0.0106	0.0100	0.0015	-0.0019
		(0.0231)	(0.0244)	(0.0212)	(0.0225)	(0.0228)	(0.0207)	(0.0206)
	Unexplained	0.1528	0.1329	0.1540	0.1404	0.1695	0.1318	0.1015
		(0.0235)***	(0.0244)***	(0.0233)***	(0.0283)***	(0.0224)***	(0.0197)***	(0.0199)***
Predicted Gap	Personal	-0.0101	-0.0102	-0.0116	-0.0085	-0.0069	-0.0090	-0.0081
		(0.0042)**	(0.0047)**	(0.0050)**	(0.0053)	(0.0054)	(0.0045)**	(0.0045)*
	Household	-0.0050	-0.0078	-0.0093	-0.0086	-0.0120	-0.0126	-0.0135
		(0.0029)*	(0.0031)**	(0.0035)***	(0.0037)**	(0.0039)***	(0.0039)***	(0.0039)***
	Regional	0.0299	0.0358	0.0466	0.0276	0.0290	0.0231	0.0197
		(0.0210)	(0.0226)	(0.0182)**	(0.0197)	(0.0207)	(0.0183)	(0.0189)
N		99,524	108,986	93,522	99,432	98,912	78,311	80,085
Explained (% of total)		8.78	11.75	14.30	7.02	5.57	1.12	-1.91

Note: Standard errors are reported in parenthesis. *p-value≤0.10, ** p-value≤0.05, *** p-value≤0.01

Figure 1.6: Comparing Counterfactual Populations



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Chapter 2

The Two Bengals: Female Labor Force Participation in West Bengal and Bangladesh[1]

1 Introduction

Till the British granted independence to India and Pakistan in 1947, the area that now covers West Bengal and Bangladesh was part of the larger Bengal presidency under colonial rule. The war of 1971 saw East Pakistan gain independence from Pakistan and embark on a new political journey as the country now known as Bangladesh. Both West Bengal and Bangladesh have undergone rapid changes, both economic and political over the last 68 years but retain a shared culture, history and topography. Despite these commonalities, both regions exhibit very different levels of socio-economic development, one of which is the wide disparity in female labor force participation. Rapid development in garment manufacturing since the 1990s and more recently, community and health service, has driven young women to join the labor force in large numbers in Bangladesh. On the other hand, LFPR for women remains abysmally low in West Bengal and is among the lowest across all major Indian states.

The aim of this paper is twofold- firstly, we want to study what proportion of the LFPR differences between women from the two regions can be explained by differences in observable characteristics and second, we want to know how much each category (individual, household, regional) of observables explain this gap in LFPR[2]. We employ two widely used decomposition methods to disaggregate the gap into an explained and unexplained part, and then use further decomposition to disaggregate the explained gap into various components. The paper is divided as follows: the second section offers a brief review of

[1] This paper is co-authored with Maitreyi Bordia Das.

[2] Unless specified, throughout the paper we refer to 'gap' as the difference between the LFPR of women in Bangladesh and the LFPR of women in West Bengal (or vice-versa).

literature related to economic and political participation of women in Bangladesh and West Bengal, the third section details the methodology, the fourth section explains our data and summary statistics, the fifth section explains the main results and the sixth section concludes.

2 Review of Literature

Female labor supply has been a subject of widespread economic enquiry (Altonji & Blank, 1999; Blau & Kahn, 2013) for many decades. At the micro level, economists have studied the effect of mother's labor supply on outcomes such as cognitive development and schooling of children (Blau & Grossberg, 1992; Brooks–Gunn, Han, & Waldfogel, 2002; Ruhm, 2004), whereas at the macro level various studies document the relationship between female LFP and economic growth (Bhalotra & Umana-Aponte, 2010; Klasen & Pieters, 2012). There is also an extensive literature on the complex relationship between female labor supply and fertility decisions. Of particular interest to us is the wave of relatively recent literature that studies the role of culture and attitudes in determining economic outcomes (Almond et. al, 2013), particularly female labor supply (Antecol, 2003; Fernandez, 2007). Culture, though hard to quantify, could play an important role in explaining difference in outcomes for females across social groups, religions and even regions. This section outlines some of the major research on female labor force participation and employment in Bangladesh and West Bengal to identify broad trends in the literature and areas for future research.

2.1 Female labor in Bangladesh

Bangladeshi women's participation in paid work has risen rapidly in the last two decades sparking a renewed academic interest in studying their labor market behaviors and outcomes. This increase in female LFP is driven largely by two major sectors- the NGO and services sector and the garment manufacturing sector. The importance of the readymade garment (RMG) sector to the economy of Bangladesh cannot be underscored. The RMG sector is the largest manufacturing industry in the country and the single largest source of foreign exchange, making up almost 3/4th of total exports of Bangladesh. The industry started small in the late 1970s, grew rapidly in the 1980s and flourished in the 1990s, aided largely by tariff-free access to the US markets. International financing and buying houses entered the Bangladeshi RMG sector in the early 1990's opening the sector to a wider international market. The industry grew rapidly with a large number of RMG factories concentrated heavily in downtown Dhaka, and Chittagong serving as the main port. There were concerns that the removal of multi-fiber agreement quotas in 2005 would hurt Bangladeshi exporters however, contrary to all predictions the Bangladesh textiles and garments industry has not only survived but has actually thrived in the years following 2005. Not only have the exports been increasing in real and nominal terms, the contribution of the textiles and garments industry to total exports also peaked at 74-75% in 2008-09[3]. Owing to the fact that the sector is heavily dependent on a large workforce consisting mainly of low paid young female labor, it is not surprising that Bangladesh has managed to remain competitive in the international RMG market despite increased competition from countries like Cambodia, Vietnam and the Philippines. However, women's conditions of work, wages and benefits at these factories has sparked national, and more recently international debate following a slew of devastatingly fatal accidents involving garment factories (New York Times, 2013). Islam and Zahid (2012) survey 110 respondents from 11 factories in Dhaka to study the socio-economic status of female garment workers. Among other findings, they show that these women report a marked increase in frequent and occasional illness after beginning work in RMG factories compared to before. An earlier study (Paul-Majumder & Begum, 2000) uses survey data from 1990-1997 and finds evidence for high gender-based gaps in wages and access to benefits as well as significantly higher job volatility for women[4]. At the other of the spectrum, some authors have argued that the spread of the RMG sector in Bangladesh has benefitted young women. Heath and Mobarak (2015) use a survey of close to 1400 households in 60 villages around Dhaka and find that girls who live in villages where a garment factory is within commuting distance, are more likely to stay in school and to delay marriage and childbirth. There are others who offer a more neutral stance on the RMG sector. Hossain (2012) concludes that despite very obvious wage and benefits inequality among male and female workers in RMG

[3] Author's calculations from data available with Bangladesh Bank, Central Bank of Bangladesh
[4] Also see War on Want (2011)

manufacturing, work in the sector has led to socio-economic empowerment of women and girls in the form of more mobility, consciousness of rights and socio-political agency.

The trends seen in the RMG sector are mirrored in the general patterns of female employment in Bangladesh. Aggregated data shows that despite agriculture being the single largest employer of women in the country, the proportion of women in this sector is the lowest across all South Asian countries (World Bank, 2008). Despite the very visible international presence that the RMG sector of Bangladesh enjoys, the largest increase in female employment has been in the NGO and services sector. It is estimated that between 1999-00 and 20020-03, female employment in this sector grew by an estimated 29% per annum (ibid.). The rapid spread of microfinance in the country has also contributed to increasing women's employment in small microenterprises. Afrin et al (2009) use survey data from women belonging to two microcredit institutions and find that borrowing small amounts of money from these institutions led to an increase in female entrepreneurship. This effect, they argue, manifests itself through the development of financial management skills and group identity. There is conflicting evidence on the growth (or decline) of gender based gaps in employment and wages in Bangladesh over the last decade. Ahmed and Maitra (2011) find that wage gaps between men and women exist at all wage levels and the gap is, in fact, larger at lower levels of wages. In an updated paper using the 2009-10 LFS, Ahmed and McGillvray (2015) find that between 1999-2010 wage gap between men and women fell in the last decade, driven by rapid narrowing of the gap at low wage levels.

No discussion of female in labor in Bangladesh is complete without looking at the role of women in agriculture, the sector that currently employs close to 60% of the female labor force. Researchers have looked at various aspects of agriculture and female labor including whether female work on family farms leads to increases in agricultural productive (Rahman, 2010) and an increase in autonomy (Anderson & Eswaran, 2009). Rahman (2010) uses a survey of over 1800 households in 16 villages in Bangladesh to study the role of female labor in improving productivity and finds that female labor contributed nearly

28% of total labor use on farms, with most of this coming from the family. He further finds that female labor is relatively easily substitutable for male labor in terms of productivity, thus arguing in favor of expanding markets for hired female agricultural labor, a conclusion that is strengthened by the findings of Anderson and Eswaran's (2009). They find that female labor outside the family farm contributed to increasing female autonomy by providing women access to wage income[5]. On the other hand, while work on own family farms generated non-wage income, it afforded no agency or autonomy to women whose labor was seen as free and thus devalued in the household.

There is no consensus in academic research on whether Bangladeshi women's increased economic participation is something to be celebrated, particularly given reports of workplace harassment, unequal wages[6], lack of access to health and maternity benefits etc. Hossain and Tisdell (2005) use large scale data to measure improvements in female education, wages and employment and find that not only have there been remarkable improvements in education, but that higher education is positively correlated with increased work participation. While this may seem like an obvious conclusion, the neighboring country of India exhibits an entirely opposite trend, with LFP falling for women with progressively higher levels of education.

2.2 Women's work in West Bengal

The scholarship on female labor in West Bengal has been largely restricted to small scale qualitative studies, with a few state-wide studies using survey data. One area that has attracted widespread attention is political reservation for women in local governance, not only in West Bengal, but across all states of India. Pardhan et al (2010) study the reservation of seats in local government for SC/ST and women and its impact on, among other things, female headed households in West Bengal. Contrary to what theory predicts, they find that constituencies that were reserved for women saw no improvement in benefits targeted to female-headed households. On the other hand, female- headed households in constituencies

[5] This is also corroborated by Kabeer et al (2011)
[6] For a discussion of how the gender wage gap in Bangladesh has changed over time see Ahmed & McGillivray (2015)

reserved for SC/ST candidates experienced better targeted policies and the villages themselves received more benefits. A contrary finding is reported by Chattopadhyay and Duflo (2004) who study female participation in village meetings and public goods provisions in villages with and without a female village-head. They find that in West Bengal, not only did women participate more in village meetings when their head was a female, but they also demanded, and got, better access to drinking water, and more importantly better roads. Roads are important for women in West Bengal because they are the main source of labor on these roads (ibid).

While the spread of micro-finance in India is relatively nascent, the country has experimented successfully with the concept of women cooperatives. This cooperative movement took root in western India but slowly spread towards other parts of the country. However, Mayoux (1995) reports that the success of such cooperatives may be limited. In a study of weaving and handloom cooperatives in West Bengal, she finds that very few cooperatives operate as such, and many have either failed or serve as fronts for male merchants who install female relatives as proxy heads. This is consistent with findings regarding political reservations for women, where researchers have often found that women serve as lame-duck candidates for their husbands who are incarcerated or otherwise ineligible to stand for elections.

It is argued that low female LFP in West Bengal is due to the fact that women are not involved in agriculture as much as in other states. Despite that, agriculture and allied sectors employ close to 42% of the rural female workforce in West Bengal. Sinha (2005) examines rural female work participation rates (WPR) in 4 districts within West Bengal using data from the Indian Census and finds that districts with better infrastructure and higher levels of education exhibit lower rural female WPR. While this may seem counterintuitive, it points to a troubling trend of female LFP in India as whole. Entry into the labor force does not appear to be a sign of empowerment, rather a sign of acute distress. In the previous chapter I show how female LFPR is highest for the lowest income groups and begins to decline rapidly as incomes increase, particularly for Hindus and lower caste groups.

Despite the commonality of language and culture across the state of West Bengal, there is also considerable heterogeneity based on caste and religion. Muslims, who form roughly 14% of the Indian population, make up more than 25% of the population of West Bengal. Muslim women have had, and continue to have low rates of labor force participation. While there are some who argue that this is due to the conservative nature of the community that restricts women's mobility, the evidence for this is largely anecdotal and not backed by data. One such anomaly to this norm are the districts of Murshidabad and South 24 Parganas[7] where female LFPR is comparatively quite high. Chakraborty & Chakraborty (2010) use a primary survey data to study how observable covariates such as education, ownership of land and age affect female LFPR in these districts, and to study how much of the male female wage gap is attributable to differences in endowments or discrimination. They find that the high female LFPR in these two districts is due to the concentration of women in home based self-employment. However, they find that both Muslim men and women in these districts earn lower wages indicating lack of access to well-paying jobs for members of this community[8]. These issues point to the complex nature of discrimination faced by women in heterogeneous state such as West Bengal. This discrimination is mediated not only through the lens of gender, but also through multiple layers of caste, religion and ethnicity. A recognition of the multi-faceted nature of this exclusion is critical to understanding both the presence and absence of women from the labor force in West Bengal.

Barring a recent World Bank report on Bangladesh (World Bank, 2008) we are not aware of any study that has compared labor and employment outcomes between Bangladesh and West Bengal. Basu and Amin (2000) study the remarkable decline in fertility in Bangladesh and compare it with the equally impressive decline in fertility in West Bengal over the two decades following 1970. This, they argue, is due to the exchange and diffusion of attitudes between both regions due to the common Bengali language that facilitated exchange of progressive ideas and attitudes. The common language allowed the formation

[7] Both these districts have a very high concentration of Muslims- Mushidabad (63.67%) and South 24 Parganas (33.3%)
[8] For an analysis of caste and religion based ethnic employment enclaves see Bordia Das (2008)

of a common Bengali identity and nationalism that led to '*a secular society that is somewhat at odds with the general socioeconomic development of the regions'*. Banerjee et al.(2002) study tenancy reforms in West Bengal and compare it with Bangladesh where no such land reforms took place and find that the reforms led to a significant improvement in agricultural productivity in West Bengal. Other than a handful of these studies, no other research has exploited the homogenous culture and geography but contrasting political organization that characterizes West Bengal and Bangladesh.

3 Methodology

Our primary outcome of interest is mean female labor force participation rate differences between women from Bangladesh and West Bengal. The aim of this paper is to explore the contribution of observable background characteristics in explaining the LFPR gaps between these two groups of women. Our methodology is twofold- we first examine the combined role of all covariates in explaining the LFPR gaps and this gives us the total, predicted and unexplained gap. We then look at the role of individual characteristics in explaining the total and the predicted gap. We use two methods for our overall decomposition analysis- DFL method based on DiNardo, Fortin and Lemieux (1996) and the OB method based on Oaxaca (1973) and Blinder (1973). For assessing the role of individual characteristics, we use an extension of the OB method. We use two decomposition methods as a robustness check and in a correctly specified model, the two estimates should be quite similar to each other. Moreover, the OB method provides a very simple and intuitive way of further decomposing the explained gap, something that the DFL method does not. Our observable covariates include age categories, marital status, education categories, rural residence indicator, number of children below the age of 5, household size, indicator for female headed household, and age of the household head. We also include an indicator for whether the district of the respondent is a border district between the two countries, in order to capture some regional pattern in the labor market behavior of women[9].

[9] The assumption here is that women living in districts on either side of the border are likely to be similar in all respects except their country of residence and hence the political regime under which their district operates. Including this indicator allows us to potentially capture the effect of differences in political regime (and political history) on labor market participation.

3.1 DFL method

Reweighting methods continue to be a popular tool in economics to study gender, ethnicity and race based gaps in various health and labor market outcomes[10]. The intuition behind reweighting is simple- if we want to study outcome differences between group B and W, we reweight group B so that its distribution of observables closely matches that of W, while retaining its own mapping from observables to outcome. Essentially, we give more weight to those Bs whose observables are similar to the Ws in our sample and progressively less weight to the Bs whose background characteristics are different from the Ws. In our sample, the B signifies Bangladeshi women while W refers to women from West Bengal.

To begin, define the probability density for outcome y of country group c with background characteristics X as:

$$F(y|c) = \int_X F(y|c,X)dF(X|c) \tag{1}$$

From here it is easy to construct a valid counterfactual density of the following form:

$$F\left(y\middle|c_{y|X} = B, c_X = W\right) = \int_X F(y|c = B, X)dF(X|c = W) \tag{2}$$

This counterfactual density is valid only when the changing the marginal distribution function from $dF(X|c = B)$ to $dF(X|c = W)$ leaves the conditional distribution $F(y|c = B, X)$ unchanged. Using weights of the form $\varphi_{B\to W}(X)$ the counterfactual density in (2) can be written as

$$F\left(y\middle|c_{y|X} = B, c_X = W\right) = \int_X F(y|c = B, X)\varphi_{B\to W}(X)dF(X|c = B) \tag{3}$$

Where using Bayes' rule, we can write $\varphi_{B\to W}(X)$ as

$$\frac{dF(X|c = W)}{dF(X|c = B)} \equiv \frac{\Pr(c=W\,|X)}{\Pr(c=B|X)} * \frac{\Pr(c=B)}{\Pr(c=W)} \tag{4}$$

We use logit (any binary model can be used) to calculate $\Pr(c = i\,|X)$, which is the probability of being from country group i as a function of background characteristics X. The second part, that is

[10] For a comprehensive review of decomposition methods in economics see Fortin et al (2010). For an application of DFL method to studying racial gaps in infant mortality rates in the US see Elder et al. (2011)

$\Pr(c = i)$ is simply the unconditional proportion of population in group i. In constructing the counterfactual weights, we use data for Bangladeshi women pooled with the corresponding comparison group that is West Bengal women, and then obtain three set of means: mean Bangladeshi female LFPR (B), mean West Bengal female LFPR (W) and mean counterfactual Bangladeshi female LFPR (B'). The gaps in labor force participation are calculated as follows: Total Gap (T) = B – W, Explained Gap (E) = B - B' and Unexplained Gap (U) = B' - W.

3.2 Oaxaca-Blinder method

The Oaxaca-Blinder (OB) method for wage decomposition is the first and one of the most well-known decomposition techniques in economics. The original model used differences in means to break down male-female wage gaps into an explained component that can be attributed to differences in endowments such as education and experience and a residual component that is attributed to discrimination (and other unobservable characteristics).

In keeping with the notation developed in the previous section, let the groups be denoted by B and W. We are interested in knowing how much of the total gap T can be explained by the covariates X and how much remains unexplained.

$$T = E(y_B) - E(y_W)$$

Where $y_c = F(X'_c\beta_c)$ and F is a mapping of X to y. In our case, the mapping is linear, that is, $y_c = (X'_c\beta_c)$. According to the OB model, we can estimate T by using the sample differences in mean values of y_B and y_W. More formally

$$T = \overline{y_B} - \overline{y_W} = \left[\overline{(X'_B\beta_B)} - \overline{(X'_W\beta_B)}\right] + \left[\overline{(X'_W\beta_B)} - \overline{(X'_W\beta_W)}\right] = E + U \qquad (5)$$

Here the first part is explained due to differences in characteristics, whereas the second part is unexplained or due to differences in coefficients or returns to characteristics. An extension of the OB also allows us to calculate the role of individual covariates (or group of covariates) in predicting the explained gap. These estimates are calculated as $\left[\overline{(Z'_B\beta_B^Z)} - \overline{(Z'_W\beta_B^Z)}\right]$ where Z_i is a subset of the variables from X and $\beta_B^Z$is the corresponding coefficient from regressing y on Z for group B.

4 Data and Descriptive Statistics

We use two main sources of data for our analysis- the 66th and 68th rounds of National Sample Survey (NSS) of India and the 2010 Bangladesh Labour Force Survey (LFS). The NSS on Employment and Unemployment in India is a nationally representative survey, usually conducted every five years to provide a comprehensive assessment of the labor market situation in the country. Each round covers between 100,000-120000 households and 450,000-600,000 individuals. We pool the data on West Bengal for the 2009-10 (66th) and the 2011-12 (68th) rounds to provide us with adequate sample size for the state. Breaking convention, the 68th round of the NSS was conducted 2 years after the previous round compared to the norm of 5 years. Since the period between the two surveys is relatively short we can pool observations from the two surveys without any loss of methodological rigor.

Like the NSS, the Bangladesh LFS is conducted at regular intervals to measure employment outcomes in the country. It is a nationally representative survey that covers close to 200,000 individuals and we use data from the last publicly available round which was conducted in 2010. Our working sample consists of women between the ages of 15-59. We restrict our sample to women below the age of 60 as LFPR drops quite dramatically for women over the age of 60 which incidentally, is also the official retirement age in the countries. However, the retirement age legislation applies to only a small proportion of women working in the organized and public sectors in the two countries, and LFPR begins to drop after the age of 50 for women in both regions, particularly in Bangladesh. The NSS asks information on LFPR using 3 different measures- usual status (one year reference), weekly status (one week reference) and daily status. The LFS however only asks information using the one-week reference period. We hence only use the weekly status measurement for NSS to ensure comparability with the LFS. A person is considered as being in the labor force if they report being employed or engaged in seeking employment. Unpaid own domestic work is excluded from the definition of employment, however work in household based enterprise and on own family farms is counted as employment.

We include various individual, household and regional level controls in our main analysis as well in the extension. At the individual level, we control for marital status and control for level of education by dividing it into five mutually exclusive categories based on highest level of completed schooling-no education, complete primary school or lower, middle school, secondary and higher secondary and college and above. Controls for household head's education are similarly constructed. Controls for age of respondent and age of head are also added. To control for the effect of fertility decisions and family size on labor market behavior, we include as covariates, household size and the total number of children below the age of 5 in the household. This is reasonable since child rearing responsibilities in India are often shared among all women of the household when living in joint families.

Concurrent with recent literature, household income and wealth is believed to be an important component driving the decision of women to participate in the labor force. The NSS does not report measures of income but does provide monthly household per capita consumption expenditure. The LFS provides no information on income or household consumption. To control household wealth and income we control for characteristics of the household head and male household members that we believe proxy for some measure of permanent household income. Unless specified otherwise, whenever the full sample of women is used, we also control for minority status where minority is defined as being non-Muslim in Bangladesh and non-Hindu in West Bengal and rest of India.

Table 2.7 shows a broad overview of our sample. Bangladeshi women in our sample are marginally younger, with an average age of 31.7 years compared to 32.4 years for women from West Bengal. They are also more likely to be married and in general have lower levels of education. The average Bangladeshi household is more likely to be rural and has 5.15 members, whereas in West Bengal households are slightly smaller with 4.8 members on average. Households in West Bengal however are slightly more likely to be female headed. While the differences in individual and household characteristics between the two groups is not very large, we find large gap in rates of labor force participation.

The stark difference in female LFPRs in the two countries is quite evident in the descriptive statistics. Table 2.8 shows the LFPR for our sample of women in West Bengal is 20.9% compared to 38.2% for women in Bangladesh. This disparity seems restricted to women, since men from the two regions show similar LFPRs on average. Conventional wisdom dictates that LFPR should rise with education, since accumulation of human capital affords more employment options to the individual and the LFPR of women in Bangladesh confirms this particularly at the very highest level of education where LFPR rises dramatically. Paradoxically, West Bengal exhibits the exact opposite trend with LFPR for women falling with progressively higher levels of education before rising at the college and higher level. If we were to argue that culture is an important driver of the decision to participate in the labor force, and that religion is an important marker of culture, we would expect Muslim (or Hindu) women in both regions to have similar rates of LFPR. However, we see that wide disparities in LFPR persist even when disaggregating by religion. In fact, unlike the rest of India, Muslim women in West Bengal have a higher rate of female LFP compared to Hindu women.

As Table 2.9 shows, the distribution of female labor force across types of employment also varies dramatically between the two regions, whereas the male labor force is more similarly distributed. Close to 80% of Bangladesh's female labor force reports being self-employed, while only 50% of those in West Bengal report working in self or family owned enterprises. The other staggering difference is the wide gap in those who report being casual laborers- 25% for West Bengal versus 6% for Bangladesh. A cursory look at these descriptive statistics may lead us to ask whether female employment in West Bengal could be seen as a sign of distress rather than empowerment. A closer look at the distribution of workforce by industry will help us better understand where women are being employed.

Tables A4 and A5 give details on the industry wise distribution of the female workforce in West Bengal and Bangladesh. In contrast to the rest of India, where a large proportion of people continue to depend on agriculture for employment, it is the manufacturing industry which is largest provider of employment for women in West Bengal. Agriculture and allied sectors employ 28% of the female workforce in the state followed by education at 9%. It is worth noting that industries that are traditionally considered better paying such as financial services, communication, administrative services etc., employ a very small proportion of the female work force in WB which is surprising considering close to 18% women report being in regular or salaried employment. This means that even those women who are in regular employment, are predominantly employed in traditionally low paying industries. One such industry is paid domestic work, which is captured by the 'activities of households as employers' industry classification. This sector employs around 9.4% of the West Bengal female workforce, a sizeable proportion.

Like West Bengal, the two most important industries employing women in Bangladesh are Agriculture and Manufacturing. Despite the spectacular growth of manufacturing in the country over the last two decades, agriculture and allied sectors continue to employ a vast majority of the country's female workforce. On the other hand, close to 12% of women in the country are employed in manufacturing, of which the readymade garment industry is an important part. This is followed by domestic and other service work at 9% and trade at 6%. The education sector, which employs close to 9% of West Bengal women, plays a much smaller role in Bangladesh, however like West Bengal, the proportion of Bangladeshi women in well-paying formal sector industries is limited.

We see that women from both the regions have very distinct observables and the workforce distribution is also quite dissimilar. Before we move on to our main result we run a simple OLS regression of labor force partition on all our observables. While this may not be a perfect specification, it helps us understand the relation between LFP and observables for the two groups and allows us to examine which variables matter in explaining LFP in the two regions.

As Table 2.1 shows, not only are the observables for the two groups very different, their LFP response to the observables is also markedly different. Perhaps the most striking is the correlation between education and LFP. While higher level of education is associated with a strong positive probability of being in the labor force for Bangladeshi women, the opposite seems to be the case for women from West Bengal. As an example, women with high school education and significantly less likely to be employed in West Bengal compared to women with no education. In comparison, compared to women with no education, Bangladeshi women's probability of being in the labor force is higher for every level of education. Similarly, while being married is a significant negative predictor of labor force participation in West Bengal, it predicts the opposite in Bangladesh. West Bengal women from female headed households are much more likely to be in the labor force, this could be driven by the fact that female headed households tend to be more impoverished. Paradoxically, we see the opposite effect in Bangladesh. Having at least one male salaried worker in the household is associated with a significantly lower probability of women working in both regions, though the result is much more magnified for Bangladesh. Unlike the rest of India, living in a rural area does not predict a higher rate of female LFP for women in West Bengal. In fact, on aggregate the rural-urban female LFPR in West Bengal is quite similar. The magnitude and direction of the coefficients on the other covariates are in the direction we would expect. These results will help us better understand the findings from our main decompositions.

5 Main Results

Our first method for the decomposition analysis is the Oaxaca-Blinder method. We use this method to decompose the wage gap into a component that is explained by differences in mean endowment levels and the other that is unexplained or due to unobservables. The OB method also allows us to further decompose the explained portion into three parts- individual, household and regional[11].

[11] Personal includes dummies for each of the age groups, dummies for each of the education categories, and an indicator for marital status. Household category includes HH size, indicator for female headed household, indicator for being a religious minority, number of children under the age of 5 in the household, and characteristics of male household members and the HH head. Finally, the regional category includes an indicator for rural residence and indicator for living in a border district.

The OB method predicts a lower gap than the 17.3 percentage points that exists. That is, if both groups of women had the same mean observable characteristics, we would expect the LFPR difference between the two groups to be lower by 4 percentage points. More broadly, the mean characteristics of women that predict a lower LFPR in West Bengal, predict a slightly higher LFPR in Bangladesh. More disaggregated analysis shows that this effect is driven largely by personal and regional characteristics, more specifically, by the education distribution of women in the two regions and the distribution of women in districts on either side of the border[12].

Our second decomposition method is the DFL method, which allows us to reweight the population so that both groups have the same mean observable characteristics while retaining their own mapping from observables to outcomes. In other words, we reweight the Bangladeshi population is such a way to construct a counterfactual distribution of observables which is nearly identical to the distribution of characteristics for the West Bengal group. To see whether we are in fact able to construct such a distribution we can look at the summary statistics for the counterfactual Bangladeshi population and see how well it compares to actual distribution of characteristics for the West Bengal group. As we can see in Table 2.3, for all the indicators, the counterfactual distribution is very similar to the actual distribution. In particular, the distribution across various levels of education, which was different between the original two groups, now looks nearly identical.

Both the DFL and OB methods give us results that are similar in magnitude and direction. The DFL method predicts that if women in Bangladesh had the average characteristics of women in West Bengal then their LFPR would have been lower by 4.7 percentage points on average. This paradoxical result is magnified even more if we consider the fact that, compared to the original group, the counterfactual group

[12] Border districts in West Bengal include North 24, Nadia, Murshidabad, Maldah, Dakshin Dijnapur, Uttar Dijnapur, Jalpaiguri & Koch Behar. Border districts in West Bengal include Chiadanga, Satkhira, Jessore, Jhenaidah, Meherpur, Kushtia, Rajshahi, Nawabganj, Naogaon, Joypurhat, Dinajpur, Thakurgaon, Panchgarh, Nilphamari, Lalmonirghat & Kurigram.

has a smaller HH size, is slightly better educated and is less likely to be married on average, all of which characteristics have been shown to increase participation rates for women.

6 Extensions

In this section, we conduct additional analysis to study the main results in more detail. In addition to studying various sub-groups, we also introduce an additional comparison group to better understand the processes that may explain the disparity in female LFPR between West Bengal and Bangladesh.

6.1 How do results vary for different sub-groups?

Table 2.4 shows the Oaxaca-Blinder decomposition for three different sub-groups in West Bengal and Bangladesh. As mentioned previously, in our main specification we control for whether respondent lives in a border-district between the two regions with the assumption that these two groups are likely to share common cultural and agro-climatic conditions but differ in the political conditions under which the district operates. In this sub-section, we restrict our sample to these border districts only. We find that LFPR is higher for respondents who live in the border districts on either side, which is expected since this is the region where a lot of agricultural activity is concentrated. However, like our main results, we find that background characteristics are unable to explain the reason for the 20.3 percentage point gap in female LFPR between the two groups. We conduct a similar analysis for the sub-groups of religious minorities and Muslims. West Bengal has one of the highest proportion of Muslims across states in India and we wanted to study whether religious identity matters in explaining some of the large gap in female LFPR in the two regions. We find that the results for both the minority and Muslim sub-group mirror the main results. In both cases, background characteristics predict a negative LFPR gap between the two regions- while in case of minority religious group this effect is driven by regional variables, in case of Muslims it is largely driven by household characteristics.

6.2 Do results change with different mappings?

Decomposition methods can give different results based on which group is used as the reference category. In both our main and sub-group analysis of previous sections, we have used Bangladesh as the reference category. The Oaxaca-Blinder methodology allows us to use as the reference category, either of the two groups, as well as a pooled sample of both groups (Neumark, 1988; R. L. Oaxaca & Ransom, 1994)[13]. In this section, we show how the results vary based on the choice of reference category.

For each of the components in Figure 1, we graph three bars that show the predicted gap based on using Bangladesh, pooled sample and West Bengal as the reference category respectively, in addition to the total overall gap. While there are some differences in magnitude based on the different reference categories, the direction of the gaps is largely similar overall. Disaggregating by individual covariates also shows that the three reference groups give broadly similar results. As an example, regional distribution explains -0.95% of the total gap if Bangladesh is used as the reference, in comparison to -0.99% and -0.80% if the pooled or the West Bengal sample is used respectively.

6.3 How do the two regions compare with the rest of India?

To further understand the disparate female LFPR in the two regions, we introduce an additional comparison group, rest of India[14]. In Tables 5 & 6, we use the India group as our reference category and compare it with the West Bengal and Bangladesh populations. Like the previous table, we also decompose gaps between religious sub-groups. Female LFPR in the India sample is significantly higher than in West Bengal, at 28.7% compared to 20.9%. However, decomposition predicts a negative LFPR gap between the two groups. Detailed analysis[15] indicates that this is driven predominantly by the Muslim and rural variable. In West Bengal being Muslim is not a predictor of lower levels of LFPR, however in the India

[13] For detailed implementation see Jann (2008)

[14] The rest of India sample includes 17 major states of India, excluding WB. Together with West Bengal, these states cover roughly 92-95% of India's population. The states included in our analysis are Uttar Pradesh, Bihar, Maharashtra, Madhya Pradesh, Andhra Pradesh, Tamil Nadu, Karnataka, Gujarat, Rajasthan, Orissa, Kerala, Assam, Punjab, Jammu & Kashmir, Jharkhand, Uttaranchal and Chhattisgarh. In this subsection, we use India as the reference category.

[15] Not shown

sample, being Muslim is associated strongly with low female participation[16]. Similarly, unlike the rest of India, living in rural areas in West Bengal is not associated with higher levels of female employment. This could be in part due to the falling importance of agriculture in the state, both in terms of its share in employment and in state domestic product.

If we consider the minority sub-sample, we find that covariates more than explain the entire 1.09 percentage point gap between the two groups. As mentioned previously, West Bengal is one of the only major states in India, where Muslim LFPR is at par or slightly higher than LFPR for Hindus. We see that in the Muslim sub-sample, West Bengal female LFPR is significantly higher than the rest of India. Of this 6.2 percentage point gap, 20% is explained by observable covariates, particularly household and regional characteristics- unlike for Hindus, being in rural areas is associated with higher female LFPR among Muslims in West Bengal.

We do a similar analysis comparing the rest of India with Bangladesh. For all the three sub-samples, Bangladesh has significantly higher LFPR, than India. In the full sample, of the total 9.6 percentage point gap, only 0.63% is explained by differences in covariates. This effect is largely driven by the household characteristics, in particular minority status. In Bangladesh, being a religious minority is associated with higher female LFPR, whereas in India it is the opposite, driven by the low LFPR of Muslims who are a minority in India. Similarly, as per Table 2.13, being in rural areas in Bangladesh is associated with only slightly higher LFPR, however for the rest of India, rural areas have significantly higher female participation. This rural residence is what drives the explained portion of the minority and Muslim sub-sample gap between Bangladesh and Rest of India. On the other hand, personal characteristics predict a positive LFPR gap- if the rest of India had lower levels of education like Bangladesh, they would have exhibited between 1.3-1.5 percentage points higher rates of female participation. This is because unlike Bangladesh, higher levels of education are associated with lower rates of female participation in India.

[16] See Table 2.13

7 Conclusion

In this chapter, we attempt to study the factors driving the divergent female labor force participation rates in West Bengal and Bangladesh, two historically, culturally, topographically and linguistically similar regions who have had a disparate political and development paths over the last six decades. We used decomposition methods to parse out the contribution of observable characteristics in explaining gaps in LFPR for the entire population as well as for various regional and religious sub-groups. We found in our analysis that background characteristics do not help explain the significantly lower rates of female employment in West Bengal compared to Bangladesh and even compared to the rest of India. One explanation given for the withdrawal of women from the labor force in West Bengal is the declining importance of agriculture in the state. Table 2.10 shows that even though agriculture is the single largest sector employing women in the state, it's share has declined substantially in the last 25 years, from 45% to 28%. In comparison, in the neighboring states of Bihar and Assam, more than 70% of women were employed in agriculture in 2011-12. Agriculture's share of employment is much lower even when compared with the all-India average of 59%. While manufacturing has risen in relative importance, most of the work in this sector is in the unorganized tobacco and textile industries, where wages are low and erratic.

These results lead us to question what is driving the LFP behavior of women in the two regions. Several sociological and anthropological studies have bemoaned the lack of mobility that women in the South Asian region suffer from. These restrictions on mobility often lead to girls being pulled out of school earlier than boys and ultimately to women and girls being disallowed from seeking employment outside of their homes. Interestingly, this is even more the case for relatively affluent upper caste/class households, where women are seen as bearers of household honor (Eswaran, Ramaswami, & Wadhwa, 2013). Perhaps the most glaring manifestation of this is the significantly higher LFPR of Schedule Caste/Schedule Tribe women at the all-India level compared to upper caste Hindu women. If this is indeed the case, then this could explain our results to some extent. By giving more weight to those Bangladeshi women who are better educated, unmarried, urban and young, we may be capturing the effect of being relatively 'elite'. This effect of unobservables on LFP decisions is not entirely captured by observable covariates and perhaps represents the unmeasured effect of culture. An additional factor that we cannot explicitly control for is the widely varying political organization of the two countries. Until recently, West Bengal had been under the leadership of the Communist Party of India for nearly four decades, while Bangladesh oscillated between military rule and democracy with a stress on free-market policies. These differing political trajectories have created widely varying economic structures which have in turn led to divergent demands for female labor in the two countries.

APPENDICES

APPENDIX A

MAIN TABLES AND FIGURES

Table 2.1: OLS of LFP (x100) on Observables

	West Bengal	Bangladesh	Difference
Education Level			
No Schooling	Excluded	Excluded	
Primary or Lower	-4.414	4.543	-8.957
	(1.812)**	(0.625)***	(1.915)***
Middle	-10.018	6.572	-16.591
	(2.130)***	(0.746)***	(2.255)***
Secondary & *H Secondary*	-11.353	1.812	-13.166
	(2.283)***	(0.749)**	(2.401)***
College & *Higher*	6.374	38.143	-31.769
	(2.945)**	(2.136)***	(3.637)***
Age Group			
15-24	Excluded	Excluded	
25-39	12.799	7.738	5.061
	(1.826)***	(0.649)***	(1.936)***
40-49	6.040	9.125	-3.085
	(2.189)***	(0.781)***	(2.323)
50-59	-2.175	-28.521	26.346
	(2.320)	(0.676)***	(2.415)***
Married^	-12.121	11.954	-24.074
	(1.788)***	(0.619)***	(1.891)***
HH Size	-0.292	0.962	-1.254
	(0.325)	(0.125)***	(0.348)***
Children under 5	-0.257	-1.644	1.387
	(1.124)	(0.309)***	(1.165)
Female headed^	9.440	-8.573	18.013
	(2.645)***	(1.148)***	(2.882)***
Adult Salaried Male in HH^	-3.381	-21.594	18.213
	(1.372)**	(0.559)***	(1.48)***
HH Head Age Group			
Under 30	Excluded	Excluded	
30-45	-6.010	-1.481	-4.529
	(2.494)**	(0.749)**	(2.603)**
45-60	-4.077	-0.913	-3.164
	(2.558)	(0.770)	(2.669)
Above 60	-3.259	-3.204	-0.056
	(2.892)	(0.859)***	(3.015)
HH Head Education			
No Schooling	Excluded	Excluded	
Primary or Lower	-1.713	1.744	-3.456
	(1.685)	(0.603)***	(1.788)**
Middle	-3.784	2.542	-6.326

Table 2.1 (cont'd)

	(1.961)*	(0.733)***	(2.092)
Secondary & *H Secondary*	-3.726	3.720	-7.446
	(2.117)*	(0.704)***	(2.229)***
College & *Higher*	-3.203	-1.474	-1.729
	(2.614)	(1.129)	(2.846)
Minority^	-0.064	4.624	-4.688
	(1.492)	(0.655)***	(1.628)***
Rural^	-1.146	0.644	-1.790
	(1.194)	(0.522)	(1.302)
Border^	4.180	5.206	-1.026
	(1.237)***	(0.510)***	(1.338)
Constant	35.852	22.672	13.180
	(3.193)***	(1.039)***	(3.355)***
N	15,396	53,857	
R^2	0.05	0.11	

Note: Sample includes persons aged 15-59, who are not heads of household. Activity based on self-reported status in week preceding survey. Robust standard errors in parenthesis ^Binary (1=yes, 0=no) ***Significant at 1% **Significant at 5% *Significant at 10%

Table 2.2: Decomposition of Female LFPR Gap

		Oaxaca-Blinder method	DFL Method
LFPR	Bangladesh	38.21	38.21
		(0.221)***	(0.221)***
	West Bengal	20.92	20.92
		(0.596)***	(0.599)***
Gap	Total	17.30	17.30
		(0.636)***	(0.638)***
	Explained	-4.064	-4.743
		(0.314)***	(0.419)***
	Unexplained	21.361	22.04
		(0.690)***	(0.697)***
Explained Gap	Personal	-2.369	
		(0.239)***	
	Household	-0.740	
		(0.199)***	
	Regional	-0.955	
		(0.104)***	
N		69,253	69,253

Note: Sample includes persons aged 15-59, who are not heads of household. Activity based on self-reported status in week preceding survey. Robust standard errors in parenthesis ^Binary (1=yes, 0=no) ***Significant at 1% **Significant at 5% *Significant at 10%

Table 2.3: Descriptive Statistics for Counterfactual Population

	Bangladesh Counterfactual	West Bengal
Education Level		
No Schooling	0.2790	0.2941
Primary or Lower	0.3303	0.3265
Middle	0.1781	0.1772
Secondary & H Secondary	0.1528	0.1462
College & Higher	0.0598	0.0560
Age Group		
15-24	0.2805	0.2985
25-39	0.4266	0.4180
40-49	0.1825	0.1766
50-59	0.1105	0.1070
Married^	0.8150	0.8027
HH Size	4.7624	4.7615
Children under 5	0.4058	0.4076
Female headed^	0.0533	0.0557
Adult Salaried Male in HH^	0.1865	0.1870
HH Head Age Group		
Under 30	0.1067	0.1081
30-45	0.3803	0.3849
45-60	0.3741	0.3669
Above 60	0.1389	0.1401
HH Head Education		
No Schooling	0.2737	0.3048
Primary or Lower	0.3573	0.3474
Middle	0.1444	0.1409
Secondary & H Secondary	0.1372	0.1259
College & Higher	0.0874	0.0809
Minority^	0.2717	0.2620
Rural^	0.7317	0.7339
Border^	0.3847	0.4089
N	53,857	15,396

Note: Sample includes persons aged 15-59, who are not heads of household. Activity based on self-reported status in week preceding survey. Robust standard errors in parenthesis ^Binary (1=yes, 0=no) ***Significant at 1% **Significant at 5% *Significant at 10%

Table 2.4: Decomposition of Female LFPR Gap by Sub-Group

		Only Border Districts	Minority	Muslim
LFPR	Bangladesh	44.1028	42.0292	37.7405
		(0.4756)***	(0.6511)***	(0.2350)***
	West Bengal	23.8449	22.4814	22.3587
		(1.0129)***	(1.3237)***	(1.3495)***
Gap	Total	20.2579	19.5478	15.3818
		(1.1189)***	(1.4752)***	(1.3698)***
	Explained	-1.2036	-5.9742	-4.4035
		(0.7032)*	(0.8595)***	(0.5094)***
	Unexplained	21.4615	25.5220	19.7854
		(1.2684)***	(1.6785)***	(1.4358)***
Explained Gap	Personal	-0.9076	-1.6733	-0.7585
		(0.4670)*	(0.5782)***	(0.4140)*
	Household	-0.5058	-1.4484	-2.0094
		(0.5301)	(0.4211)***	(0.2313)***
	Regional	0.2098	-2.8525	-1.6356
		(0.1048)**	(0.5858)***	(0.1929)***
N		17,409	10,116	50,665

Note: Sample includes persons aged 15-59, who are not heads of household. Activity based on self-reported status in week preceding survey. Robust standard errors in parenthesis ^Binary (1=yes, 0=no) ***Significant at 1% **Significant at 5% *Significant at 10%

Table 2.5: Decomposition of Female LFPR Gap (West Bengal & India)

		Full Sample	Minority	Muslim
LFPR	Rest of India	28.6547	21.3907	16.1950
		(0.1900)***	(0.3613)***	(0.3980)***
	West Bengal	20.9161	22.4814	22.3587
		(0.5960)***	(1.3237)***	(1.3495)***
Gap	Total	7.7386	-1.0906	-6.1637
		(0.6255)***	(1.3722)	(1.4070)***
	Explained	-1.1828	-2.1073	-1.2811
		(0.1923)***	(0.3419)***	(0.3201)***
	Unexplained	8.9214	1.0167	-4.8826
		(0.6353)***	(1.4215)	(1.4494)***
Explained Gap	Personal	-0.0647	1.1812	0.2604
		(0.1354)	(0.2704)***	(0.2111)
	Household	-0.9323	-1.4789	-0.5036
		(0.1166)***	(0.2505)***	(0.2371)**
	Regional	-0.1858	-1.8096	-1.0379
		(0.0491)***	(0.1738)***	(0.1932)***
N		218,094	47,378	34,477

Note: Sample includes persons aged 15-59, who are not heads of household. Activity based on self-reported status in week preceding survey. Robust standard errors in parenthesis ^Binary (1=yes, 0=no) ***Significant at 1% **Significant at 5% *Significant at 10%

Table 2.6: Decomposition of Female LFPR Gap (Bangladesh & India)

		Full Sample	Minority	Muslim
LFPR	Rest of India	28.6547	21.3907	16.1950
		(0.1900)***	(0.3613)***	(0.3980)***
	Bangladesh	38.2130	42.0292	37.7405
		(0.2211)***	(0.6511)***	(0.2350)***
Gap	Total	-9.5582	-20.6385	-21.5455
		(0.2915)***	(0.7446)***	(0.4622)***
	Explained	-0.6311	-0.4349	0.3862
		(0.1260)***	(0.2281)*	(0.2676)
	Unexplained	-8.9272	-20.2036	-21.9317
		(0.3155)***	(0.7801)***	(0.5516)***
Explained Gap	Personal	1.3685	1.5041	1.2875
		(0.0797)***	(0.1437)***	(0.1360)***
	Household	-1.6369	-0.7635	-0.2819
		(0.1063)***	(0.1554)***	(0.2111)
	Regional	-0.3626	-1.1755	-0.6194
		(0.0275)***	(0.1154)***	(0.1146)***
N		256,555	50,404	78,384

Note: Sample includes persons aged 15-59, who are not heads of household. Activity based on self-reported status in week preceding survey. Robust standard errors in parenthesis ^Binary (1=yes, 0=no) ***Significant at 1% **Significant at 5% *Significant at 10%

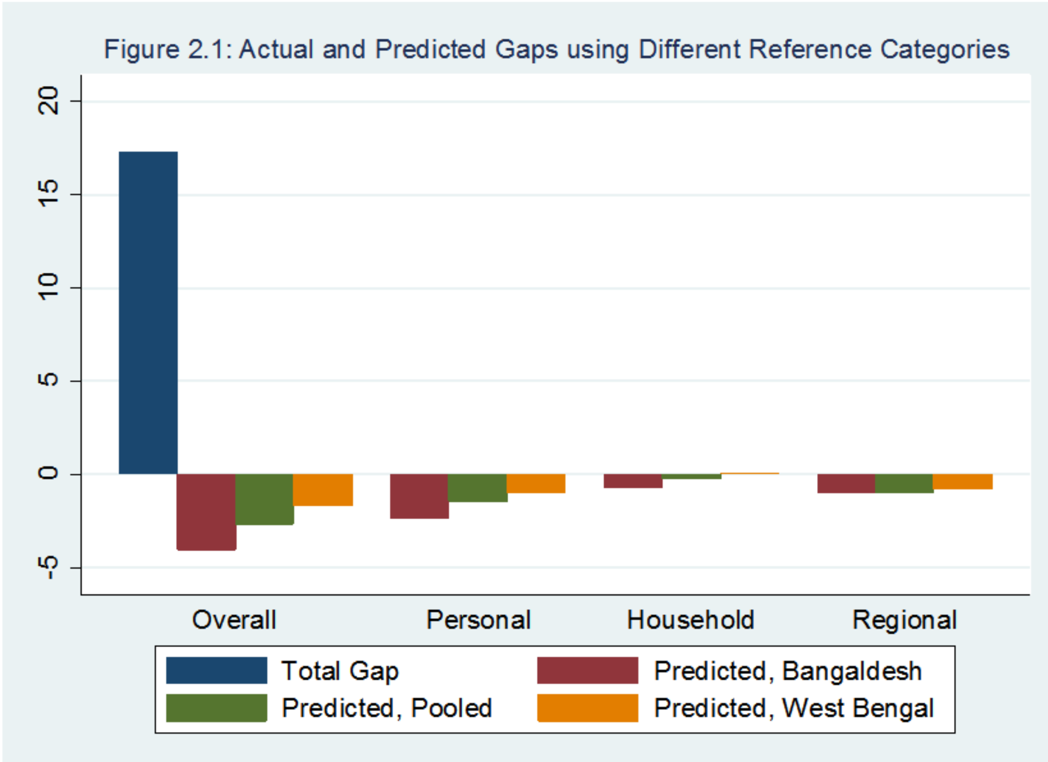
Figure 2.1: Actual and Predicted Gaps using Different Reference Categories
20
15
10
5
0
-5
Overall
Personal
Household
Regional
Total Gap
Predicted, Bangaldesh
Predicted, Pooled
Predicted, West Bengal

APPENDIX B

SUPPLEMENTARY TABLES

Table 2.7: Summary Statistics

	West Bengal	Bangladesh	Rest of India
Education Level			
No Schooling	0.2941	0.4050	0.3701
Primary or Lower	0.3265	0.2149	0.2017
Middle	0.1772	0.1438	0.1557
Secondary & *H Secondary*	0.1462	0.2242	0.2020
College & *Higher*	0.0560	0.0121	0.0705
Age Group			
15-24	0.2985	0.3424	0.3065
25-39	0.4180	0.3844	0.4025
40-49	0.1766	0.1679	0.1792
50-59	0.1070	0.1053	0.1118
Married^	0.8027	0.8180	0.7736
HH Size	4.7615	5.1541	5.4888
Children under 5	0.4076	0.6812	0.5808
Female headed^	0.0557	0.0345	0.0540
Adult Salaried Male in HH^	0.1870	0.1893	0.2063
HH Head Age Group			
Under 30	0.1081	0.1381	0.1004
30-45	0.3849	0.3704	0.3896
45-60	0.3669	0.3334	0.3859
Above 60	0.1401	0.1581	0.1242
HH Head Education			
No Schooling	0.3048	0.4627	0.3230
Primary or Lower	0.3474	0.2061	0.2502
Middle	0.1409	0.1150	0.1536
Secondary & *H Secondary*	0.1259	0.1706	0.1801
College & *Higher*	0.0809	0.0455	0.0931
Minority^	0.2620	0.1102	0.1693
Muslim^	0.2525	0.8898	0.1203
Rural^	0.7339	0.7533	0.7136
Border^	40.89	22.30	
N	15,396	53,857	202,698

Note: For definition of Rest of India see Footnote 12 , Women age 15-59 ^Binary (1=yes, 0=no)

Table 2.8: Labor Force Participation Rates

	West Bengal		Bangladesh		Difference	
	Mean	S.E	Mean	S.E	Mean	S.E
Total						
Male	73.208	0.869	63.898	0.333	9.310	0.931
Female	20.916	0.599	38.213	0.221	-17.297	0.638
By Religion						
Minority	39.928	1.250	49.546	0.547	-9.619	1.364
Non-Minority	37.337	0.622	45.468	0.202	-8.131	0.654
Muslim						
Hindu						
By Education						
No schooling	32.103	1.281	43.210	0.324	-11.107	1.322
Primary or lower	41.915	1.075	54.171	0.403	-12.256	1.148
Middle	34.875	1.252	51.910	0.480	-17.034	1.341
Secondary & Higher Secondary	33.141	1.112	37.102	0.354	-3.961	1.167
College & Higher	59.485	1.392	76.164	1.232	-16.679	1.859
Male						
By Religion						
Minority	76.065	1.796	66.341	0.924	9.724	2.020
Non-Minority	72.202	0.987	63.581	0.356	8.621	1.050
Muslim	63.581	0.356	63.581	0.356	12.660	1.864
Hindu	66.245	0.969	66.245	0.969	5.957	1.383
By Education						
No schooling	86.278	2.749	80.238	0.660	6.040	2.827
Primary or lower	86.959	1.309	81.774	0.567	5.185	1.427
Middle	66.102	2.000	69.710	0.739	-3.608	2.132
Secondary & Higher Secondary	54.553	1.770	41.818	0.551	12.735	1.854
College & Higher	87.736	1.187	81.812	1.452	5.925	1.875
Female						
By Religion						
Minority	22.481	1.347	42.029	0.651	-19.548	1.496
Non-Minority	20.361	0.655	37.741	0.235	-17.380	0.696
Muslim	22.359	1.373	37.741	0.235	-15.382	1.393
Hindu	20.361	0.655	40.810	0.681	-20.450	0.944
By Education						
No schooling	26.006	1.308	36.458	0.343	-10.451	1.352
Primary or lower	20.791	1.069	41.948	0.480	-21.157	1.172

Table 2.8 (cont'd)

Middle	15.151	1.207	42.154	0.592	-27.003	1.344
Secondary & Higher Secondary	13.413	1.082	33.624	0.458	-20.212	1.174
College & Higher	32.747	1.937	68.785	2.061	-36.038	2.828

Note: Sample includes persons aged 15-59, who are not heads of household. Activity based on self-reported status in week preceding survey.

Table 2.9: Distribution of Labor Force

		West Bengal		Bangladesh		Difference	
		Mean	S.E	Mean	S.E	Mean	S.E
Male							
	Casual	0.332	0.012	0.266	0.004	0.066	0.012
	Regular Wage/Salaried	0.167	0.008	0.220	0.004	-0.053	0.009
	Self Employed	0.410	0.011	0.459	0.004	-0.049	0.012
	Unemployed	0.091	0.006	0.055	0.002	0.036	0.007
Female							
	Casual	0.222	0.015	0.051	0.002	0.171	0.015
	Regular Wage/Salaried	0.161	0.010	0.094	0.002	0.067	0.010
	Self Employed	0.545	0.016	0.820	0.003	-0.275	0.016
	Unemployed	0.072	0.008	0.034	0.001	0.038	0.008
By Religion							
Female							
Minority	Casual	0.194	0.028	0.073	0.005	0.122	0.028
	Regular Wage/Salaried	0.082	0.015	0.097	0.006	-0.015	0.016
	Self Employed	0.665	0.032	0.801	0.008	-0.136	0.033
	Unemployed	0.059	0.016	0.029	0.003	0.029	0.016
Non-Minority	Casual	0.233	0.017	0.048	0.002	0.185	0.017
	Regular Wage/Salaried	0.192	0.012	0.094	0.002	0.098	0.013
	Self Employed	0.498	0.018	0.823	0.003	-0.325	0.018
	Unemployed	0.077	0.009	0.035	0.001	0.042	0.009

Note: Sample includes persons aged 15-59, who are not heads of household. Activity based on self-reported status in week preceding survey.

Table 2.10: Distribution of Female Workforce by Top 10 Industry- West Bengal

International Standard Industrial Classification – 2 digit level	1983	1999	2011
Agriculture	44.82	43.12	28.31
Manufacture of Tobacco	4.71	14.24	20.44
Other service activities	13.61	8.18	8.23
Manufacture of textiles	3.74	5.7	9.65
Education	4.73	4.24	9.61
Manufacture of food and beverage	6.38	4.1	1.26
Retail trade	4.71	5.2	3.88
Manufacture of apparel	2.54	1.15	3.65
Wood Work	2.22	3.63	0.71
Health and social work	1.92	1.53	2.44

Table 2.11: Distribution of Female Workforce by Top 10 Industry- All India

International Standard Industrial Classification – 2 digit level	1983	1999	2011
Agriculture	74.49	73.84	58.6
Education	2.11	2.86	5.66
Other service activities	3.44	3.04	4.12
Retail trade	3.09	3.78	4.08
Construction	2.09	1.89	5.8
Manufacture of Tobacco	2.41	2.48	3.48
Manufacture of textiles	1.96	1.99	3.07
Manufacture of apparel	1.61	0.57	3.45
Manufacture of food and beverage	1.22	1.22	1.24
Public administration, Defence	1.01	1.11	0.91

Table 2.12: Distribution of Female Workforce by Top 10 Industry- Bangladesh

International Standard Industrial Classification – 2 digit level	2010
Agriculture	64.77
Other service activities	9.16
Manufacture of apparel	7
Retail trade	6.13
Education	2.04
Manufacture of textiles	1.74
Land transport	1.38
Construction	1.34
Manufacture of food and beverage	1.13
Health and social work	1.02

Table 2.13: OLS of LFP (x100) on Observables

	West Bengal	Bangladesh	Rest of India
Education Level			
No Schooling	Excluded	Excluded	Excluded
Primary or Lower	-4.631	4.512	-1.873
	(1.816)**	(0.626)***	(0.584)***
Middle	-10.083	6.643	-7.177
	(2.134)***	(0.747)***	(0.617)***
Secondary & H Secondary	-11.523	1.878	-9.800
	(2.289)***	(0.749)**	(0.613)***
College & Higher	6.490	38.154	10.039
	(2.948)**	(2.142)***	(0.839)***
Age Group			
15-24	Excluded	Excluded	Excluded
25-39	12.848	7.755	14.368
	(1.826)***	(0.650)***	(0.576)***
40-49	5.866	9.127	15.269
	(2.188)***	(0.783)***	(0.700)***
50-59	-2.196	-28.530	9.191
	(2.309)	(0.677)***	(0.781)***
Married^	-12.070	12.165	-3.021
	(1.782)***	(0.619)***	(0.570)***
HH Size	-0.344	0.897	-1.074
	(0.325)	(0.125)***	(0.087)***
Children under 5	-0.355	-1.784	-1.036
	(1.129)	(0.309)***	(0.261)***
Female headed^	9.224	-9.043	4.940
	(2.647)***	(1.148)***	(0.812)***
Adult Salaried Male in HH ^	-3.119	-21.928	-1.798
	(1.369)**	(0.558)***	(0.417)***
HH Head Age Group			
Under 30	Excluded	Excluded	Excluded
30-45	-6.070	-1.476	-0.575
	(2.496)**	(0.750)**	(0.736)
45-60	-3.965	-0.955	0.676
	(2.552)	(0.770)	(0.760)
Above 60	-3.447	-3.344	-0.266
	(2.888)	(0.859)***	(0.887)
HH Head Education			
No Schooling	Excluded	Excluded	Excluded
Primary or Lower	-2.096	1.804	-1.659

Table 2.13 (cont'd)

	(1.673)	(0.603)***	(0.552)***
Middle	-4.118	2.523	-5.224
	(1.957)**	(0.733)***	(0.624)***
Secondary & *H Secondary*	-4.105	3.774	-9.676
	(2.110)*	(0.704)***	(0.610)***
College & *Higher*	-3.875	-1.349	-14.504
	(2.608)	(1.131)	(0.715)***
Minority^	0.641	4.431	-7.165
	(1.486)	(0.656)***	(0.420)***
Rural^	-1.022	1.229	9.123
	(1.199)	(0.520)**	(0.353)***
Constant	37.901	23.736	29.826
	(3.117)***	(1.032)***	(0.950)***
N	15,396	53,857	202,698
R^2	0.04	0.11	0.07

For definition of rest of India see Footnote 12, Robust standard errors in parenthesis ^Binary (1=yes, 0=no)
***Significant at 1% **Significant at 5% *Significant at 10%

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Chapter 3

Communal Violence and Human Capital Accumulation in India

1 Introduction

This paper aims to answer a straightforward albeit complex question- how does religious identity and conflict determine long-term education outcomes for religious minorities? This pertinent question has been asked and investigated by the scholars in different contexts over time. Religious identity has often been used as a tool for both political and economic mobilization and exclusion. This exclusion manifests itself in the form of wide inter-group inequality, ghettoization, ethnic enclaves and in extreme cases, violent conflict. The causes and consequences of violent conflict, particularly civil war, mass violence and ethnic conflict, has attracted considerable scholarly attention across disciplines. However, there is much less research on the how small isolated and geographically dispersed incidences of violence can lead to long term deficit in human capital accumulation for entire communities. This effect could be driven by the immediate loss of life and livelihood following conflict. However repeated conflict also ingrains a culture of fear in the minds of the victimized community that implicitly determines economic behavior in the long-run. This paper deals with one such group, namely Indian Muslim.

I use data on education from the 64th (2007-08) and 71st (2014) round of the National Sample Survey on Participation and Expenditure on Education in India to study the effect of both contemporaneous as well as cumulative violence on both stock and flow education decisions of religious minorities. Data on violence is derived from newspaper reports of Hindu-Muslim violence from 1950-2006, compiled by various researchers using the Mumbai (Bombay) edition of the Times of India, a leading English language daily in India (Iyer & Shrivastava, 2015; Mitra & Ray, 2014; Varshney & Wilkinson, 2006). Since the education data I am able to use is relatively recent, in this paper I only consider reports of violence from

1986 to 2006. This period marked some of the deadliest incidents of communal violence in India, including nationwide riots following the Babri Masjid Demolition in 1992 and the Gujarat riots of 2002, among others. Some of the education outcomes I consider are, dropout rate, years of completed education, age at dropout from school and probability of primary school completion. I find that communal violence has only a small effect on educational enrolment and completion decisions of minorities and this effect is restricted to girls.

2 Review of Literature

The persistent effect of violence on anthropometric outcomes has been widely studied in various countries (Akresh, Caruso, & Thirumurthy, 2014; Akresh, Lucchetti, & Thirumurthy, 2012; Bundervoet, Verwimp, & Akresh, 2009; Minoiu & Shemyakina, 2014). On the other hand, the scholarship on conflict and schooling is relatively new and evolving (Baez, 2011; Chamarbagwala & Morán, 2011; León, 2012; Shemyakina, 2011). In the Indian context, most recent research has attempted to study the causes of violence, ranging from ethnic and radical leftist to separationist and insurgent violence (Bohlken & Sergenti, 2010; Gomes, 2015; Jha, 2014; Mitra & Ray, 2014; Sarsons, 2015; Sharma, 2015; Wilkinson, 2004), while there is very little evidence on the consequences of such violence, especially for children from minority communities who suffer disproportionately due to such conflict. This paper attempts to bridge this gap in literature by studying the effect of religious violence in India on schooling of Muslim children.

Most of the previous research on education and conflict has focused on large scale violence such as civil war and ethnic conflict. Mass violence of this kind is marked by long periods of intense conflict followed (and/or preceded) by periods of relative peace. This form of conflict allows researchers to more accurately identify both cohorts affected, and not affected, by violence. This identification strategy has been used by several researchers to identify the causal impact of violence on education. Chamarbagwala & Morán (2011) study the impact of exposure to the Guatemalan civil war on educational attainment and find large negative impact for Mayan men and women, who represent the poorest and most vulnerable section of the Guatemalan population. Verwimp & Van Bavel (2013) follow a similar estimation strategy and find that the negative effect of violence on schooling, measured as probability of primary school completion, is exacerbated for boys relative to girls. Shemyakina (2011) on the other hand finds in her study of violent conflict in Tajikistan, that girls suffer disproportionately compared to boys on measures of educational attainment. One of the few such studies based on the Indian context (Singh & Shemyakina, 2016) looks at the effect of the Punjab insurgency on the education of girls and finds that girls exposed to violence exhibit lower levels of educational attainment and this effect is likely driven by reduction in education expenditure following conflict.

The nature of communal violence in India is distinct from such kinds of mass violence because it is sporadic in nature, spread over time and is marked by short bursts of violence followed by extended periods of peace. There is a growing body of economic research on this kind of sporadic localized violence and its effect on human capital outcomes. Brown and Velasquez(2017) study the effect of gang-related violence in Mexico on human capital outcomes of Mexican children using panel data and find that children, particularly males, exposed to violence have lower levels of education and are more likely to be engaged in employment. Duque (2013) similarly studies the effect of early life exposure to neighborhood crime and violence in Colombia and finds that an increase in exposure to violence in-utero or in early life, reduces school enrolment and increases the probability of being behind grade. Several such papers have looked at the effect of exposure to gang violence and crime on education and health outcomes (Gershenson & Tekin, 2017; Jarillo, Magaloni, Franco, & Robles, 2016; Torche & Villarreal, 2014).

This paper aims to add to this growing body of literature by looking at if and how small but consistent instances of violence against a community can lead to permanent shortfalls in human capital accumulation through withdrawal from education and lower student achievement. While the material and physical loss following, religious violence is significant, it is also important to study the long-term impacts violence has on a community. If violence leads to reduction in human capital accumulation by Muslim children, who are often poor, it results in creating a generation of low skilled adults who are then trapped in a vicious cycle of poverty. Violence itself, through systematic targeting of Muslim businesses and institutions, could create conditions for long-term economic deprivation, which could negatively impact the resources households can allocate toward education. Moreover, if these institutions and businesses are the primary employers of Muslim youth, their decline and destruction could also disincentivize education. I am also interested in studying how violence impacts Muslim boys and girls differently. While on the one hand boys are at risk for being co-opted into the violence as participants, girls face the risk of being victims of physical and sexual violence. Girls' education is also often at the margins of the household resource allocation decision, and any decline in household resources is likely to negatively impact their education and enrolment. Through this paper, I try to shed light on the effect of short-term sporadic violence on long term schooling outcomes, with the hope of informing policy decisions on controlling violence and in directing rehabilitation efforts following periods of violence.

3 Data and Descriptive Statistics

I use data on religious violence from the Wilkinson-Varshney (2006) dataset on religious violence in India from 1950-1995 and subsequently updated by Mitra and Ray (2014) till 2000 and by Iyer and Srivastava (2015) till 2006[1]. The original dataset, and the subsequent updates, were compiled using newspaper reports from the Bombay (now Mumbai) edition of the Times of India. Each daily edition of the newspaper was scanned for any report of violent conflict or confrontation involving Hindus and Muslims[2]. I have compiled the violence dataset from three different sources to create a panel of district level data covering five decades. I have also cleaned and coded the violence data to fill missing information by matching the data with administrative and census records. To the best of my knowledge, my paper is

[1] I use Mitra and Ray (2014) for data from 1996-2000 & Iyer and Srivastava (2015) for data from 2001-2006. The latter have also collected data for the 1996-2000 period but I do not utilize their data for that period.

[2] The Iyer and Srivastava (2015) dataset also includes instances of conflict between Hindus and other non-Muslim religious groups as well as between Muslims and non-Hindu religious groups. I do not include such instances in my sample.

also the first to combine this violence dataset with large scale survey data to study the causal impacts of communal violence in a large and democratic country such as India.

I use data on the 15 major states in India by population based on the 1991 census, these states are Uttar Pradesh (including Uttarakhand), Bihar (including Jharkhand), Maharashtra, West Bengal, Madhya Pradesh (including Chhattisgarh), Tamil Nadu, Rajasthan, Karnataka, Gujarat, Andhra Pradesh, Odisha, Kerala, Assam, Haryana and Punjab. Together these states comprise close to 95% of India's total population. I exclude the state of Jammu and Kashmir from my analysis both because its low population as well as the history and nature of conflict in the state which is markedly different compared with the rest of the country. As the figure below shows, there is considerable heterogeneity across years in the number of casualties, with some years with high number of casualties and some with very few. The spike in violence following the Babri Masjid demolition in 1992 and the subsequent countrywide riots, as well as the mass violence in Gujarat in 2002, is clearly reflected in the number of casualties in these two years. There is also considerable heterogeneity across states with some states such as Gujarat and Maharashtra reporting consistently high number of incidents and casualties, and others such as Punjab and Tamil Nadu reporting very few.

Data on schooling outcomes comes from two consecutive rounds of the National Sample Survey (NSS) Participation in Education (Schedule 25.2) covering the period between 1983 and 2014. The Participation in Education survey includes detailed information on schooling choices and decisions. In particular, this dataset contains self-reported information on age of entry and exit from the education system. I use this information to create a novel panel dataset for each respondent using retrospective information on school entry and exit and this allows me to exploit the time-series nature of schooling decisions to capture more dynamic responses to incidences of violence.

Each round of the Participation in Education survey covers over 360,000 respondents and is representative at the region level[3]. For preliminary analysis, I used four rounds of the survey conducted in 1986-87 (42nd Round), 1995-96 (52nd Round), 2007-08 (64th Round) and 2014 (71st Round), however the results reported in this chapter are restricted to the 64th and 71st round due to limited information on background characteristics reported in the 42nd and 52nd round[4]. Combining the two round, I get a sample of roughly 284,300 respondents of which roughly 15% are Muslim.

The average age of the respondents is 16.6 years and is equally divided between males and females. Muslims are much more likely to report living in urban areas, which is consistent with the overall distribution of Muslim population in India. Muslims also have slightly larger household size and are likely to drop out of school at earlier ages than non-Muslims. The average age of starting school is about 5.5 years and more than 93% of the sample reports their school entry age as 6 years or less.

3.1 Creating the retrospective panel

I plan to conduct my analysis using both individual cross-section data as well as a constructed retrospective panel. As mentioned previously, the NSS survey on education provides information on the age at entry into school and if the respondent is currently not in school, then she is also asked about her age at exit from school along with the grade and level of education completed before exit. This information is collected from all individuals between the ages of 5 and 29. With this information I can create a retrospective panel of enrolment for each individual from the time of entry in school to the time of exit[5].

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[3] Over time, the number of districts in India has changed due to splitting of districts into two or more parts. A majority of the districts were clean splits so I can trace the new districts back to the old parent district. For both the violence and schooling data, I define the districts as they were in 1980 which is the time of the first school-choice observation in my sample.

[4] An alternative dataset that could have been used is the more frequently conducted NSS Employment and Unemployment survey, which is larger in scope and covers close to 600,000 respondents. It has more detailed information on post-education employment outcomes but also contains some information on education decisions at terminal education levels such as primary, middle, secondary etc. However, since I want to capture the temporal education decisions of minorities, I require information on the schooling decisions over time which this dataset does not provide. Therefore, in this chapter, I report the results using only the Education survey of the NSS.

[5] As an example, if in the 2014 survey a 15-year-old reports age at entry in school as 5 and age at exit as 11, then she is considered to have entered school in 2004 and exited in 2010. In the years between 2004 and 2010 I consider the child as being enrolled in school, and in the years following the child is considered dropped out.

This gives me multiple year-age combinations for each individual allowing me to create a panel of schooling history from cross-section data. The data is right censored because I do not observe behavior after the age of 29 or the age at survey, and I also do not observe the future behavior of individuals who are interviewed while they are still in school or of school going age. For example, if the respondent is 10 years old when she is interviewed in 1995, then she is considered in the study only till 1995. I make no ex-ante assumptions about future schooling choices. Since I am interested in schooling outcomes I consider the outcomes for individuals till they attain the age of 18 or graduate from high-school, whichever occurs sooner. This means that individuals enter the sample when they reach the age of 5 or 6, depending on the school entering age for the state, and exit when they reach age 18 or exit school. Expanding the data in this way gives me 2.1 million person-year observations, covering 402 districts in 15 states over a 21-year period[6].

In an alternative specification, I model the dropout decision in a discrete time hazard model framework. As in the main specification, I still use the retrospective panel but in this case a person enters my sample when they turn 6 and exit when they drop out or turn 18, whichever is sooner. Unlike the main specification, I have no observations for individuals beyond their year of dropout. As an example, if an individual drops out at age 15, there are no entries for that individual at age 16-18, whereas in the retrospective panel I would code the individual as "0" for being (un)enrolled at ages 16-19. Along with

Similarly, a 15-year-old child in the 2014 survey who never enrolled in school is counted as being unenrolled for the entire duration.

[6] This individual panel information can also be used for regional level analysis. I can collapse the data for each individual-region-year combination to obtain the enrolment and/or dropout rate for each region by year. I can do this for the entire sample combined and separated by religion and gender. Similarly, from the violence dataset I can obtain region-year incidences of communal violence in terms of incidences of violence and number of casualties. It would be useful to be able to do this kind of analysis at the intensive margin using information on duration of violence, however since the violence information is extracted from newspaper reports, the data on duration of violence is not very precise. In a previous draft of the paper I restrict my analysis to the extensive margin for region level analysis. Dropout or enrolment rate in each region-year is used as the main dependent variable and lagged incidence of violence or casualties as the main independent variable. In addition, I control for other region specific characteristics based on the income, education, and employment and population profile of the region. Some income and education data at the region level is available from the Census Bureau of India and from the Planning Commission of India, the rest is interpolated from NSS data on Employment and Unemployment (Schedule 10). I find no significant effect of violence experienced in the district on the aggregate enrolment or dropout rates for the district, either overall or for Muslims separately. Results available on request.

district and time fixed effects, I also control for baseline hazard which is modeled as series of dummies to indicate the number of years an individual was enrolled before dropping out. As an example, a 6-year-old has a baseline 1, a 7-year-old is 2, an18-year-old is 13, etc. Since the maximum is age 18, this value is between 1-13. This allows for a flexible baseline hazard and the vector of coefficients on these indicators, indicates the hazard of dropping out in every period since being enrolled, where period is measured as years. I also include LPM results for comparison. Failure is coded as going from "1" (enrolled) to "0" (dropped out).

4 Methodology

The relationship between schooling and conflict can manifest itself both at the individual level, as well as at the regional level. At the individual level the effect may be driven by concerns for safety (particularly for girls), fear of recruitment into violence, destruction of local business which reduces incentives for education, income loss and targeting of religious educational institutions. This could result in high dropout rates, low completed years of schooling, schooling lags (due to gaps in education) and low test scores. The effect of violence on schooling outcomes could also be seen at the aggregated district/regional level. In particular, this is seen in the higher average dropout rates of Muslim versus Hindu children. Dropout rates are an important outcome for policy makers in India because as the country approaches 100% enrolment for primary school-age children, the next challenge is in ensuring that children stay in school to complete their education. For Muslim children, this challenge is exceptionally high, since for a long time Muslim children, especially boys, have shown significantly higher rates of dropout across all caste and religious groups. As the figure above shows, in 1983-84 both Muslim girls and boys started with dropout rates that were comparable to or even better than that for SC/STs, the group recognized by the government to be the most deprived in the country. Over time however, this gap narrowed and now Muslim boys and girls have the highest dropout rate across all socio-religious groups in the country. As of 2009-10, close to 22% of school age Muslim girls and 18% boys have either never enrolled in school or have dropped out. That this is happening while the government is celebrating universal school enrolment is indeed worrying.

I model the decision to stay in or drop out from school in each period as a binary decision that is based on a host of household and individual covariates as well as experience of violence in the short and medium term[7]. I model the probability that a respondent *i*, in district *d* is enrolled at time *t* as:

$$Pr(\text{Enrolled}_{\text{idt}} = 1 \mid \cdot) = f(conflict_{dt}, conflict_{dt-1}, conflict_{dt-2}, X_i, D_d, \delta_t)$$

Where $conflict_{dt-1}$ is a measure of incidents or casualties in district d at time t-1, X_i is a vector of time-invariant individual and household characteristics, and D_d and δ_t are district and time fixed effects.

In addition to the analysis using panel and temporal information, I also conduct the analysis at the individual level using the original cross-section dataset. However, unlike the retrospective panel which measures the effect of contemporaneous violence, in case of the cross-section analysis I attempt to measure the impact of cumulative experience of violence on aggregate schooling decisions. In this case my outcome of interest is years of completed schooling, age at dropout and an indicator for whether the respondent has completed primary school. The first two outcomes are tested on individuals who have completed the school going age of 18 by 2006, and the results for primary school completion are tested on individuals who have completed the age of 10 by 2006, which is the age of primary school completion in the country. In the former case, I measure exposure to violence as the cumulative sum of incidents or casualties in the respondent's district of residence till the age of 18, and similarly in the latter, violence is measured as cumulative experience of violence till age 10.

[7] While I model a linear relationship between violence and schooling decision, we can also hypothesize that dropout decisions follow an inverted U-shape that is, in districts that experience very little or a lot violence, the effect on dropout rates is minimal. However, in the middle districts the effect on violence is likely to be larger because violence comes as a large negative shock that is not accounted for by the household in their education demand decision.

5 Results

I start with the results of the analysis using the retrospective panel. The sample is restricted to those between ages of 6-18 in each year of the panel. I have used two measures of violence, the total incidents of violence in the district in period t, t-1 and t-2 and similarly the total casualties in period t, t-1 and t-2 in the respondent's district. I discuss here only the results using casualties as a measure of violence, however the results using incidents of violence as a measure are included in the appendix tables[8]. The outcome variable is binary[9] - whether you are enrolled in a particular year or not. In addition, I control for individual specific covariates that do not change over time such as gender and rural residence, type of household, as well as birth cohort fixed effects in each period. All the specifications have district and year fixed effects.

I estimate several specifications including interactions with indicators for being Muslim and female to estimate heterogeneous effects of violence on the decision to be enrolled. The results of the linear probability model are reported in Table 2. The probability of being enrolled is lower for older ages, rural residents, women and Muslims. The results do not show any general impact of violence on the decision to remain enrolled. While the coefficient of violence for Muslim women is negative, overall the effect of violence on enrolment is positive, and close to zero, for all groups.

This results however, is quantitatively small, indicating that violence has to be significant enough for it to have an impact on education decisions. This result is not entirely surprising given that anecdotal evidence suggests dropout in India is a permanent and irreversible decision and in very rare cases is the violence so extreme to merit a response of this kind. It is thus necessary to either use a finer measure of

[8] I expected that *casualties* better capture violence since they are reported more accurately than *incidents*. As an example, a news report that states "700 people were killed or injured in sporadic incidents of violence in Mumbai over the last week" will be recorded as 1 incidence of violence in the dataset even though there were multiple incidents across the district. However, the number of deaths or injuries is likely to be closer to the actual figure.

[9] The binary enrolment variable is multiplied by 100 for easy interpretation. For example, the coefficient on Muslim in Col 3. Table 1 says that Muslims are 9.72 percentage points less likely to be enrolled in each year compared to non-Muslims.

education achievement that can capture the small effects of sporadic violence, or explore the possible cumulative effect of violence on various schooling and education decisions. I discuss some of these measures next section as well as in the final section.

Table 3 uses lifetime experience of violence as the variable of interest to measure its impact on schooling decisions. As with the previous specification, I find that the coefficient on cumulative violence for Muslim girls is negative for total years of completed education, and probability of having completed primary school. Overall however, the effect of cumulative violence on all three indicators of education is positive and close to zero for all groups. This indicates that it would take a particularly violent incidence of rioting or for someone to have experienced significant violence during their childhood and youth for it to have a significant effect on their schooling decision[10]. As descriptive statistics show, such communal violence is rare- the average individual experiences less than 90 casualties from birth to age 18 in the form of communal violence and less than two incidences of violence in the same period. Moreover, the results indicate that for girls in general, experience of violence has a small positive effect on education outcomes, which offsets any negative coefficient for Muslim females.

6 Extensions

I found in the previous sections that communal violence in India does not have any discernible effect on the education outcomes of Muslim children, barring a small statistically significant but economically insignificant effect for Muslim girls. In this section I test some other specifications as well as restrict my analysis to other samples to see how this affects the results.

[10] As an example, doubling the mean (overall) level of violence is associated with a 0.08 increase in years of education for non-Muslim girls and a 0.04 increase in years of education for all other groups. Similarly, doubling the mean total casualties is associated with a 0.15% increase in probability of completing primary school for all groups except Non-Muslim men, for whom the probability is nearly zero.

6.1 Testing robustness of results with leads and lags

One the ways to test the robustness of the effect of lags of violence on contemporaneous education decisions is to also test the effect of leads or future incidences of violence. If the results are indeed robust, I would see no effect of violence in the future on education decisions of the present. Table 3.4 shows the effect of both contemporaneous, past and future violence on enrolment decision. As the table shows, like in the main analysis I see a small but significant negative coefficient on past and contemporaneous violence on the decision to remain enrolled for Muslim girls, however I also see that violence in period t+1 and t+2 exhibits a negative coefficient on the enrolment decision, which does not support the hypothesis that violence lowers enrolment (or increases dropout rates). I see the same pattern when measuring violence in terms of incidents of violence.

6.2 Testing results for unmarried respondents

Given the restrictions of the data, I assume that the place, more specifically the district, where the respondent is enumerated is the district where the respondent engaged in and completed schooling. This is not an entirely unreasonable assumption since inter-district migration in India is less common than migration within the same district. However, it can be argued that women who migrate after marriage are more likely to migrate out of district than other groups. If this is indeed the case, including married women in the sample, who may have migrated from another district where their schooling decisions were made in childhood, would incorrectly count them as having experienced violence in the district of enumeration (or marital residence). To account for this I restrict my retrospective and individual sample to unmarried persons, to see if and how the result changes. The results are reported in Table 3.7 and 3.8. I find that restricting the sample does not significantly alter the magnitude of effect observed in either of the two analysis. In case of the retrospective panel, I still observe a small but statistically significant negative coefficient of violence on the probability of being enrolled for Muslim girls. As before, when I test the same with adding leads of violence, I find that violence in the future also shows a negative coefficient on the enrolment decision of the present. Similarly, for the individual cross-section sample of unmarried persons, I find no difference between the full and the unmarried sample. As before, the coefficient for Muslim girls is significant but small, the magnitude for the unmarried sample is almost the same as that for the overall sample and overall violence shows a close to zero but positive correlation with education outcomes for all groups, including Muslim girls.

6.3 Testing the results with a hazard model

For an alternative specification, I model the dropout decision in a discrete time hazard model. Along with district and time fixed effects, I also control for baseline hazard which is measured as the duration the individual was in the sample before exiting the sample, where exit is defined as reaching the age of 18 or dropping out, whichever happens sooner. I use the logistic functional form and for comparison, I include results from a linear probability model. Table 3.9 reports the result for the main specification using both lags as well as an extended specification that uses both leads and lags. Like the other results, I find that the coefficient of violence on the enrolment decision of Muslim girls is small, however this result is not robust to inclusion of lead measures of violence.

7 Conclusion and Future Work

In this chapter I attempt to measure the relationship between communal violence in India and the schooling decision of Muslim children. While there has been considerable research on the causes of communal, caste-based and Maoist violence in India, there is much less research on the consequences and effects of this violence. I started the analysis with a straightforward ordinary least square regression. An OLS regression specification gives us an unbiased estimate of the relationship between dropout/enrolment rates and violence. If I were to relax the assumption of perfectly reported incidences of riots, and assume that only a fraction of actual incidences of violence are reported, then our OLS estimates may be biased downward. Even so, the OLS estimates give us, at worst, a lower bound for the coefficient estimate. However, it should be noted that a simple OLS estimate gives us the correlation between riots and dropout rates, and the implied relationship is not necessarily causal. A solution for this is to use an instrument variable approach. Several methods have been discussed in previous literature to instrument for the occurrence of violence. For future work, a method that is similar to that used by Wilkinson (2004) can be used where riots are modelled as being affected by the presence of political competition. It is widely speculated that violence is often used as a tool by political parties to polarize the electorate and create plurality for winning in a first-past-the-post system. In closely contested elections, it becomes even more imperative for the dominant parties to maintain their dominance by encouraging inter-ethnic violence and polarizing the electorate for electoral dividends. Closeness to an upcoming election and winning margin in the previous election can be used as an instrument for violence in a district in any given year. It is hypothesized that the closer a constituency is to an upcoming election and the smaller the margin of victory was in the previous election, the more likely it is for the district to experience rioting. Data on state assembly elections results from the Election Commission of India can be used to estimate the winning and margin and the dates for past and upcoming elections.

In this chapter I considered both stock and flow measures of education as outcomes of interest. In the first case I modelled the decision to dropout (or remain enrolled), as a function of contemporaneous experience of violence, where violence was measured as the total casualties or total incidents of Hindu-Muslim riots. I found that violence experienced in the period just before, had a significant but very small negative relationship on the decision to remain enrolled in school for Muslim girls, however this was offset entirely by the positive correlation between education and violence in general and for girls in particular. This finding is unusual since girls are often at the margins of the household resource allocation decision and any incidence of violence that affects household resources through disruption of economic activity is likely to result in reduction of expenditure on the schooling of girls. In addition, concerns for physical well-being and threats of sexual violence against women and girls is also more likely to result in girls being forced to stop or delay their education attainment. While I did find a statistically significant negative coefficient of violence on schooling for Muslim girls, this result was not robust, in particular, to inclusion of future violence as an additional measure. This was true across several specifications and samples. Moreover, I did not observe any correlation between school and violence for any other sub-group as well. There could be several factors driving this result. Firstly, dropout from school in India is a drastic and often permanent decision hence an event would have to be calamitous in nature to force parents to withdraw their children from school permanently. Secondly, compared to previous studies that examine the effect of civil war and large-scale violence on schooling, the nature of communal violence in India is sporadic and dispersed over time. Most of the incidents of violence result in no casualties and are short-lived. Moreover, these incidents are concentrated in certain states, districts and cities, with some states and urban areas within states much more likely to experience violence than other states and rural areas. The markedly different nature of Hindu-Muslim violence in India may be driving the lack of any significant relationship between enrolment decisions and experience of violence.

To consider if the dose-responses to violence matters more than immediate exposure, I also modelled certain stock measures of education such as years of education, completion of primary school and age of school dropout, as a function of cumulative lifetime experience of violence and found that long term exposure to violence also had only a small effect on schooling decisions. As in the main specification, these negative coefficients were significant only for Muslim girls. The magnitude of the effect was economically insignificant considering the mean exposure to violence was very small and offset by the positive coefficient for females in general. It is thus worth considering if a finer measure of educational deprivation might better capture the effect of violence on schooling. One such measure could be school performance. While sporadic and small-scale violence may not cause reduction in the quantity of schooling acquired, it could certainly affect the quality of learning, which could manifest itself in lower achievement on exams and test-scores. For future research on the relationship between communal violence and education decisions, we could consider using test score data to get a more nuanced measure of education achievement from various data sources. The only publicly available data on test scores in India at the moment is the India Human Development Survey which is a two period panel first conducted in 2004-05 and followed up in 2011-12. As a part of the survey, children aged 8-11 years were tested on reading, math and writing and scored on a progressive scale. Each of the two rounds tested roughly 12000 children. An advantage of the IHDS is that the children are tested at home and not in school, thus allowing the surveyors to interview children who may have dropped out of school or are out of school at the time of the survey. Following the vast literature that studies the impact of early life exposure to violence on later life outcomes, we may also be able to examine the impact of exposure to violence in early life on test score performance in later life.

APPENDICES

APPENDIX A

MAIN TABLES AND FIGURES

Table 3.1: Descriptive Statistics- Individual Sample

	All	Muslim		Non-Muslim	
		Male	Female	Male	Female
Age	16.588	16.048	16.341	16.527	16.805
	(0.012)	(0.044)	(0.046)	(0.018)	(0.020)
Rural	0.627	0.519	0.526	0.644	0.646
	(0.001)	(0.003)	(0.004)	(0.001)	(0.001)
Married	0.504	0.518	0.492	0.521	0.485
	(0.001)	(0.003)	(0.004)	(0.001)	(0.001)
Female	0.472	0.000	1.000	0.000	1.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
HH Size	5.821	6.491	6.614	5.575	5.823
	(0.005)	(0.019)	(0.021)	(0.007)	(0.007)
Muslim	0.150	1.000	1.000	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Age at School Start	5.531	5.650	5.675	5.494	5.523
	(0.001)	(0.005)	(0.005)	(0.002)	(0.002)
Age of Dropout	12.709	11.983	11.416	13.298	12.422
	(0.009)	(0.031)	(0.032)	(0.014)	(0.015)
Casual Labor HH	0.273	0.258	0.266	0.272	0.278
	(0.001)	(0.003)	(0.003)	(0.001)	(0.001)
Self Employed HH	0.511	0.548	0.534	0.508	0.504
	(0.001)	(0.003)	(0.004)	(0.001)	(0.001)
N	284,190	22,303	20,311	127,714	113,862

Source: Schedule 25.2 NSS on Education in India 64th and 71st Round
Standard Errors in parenthesis

Table 3.2: Effect of Casualties on Enrolment 1986-2006

	(1) Enrolled	(2) Enrolled	(3) Enrolled
Casualties at t	0.000269	-0.000214	-0.00308**
	(0.000711)	(0.000827)	(0.00101)
Casualties at t-1	0.000834	0.000803	0.000251
	(0.000625)	(0.000831)	(0.00111)
Casualties at t-2	0.000811	0.000564	-0.00106
	(0.000732)	(0.000866)	(0.00105)
Casual Labor HH	-23.65***	-23.09***	-23.07***
	(0.543)	(0.524)	(0.524)
Self Employed HH	-6.438***	-5.854***	-5.874***
	(0.390)	(0.376)	(0.380)
Rural	-6.925***	-8.041***	-7.980***
	(0.435)	(0.434)	(0.432)
Muslim		-11.54***	-12.72***
		(0.618)	(0.596)
Muslim* Casualties at t		0.00257*	0.00473***
		(0.00105)	(0.00115)
Muslim* Casualties at t-1		0.000219	0.00101
		(0.00122)	(0.00192)
Muslim* Casualties at t-2		0.00112	0.00404**
		(0.00115)	(0.00154)
Female			-10.02***
			(0.341)
Female* Casualties at t			0.00622***
			(0.000681)
Muslim*Female			2.572***
			(0.597)
Muslim*Female* Casualties at t			-0.00529***
			(0.00127)
Female* Casualties at t-1			0.00110
			(0.000888)
Muslim*Female* Casualties at t-1			-0.00253
			(0.00203)
Female* Casualties at t-2			0.00344***
			(0.000785)

Table 3.2 (cont'd)

Muslim*Female* Casualties at t-2			-0.00734**
			(0.00260)
Constant	84.22***	85.54***	90.09***
	(1.176)	(1.172)	(1.151)
N	1941021	1941021	1941021
Adjusted R^2	0.252	0.259	0.270
Mean casualties at t	3.640	Mean Enrolment All	69.343
	(0.033)		(.033)
Mean casualties at t-1	3.545	Mean Enrolment Muslim	60.688
	(0.033)		(.092)
Mean casualties at t-2	3.942	Mean Enrolment Muslim Female	56.421
	(0.035)		(.134)

Enrolment is measured as a whether the individual is enrolled a particular period or not, multiplied by 100. All specifications include district, year and birth cohort fixed effects. Linear probability model results reported. Robust standard errors clustered at the district level in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.3: Effect of Cumulative Violence (Casualties) on Individual Outcomes

	(1) Years of Education	(2) Age at Dropout	(3) Completed Primary (0/1)
Total Casualties	0.000428	0.000604*	0.00000215
	(0.000218)	(0.000246)	(0.0000145)
Muslim	-2.018***	-2.226***	-0.119***
	(0.102)	(0.111)	(0.00743)
Muslim * Total Casualties	-0.00000929	0.0000116	0.0000393***
	(0.0000851)	(0.0000783)	(0.00000916)
Female	-1.672***	-2.002***	-0.104***
	(0.0619)	(0.0669)	(0.00394)
Female * Total Casualties	0.000479***	0.000508***	0.0000289***
	(0.0000463)	(0.0000540)	(0.00000789)
Muslim * Female	0.497***	0.553***	0.0229**
	(0.106)	(0.120)	(0.00749)
Muslim * Female * Total Casualties	-0.000426***	-0.000414**	-0.0000354**
	(0.000128)	(0.000127)	(0.0000127)
Rural	-1.720***	-1.764***	-0.0683***
	(0.0779)	(0.0837)	(0.00488)
Casual Labor HH	-4.063***	-4.542***	-0.204***
	(0.0859)	(0.0963)	(0.00702)
Self Employed HH	-1.291***	-1.543***	-0.0349***
	(0.0809)	(0.0936)	(0.00379)
Constant	11.07***	18.17***	0.888***
	(0.172)	(0.190)	(0.0135)
N	75460	75396	176396
Adjusted R^2	0.211	0.209	0.105
Mean Total Casualties till age 18	87.285		
	(1.351)		
Mean Total Casualties till age 10	42.473		
	(0.524)		

Years of education is calculated using highest reported completed schooling level and status of current attendance. Age at drop-out is self-reported. For those who completed high-school age at dropout is 18. Columns 1 and 2 restricted to those who completed age 18 by 2006, the last year of available violence data and sum of casualties is the sum of casualties from birth to age 18 in the district of residence. Column 3 restricted to those older than age 10 by 2006, and sum of casualties is sum of casualties from birth to age 10 in district of residence. All specifications include district and birth cohort fixed effects. Ordinary least square results reported. Robust standard errors clustered at the district level in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

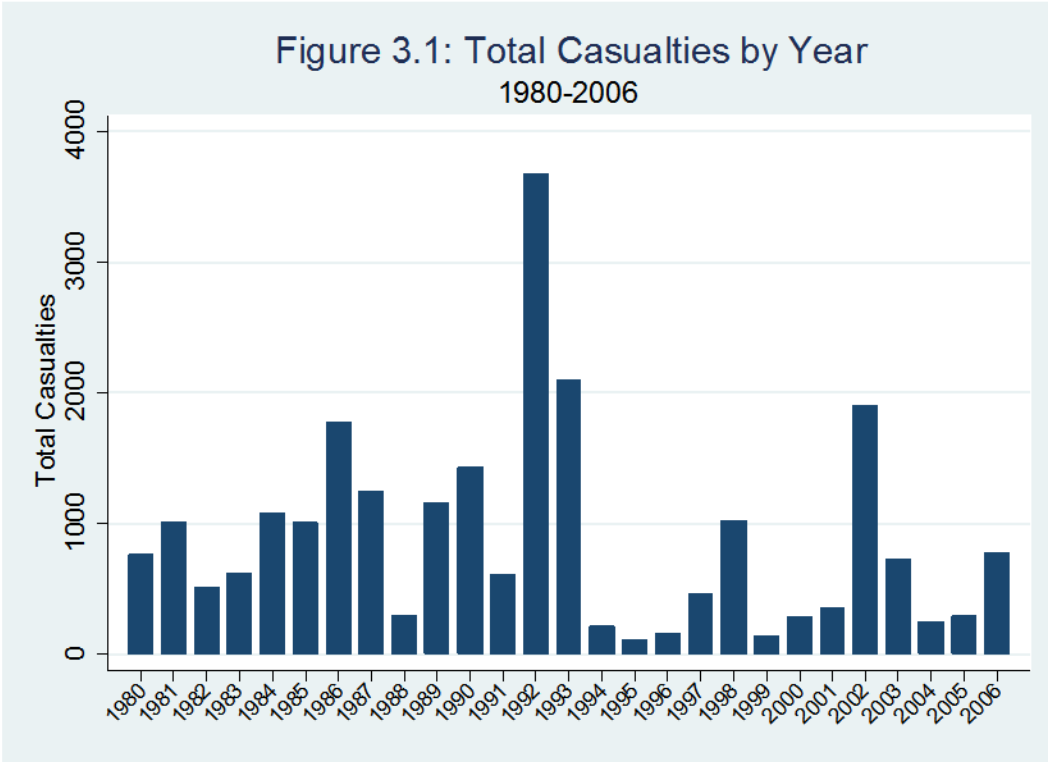
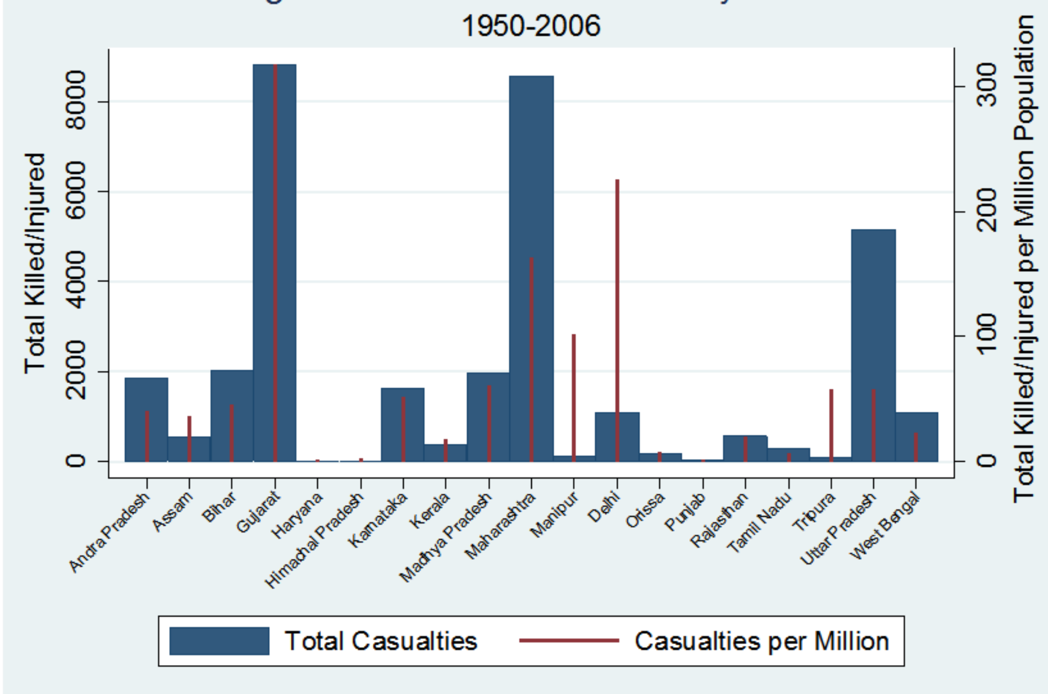


Figure 3.1: Total Casualties by Year
1980-2006
Total Casualties
0
1000
2000
3000
4000
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006

Figure 3.2: Total Casualties by State



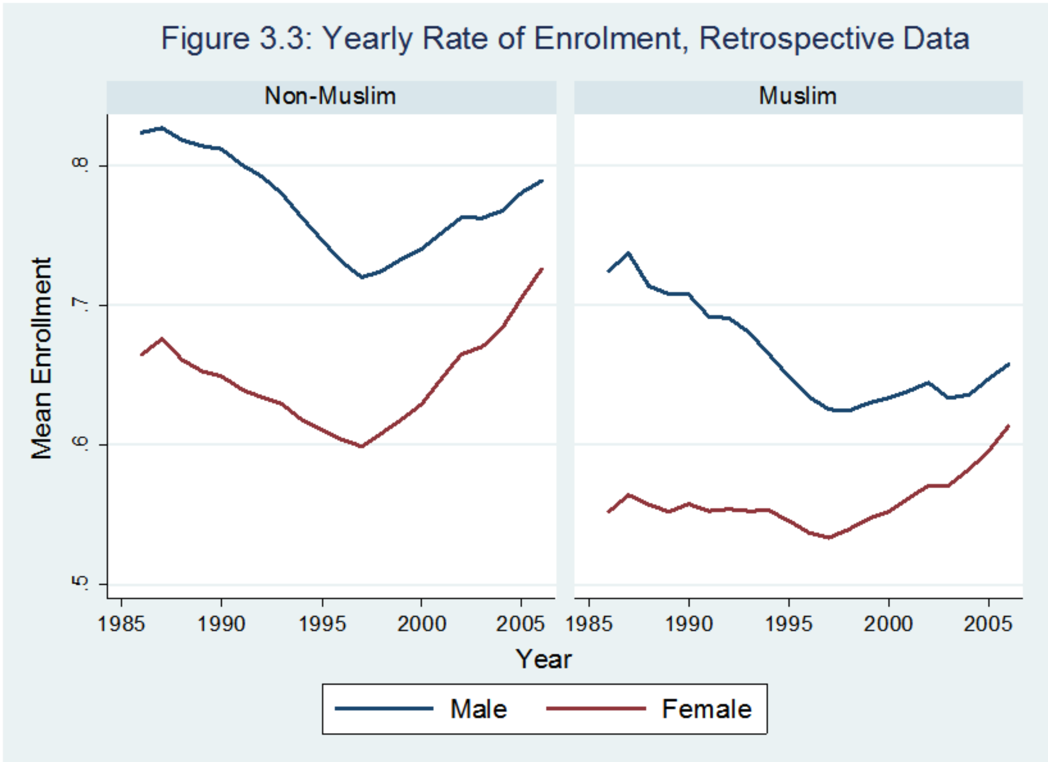


Figure 3.3: Yearly Rate of Enrolment, Retrospective Data
Non-Muslim
Muslim
Mean Enrollment
.5
.6
.7
.8
1985
1990
1995
2000
2005
Year
Male
Female

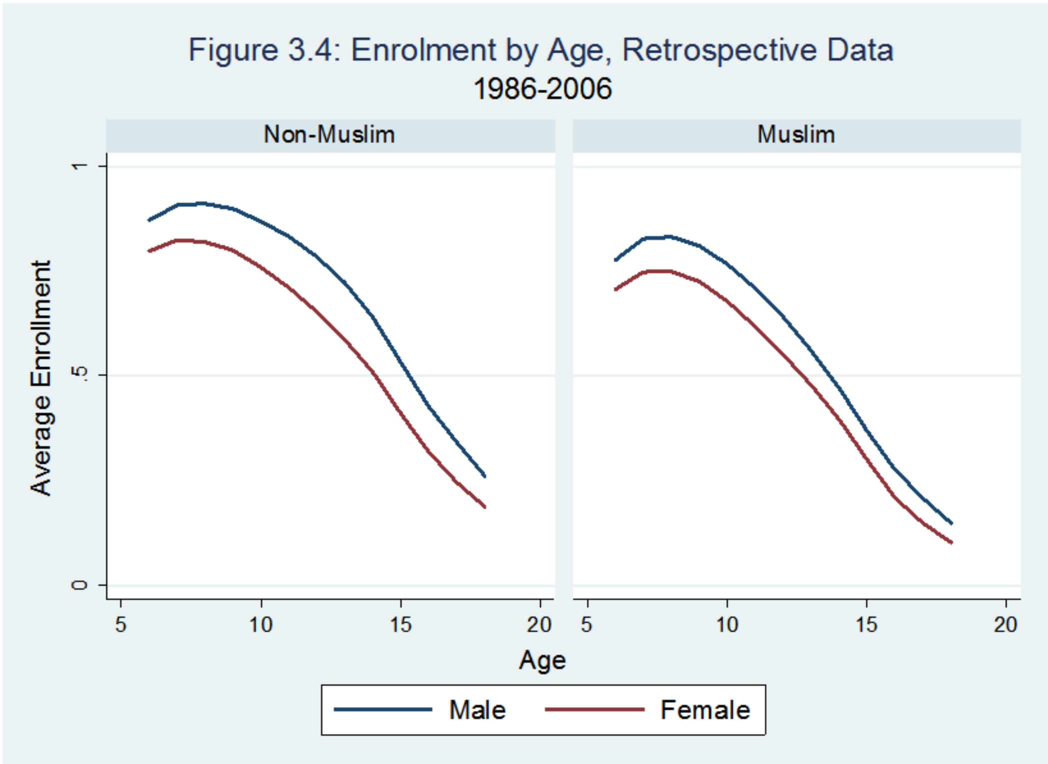


Figure 3.4: Enrolment by Age, Retrospective Data
1986-2006
Non-Muslim
Muslim
Average Enrollment
0
.5
1
5
10
15
20
Age
Male
Female

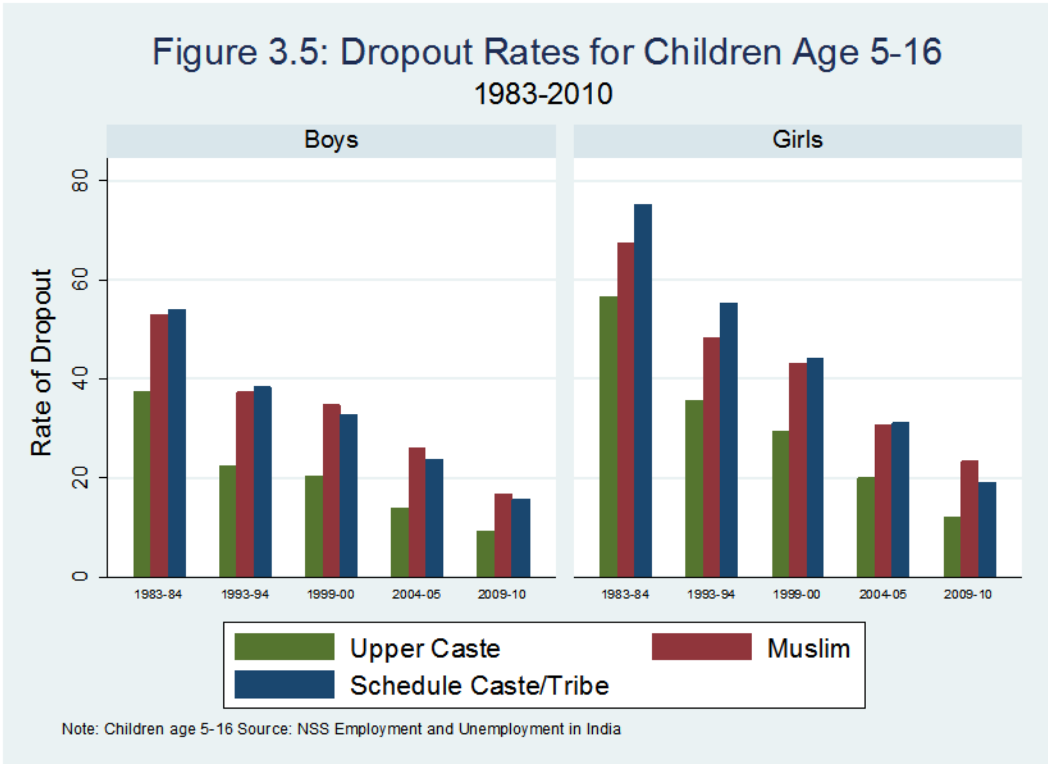


Figure 3.5: Dropout Rates for Children Age 5-16
1983-2010
Boys
Girls
Rate of Dropout
0
20
40
60
80
1983-84
1993-94
1999-00
2004-05
2009-10
Upper Caste
Muslim
Schedule Caste/Tribe
Note: Children age 5-16 Source: NSS Employment and Unemployment in India

APPENDIX B

SUPPLEMENTARY TABLES

Table 3.4: Effect of Incidents on Enrolment 1986-2006

	(1) Enrolled	(2) Enrolled	(3) Enrolled
Incidents at t	-0.0847	-0.0874	-0.332**
	(0.0944)	(0.107)	(0.124)
Incidents at t-1	-0.0187	-0.0217	-0.0754
	(0.0475)	(0.0536)	(0.0466)
Incidents at t-2	-0.123	-0.106	-0.202
	(0.0859)	(0.107)	(0.140)
Casual Labor HH	-23.65***	-23.09***	-23.07***
	(0.543)	(0.524)	(0.524)
Self Employed HH	-6.438***	-5.851***	-5.871***
	(0.389)	(0.376)	(0.380)
Rural	-6.925***	-8.041***	-7.981***
	(0.435)	(0.434)	(0.432)
Muslim		-11.48***	-12.70***
		(0.622)	(0.602)
Muslim* Incidents at t		-0.0101	0.0942
		(0.224)	(0.248)
Muslim* Incidents at t-1		-0.0109	0.0829
		(0.110)	(0.162)
Muslim* Incidents at t-2		-0.222	0.0336
		(0.218)	(0.259)
Female			-10.10***
			(0.342)
Female* Incidents at t			0.541**
			(0.172)
Muslim*Female			2.667***
			(0.607)
Muslim*Female* Incidents at t			-0.246
			(0.242)
Female* Incidents at t-1			0.119
			(0.0980)
Muslim*Female* Incidents at t-1			-0.203
			(0.181)
Female* Incidents at t-2			0.224
			(0.167)

Table 3.4 (cont'd)

Muslim*Female* Incidents at t-2			-0.599* (0.280)
Constant	84.30*** (1.187)	85.61*** (1.183)	90.19*** (1.161)
N	1941021	1941021	1941021
Adjusted R^2	0.252	0.259	0.270
Mean Incidents at t	0.145 (0.001)	Mean Enrolment All	69.343 (.033)
Mean Incidents at t-1	0.148 (0.001)	Mean Enrolment Muslim	60.688 (.092)
Mean Incidents at t-2	0.157 (0.001)	Mean Enrolment Muslim Female	56.421 (.134)

Enrolment is measured as a whether the individual is enrolled a particular period or not, multiplied by 100. All specifications include district, year and birth cohort fixed effects. Linear probability model results reported. Robust standard errors clustered at the district level in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.5: Effect of Cumulative Violence (Incidents) on Individual Outcomes

	(1) Years of Education	(2) Age at Dropout	(3) Completed Primary (0/1)
Total Incidents	0.0193	0.0302*	0.00242
	(0.0141)	(0.0150)	(0.00138)
Muslim	-2.013***	-2.221***	-0.104***
	(0.107)	(0.114)	(0.00937)
Muslim * Total Incidents	-0.00221	-0.00121	0.00132
	(0.00844)	(0.00855)	(0.00107)
Female	-1.679***	-2.011***	-0.117***
	(0.0627)	(0.0678)	(0.00524)
Female * Incidents Total	0.0169**	0.0183**	0.000754
	(0.00554)	(0.00569)	(0.000748)
Muslim * Female	0.492***	0.554***	0.0205
	(0.109)	(0.123)	(0.0119)
Muslim * Female * Incidents Total	-0.0114	-0.0126	-0.00194
	(0.0103)	(0.0107)	(0.00255)
Rural	-1.721***	-1.765***	-0.0749***
	(0.0780)	(0.0837)	(0.00552)
Casual Labor HH	-4.062***	-4.541***	-0.226***
	(0.0859)	(0.0964)	(0.00764)
Self Employed HH	-1.290***	-1.542***	-0.0313***
	(0.0811)	(0.0939)	(0.00454)
Constant	11.05***	18.14***	0.890***
	(0.173)	(0.191)	(0.0150)
N	75460	75396	76635
Adjusted R^2	0.210	0.208	0.184
Mean Total Incidents till age 18	2.915		
	(0.029)		
Mean Total Incidents till age 10	1.472		
	(0.010)		

Years of education is calculated using highest reported completed schooling level and status of current attendance. Age at drop-out is self-reported. For those who completed high-school age at dropout is 18. Columns 1 and 2 restricted to those who completed age 18 by 2006, the last year of available violence data and sum of incidents is the sum of incidents from birth to age 18 in the district of residence. Column 3 restricted to those older than age 10 by 2006, and sum of incidents is sum of incidents from birth to age 10 in district of residence. All specifications include district and birth cohort fixed effects. Ordinary least square results reported. Robust standard errors clustered at the district level in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.6: Effect of Past and Future Casualties on Enrolment 1986-2006

	(1)	(2)
	Enrolled	Enrolled
Casualties t	0.00362***	-0.00176
	(0.000952)	(0.00129)
Casualties t-1	0.00252**	-0.000911
	(0.000857)	(0.00103)
Casualties t-2	0.00245*	-0.000969
	(0.00116)	(0.00120)
Muslim		-12.58***
		(0.615)
Muslim*Casualties t		0.00273*
		(0.00125)
Female		-10.79***
		(0.368)
Female*Casualties t		0.00411***
		(0.000674)
Muslim*Female		2.633***
		(0.649)
Muslim*Female*Casualties t		-0.00383***
		(0.00109)
Muslim* Casualties t-1		0.00108
		(0.00138)
Female*Casualties t-1		0.00205**
		(0.000625)
Muslim*Female*Casualties t-1		-0.00251
		(0.00185)
Muslim*Casualties t-2		0.00362*
		(0.00148)
Female*Casualties t-2		0.00301***
		(0.000837)
Muslim*Female*Casualties t-2		-0.00688**
		(0.00233)
Casualties t+1	0.00319**	-0.00131
	(0.00101)	(0.00128)
Casualties t+2	0.00390***	-0.00349***
	(0.00102)	(0.000882)

Table 3.6 (cont'd)

Muslim*Casualties t+1		0.00276***
		(0.000813)
Female*Casualties t+1		0.00403*
		(0.00195)
Muslim*Female*Casualties t+1		-0.00499**
		(0.00153)
Muslim*Casualties t+2		0.00397*
		(0.00156)
Female*Casualties t+2		0.00734***
		(0.000928)
Muslim*Female*Casualties t+2		-0.00706***
		(0.00188)
Casual Labor HH		-23.52***
		(0.544)
Self Employed HH		-5.781***
		(0.402)
Rural		-8.438***
		(0.457)
Constant	68.46***	90.73***
	(0.0176)	(1.157)
N	1616207	1616207
Adjusted R^2	0.000	0.266

Enrolment is measured as a whether the individual is enrolled a particular period or not, multiplied by 100. All specifications include district, year and birth cohort fixed effects. Linear probability model results reported. Robust standard errors clustered at the district level in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.7: Effect of Casualties on Enrolment 1986-2006, Unmarried Sample

	(1)	(2)	(3)	(4)
	Enrolled		Enrolled	
	Only lags		Leads and Lags	
Casualties t	0.00615***	-0.000692	0.00709*	0.000768
	(0.00118)	(0.00225)	(0.00299)	(0.00247)
Casualties t-1	0.00103	0.00175	0.00557	0.000648
	(0.00269)	(0.00111)	(0.00392)	(0.00107)
Casualties t-2	0.00216	-0.000190	0.00498	0.0000556
	(0.00435)	(0.00166)	(0.00613)	(0.00153)
Muslim		-11.43***		-11.66***
		(0.773)		(0.815)
Muslim*Casualties t		0.00387		0.00185
		(0.00230)		(0.00232)
Female		-11.58***		-12.49***
		(0.410)		(0.447)
Female*Casualties t		0.00490***		0.00287
		(0.00147)		(0.00148)
Muslim*Female		2.613**		2.727**
		(0.844)		(0.928)
Muslim*Female*Casualties t		-0.00970***		-0.00666***
		(0.00181)		(0.00151)
Muslim* Casualties t-1		0.00239		0.00303
		(0.00229)		(0.00162)
Female*Casualties t-1		-0.000523		0.000655
		(0.000846)		(0.000870)
Muslim*Female*Casualties t-1		-0.00516		-0.00551*
		(0.00281)		(0.00225)
Muslim*Casualties t-2		0.00430*		0.00356
		(0.00209)		(0.00209)
Female*Casualties t-2		0.00446**		0.00437**
		(0.00151)		(0.00134)
Muslim*Female*Casualties t-2		-0.0101***		-0.00945***
		(0.00232)		(0.00229)
Casualties t+1			0.00468	0.00174
			(0.00291)	(0.00236)
Casualties t+2			0.00839***	0.0000509
			(0.00164)	(0.00181)

Table 3.7 (cont'd)

Muslim*Casualties t+1				0.000745
				(0.00230)
Female*Casualties t+1				0.00155
				(0.00251)
Muslim*Female*Casualties t+1				-0.00572*
				(0.00286)
Muslim*Casualties t+2				0.00324
				(0.00199)
Female*Casualties t+2				0.00408*
				(0.00179)
Muslim*Female*Casualties t+2				-0.0117***
				(0.00229)
Casual Labor HH		-23.86***		-24.95***
		(0.573)		(0.612)
Self Employed HH		-5.399***		-5.738***
		(0.449)		(0.509)
Rural		-8.904***		-9.425***
		(0.479)		(0.526)
Constant	63.24***	90.17***	60.19***	91.11***
	(0.0292)	(1.246)	(0.0634)	(1.268)
N	868106	868106	749919	749919
Adjusted R^2	0.000	0.354	0.000	0.337

Enrolment is measured as a whether the individual is enrolled a particular period or not, multiplied by 100. All specifications include district, year and birth cohort fixed effects. Linear probability model results reported. Robust standard errors clustered at the district level in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.8: Effect of Cumulative Violence (Casualties), Unmarried Sample

	(1) Years of Education	(2) Age at Dropout	(3) Completed Primary (0/1)
Sum of Casualties	0.00110	0.00146**	0.0000183
	(0.000592)	(0.000536)	(0.0000234)
Muslim	-2.056***	-2.252***	-0.103***
	(0.145)	(0.159)	(0.00926)
Muslim * Casualties	-0.0000202	0.0000475	0.0000386**
	(0.000126)	(0.000131)	(0.0000122)
Female	-1.939***	-2.315***	-0.117***
	(0.0705)	(0.0782)	(0.00516)
Female * Casualties	0.000359***	0.000358**	0.0000247
	(0.0000877)	(0.000118)	(0.0000132)
Muslim * Female	0.675***	0.778***	0.0205
	(0.138)	(0.160)	(0.0112)
Muslim * Female * Casualties	-0.000463***	-0.000467**	-0.0000726*
	(0.000123)	(0.000149)	(0.0000305)
Rural	-1.750***	-1.760***	-0.0750***
	(0.0944)	(0.100)	(0.00552)
Casual Labor HH	-4.104***	-4.499***	-0.226***
	(0.105)	(0.118)	(0.00764)
Self Employed HH	-1.355***	-1.566***	-0.0313***
	(0.109)	(0.122)	(0.00455)
Constant	10.86***	17.89***	0.894***
	(0.205)	(0.220)	(0.0148)
N	42507	42487	76635
Adjusted R^2	0.212	0.210	0.184

Years of education is calculated using highest reported completed schooling level and status of current attendance. Age at drop-out is self-reported. For those who completed high-school age at dropout is 18. Columns 1 and 2 restricted to those who completed age 18 by 2006, the last year of available violence data and sum of casualties is the sum of casualties from birth to age 18 in the district of residence. Column 3 restricted to those older than age 10 by 2006, and sum of casualties is sum of casualties from birth to age 10 in district of residence. All specifications include district and birth cohort fixed effects. Ordinary least square results reported. Robust standard errors clustered at the district level in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.9: Effect of Casualties on Enrolment 1986-2006, Hazard Model

	(1)	(2)	(3)	(4)
	Logit	OLS	Logit	OLS
	Only Lags		Lags and Leads	
Casualties t	-0.000211*	-0.00400***	-0.0000898	-0.00219*
	(0.0000892)	(0.000798)	(0.0000994)	(0.000917)
Muslim	-0.909***	-10.74***	-0.895***	-10.92***
	(0.0463)	(0.662)	(0.0475)	(0.687)
Muslim * Casualties t	0.000148	0.00550***	0.0000140	0.00305*
	(0.000119)	(0.00109)	(0.000145)	(0.00127)
Female	-0.894***	-10.91***	-0.932***	-11.83***
	(0.0219)	(0.395)	(0.0229)	(0.426)
Female * Casualties t	0.000392*	0.00744***	0.000225*	0.00526***
	(0.000156)	(0.00132)	(0.0000892)	(0.000727)
Muslim * Female	0.264***	1.237	0.265***	1.406
	(0.0393)	(0.685)	(0.0419)	(0.735)
Muslim * Female * Casualties t	-0.000276	-0.00322	-0.000133	-0.00247
	(0.000283)	(0.00299)	(0.000188)	(0.00247)
Casualties t-1	0.0000439	0.0000153	-0.0000256	-0.00150*
	(0.0000654)	(0.000870)	(0.0000531)	(0.000634)
Muslim * Casualties t-1	-0.0000957	0.000887	-0.0000804	0.00145
	(0.000164)	(0.00209)	(0.000108)	(0.00138)
Female * Casualties t-1	-0.00000690	0.00203**	0.0000797	0.00336***
	(0.0000584)	(0.000696)	(0.0000656)	(0.000597)
Muslim * Female * Casualties t-1	-0.0000189	-0.00182	-0.0000347	-0.00162
	(0.000111)	(0.00120)	(0.0000929)	(0.00124)
Casualties t-2	-0.0000653	-0.00179	-0.0000600	-0.00165
	(0.000127)	(0.000912)	(0.000118)	(0.000940)
Muslim * Casualties t-2	0.000155	0.00510***	0.000138	0.00465**
	(0.000135)	(0.00132)	(0.000142)	(0.00144)
Female * Casualties t-2	0.000129	0.00471***	0.000109	0.00439***
	(0.000119)	(0.000868)	(0.0000980)	(0.000733)
Muslim * Female * Casualties t-2	-0.000292*	-0.00523***	-0.000280*	-0.00539***
	(0.000117)	(0.00129)	(0.000114)	(0.00131)
Casualties t+1			-0.0000808	-0.00132
			(0.0000785)	(0.000858)
Muslim * Casualties t+1			0.0000616	0.00273***
			(0.0000661)	(0.000752)

Table 3.9 (cont'd)

Female * Casualties t+1			0.000174**	0.00409***
			(0.0000615)	(0.000869)
Muslim * Female * Casualties t+1			-0.000212	-0.00351
			(0.000153)	(0.00209)
Casualties t+2			-0.000118	-0.00374***
			(0.0000855)	(0.000752)
Muslim * Casualties t+2			0.000134	0.00590**
			(0.000252)	(0.00199)
Female * Casualties t+2			0.000262**	0.00708***
			(0.0000966)	(0.000980)
Muslim * Female * Casualties t+2			-0.000450**	-0.00638***
			(0.000141)	(0.00186)
Self Employed HH	-0.520***	-3.993***	-0.514***	-4.035***
	(0.0347)	(0.351)	(0.0359)	(0.376)
Casual Labor HH	-1.658***	-20.85***	-1.668***	-21.74***
	(0.0366)	(0.631)	(0.0374)	(0.652)
Rural	-0.621***	-7.537***	-0.643***	-8.129***
	(0.0356)	(0.455)	(0.0365)	(0.485)
Constant	2.697***	91.57***	2.711***	92.05***
	(0.0843)	(1.195)	(0.0847)	(1.204)
N	1709006	1709006	1428903	1428903
Adjusted R^2		0.240		0.247

Enrolment is measured as a whether the individual is enrolled in a period or not. For logit specification, enrolled is a binary variable, for the OLS specification, enrolled is multiplied by 100. All specifications include district and year fixed effects as well as controls for baseline hazard or duration. Robust standard errors clustered at the district level in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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