Three Essays on Female and Child Outcomes in India

by

Shampa Bhattacharjee

B. Sc (Hons.), University of Calcutta, 2006

M.S (Q.E), Indian Statistical Institute, 2008

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Abstract

Poor child health outcomes and high fertility rates are viewed as major obstacles to development in most developing countries. Chapters 2 and 3 of my thesis investigate the determinants of these outcomes in the Indian context.

The second chapter looks at the impact of political cycles on infant mortality in India. This study shows that children born 0-12 months before scheduled state assembly elections have 13.4% lower mortality risks as compared to children not born before scheduled elections and that the effect is higher for children born in more politically competitive regions. In addition, the chapter presents some evidence that mothers who gave birth before elections have more regular antenatal check-ups and at least one tetanus injection during their pregnancy. Children born before scheduled assembly elections are also less likely to suffer from low birth weight.

My third chapter tests the effect of female employment on fertility in India. The results show that female employment in manufacturing has a negative impact on fertility once the endogeneity in female employment is accounted for. However female employment in agriculture and aggregate female labour force participation

has no such effects.

The fourth chapter is joint work with Dr. Viktoria Hnatkovska and Dr. Amartya Lahiri. This chapter examines the evolution of gender gaps in India between 1983 and 2010 in education, occupation choices and wages. The chapter shows that the gaps have shrunk quite sharply between men and women in education and choice of occupations and wages. The gaps have narrowed most sharply for the youngest cohorts in the workforce, suggesting that measured gaps will continue to decline over the next two decades.

Preface

The first two chapters of this thesis are original, unpublished, independent work by the author, Shampa Bhattacharjee. The third chapter is joint work with Dr. Viktoria Hnatkovska and Dr. Amartya Lahiri at the at the Vancouver School of Economics, University of British Columbia. A version of the third chapter has been published [Bhattacharjee, Shampa, Viktoria Hnatkovska and Amartya Lahiri. 2015. "The Evolution of Gender Gaps in India". In *India Policy Forum 2014-15, volume 11, Brookings Institution and National Council of Applied Economic Research*, edited by Subir Gokarn, Arvind Panagariya, and Shekhar Shah, 119-156. New Delhi, Sage publications.]. I did the most of the empirical analysis and contributed to preparing parts of the manuscript.

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Chapter 1

Introduction

Poor child health outcomes coupled with rapid population growth are viewed as major obstacles to development in most developing countries. The problems become more acute in the Indian context, where infant mortality was 46 per thousand live births in 2013. Not only is this figure higher than developed countries (Japan: 2 per 1000, United Kingdom 4 per 1000, United States 6 per 1000), but it is also higher in comparison to other south Asian countries like Bangladesh (39 per 1000), Nepal (36 per 1000) and Bhutan (34 per 1000). Likewise, high fertility is an important concern in India, where the total fertility rate was 2.5 per woman in 2013. This is again higher compared to Bangladesh (2.2), Nepal(2.3) and Bhutan (2.2). Chapters 2 and 3 of my thesis investigate the determinants of these outcomes in the Indian context.

Chapter 2 of my thesis tests the impact of political cycles on development outcomes in India. It has been widely established in the political economy literature that politicians are concerned about winning elections and thus they adopt policies to maximize their chances of being elected. Such opportunistic behaviour on the part of politicians often results in the creation of favorable economic conditions before elections (Nordhaus (1975); Rogoff (1990); Alesina and Roubini (1992)). This can have large implications for the welfare of individuals in developing countries since the poor electorate in these countries is highly sensitive to economic fluctuations.

In this chapter, I focus on child health outcomes; infant mortality in particular. Infant mortality is an extremely important issue from the point of view of developing countries and is associated with a number of factors like maternal health, quality and access to medical care and socioeconomic conditions. According to Cutler, Deaton, and Lleras-Muney (2006) deaths in childhood comprise a significant percentage of all deaths in poor countries (30%) as compared to rich countries (less than 1%). Given that child health is an acute problem in poor countries, a politician may want to exert higher effort to improve health conditions before elections in order to secure more votes. Thus public health systems may function more efficiently during election years. The existence of political cycles also implies that the overall economic conditions improve during election years and this can show up in child health. Various development schemes (like temporary employment generation schemes) may work more efficiently under pressure from the government which translates into higher family income and improved nutritional status leading to better health outcomes.

This chapter shows that children born 0-12 months before scheduled state assembly elections have 13.4% lower mortality rate as compared to children not born before scheduled elections. My results also show that the effect of the timing of scheduled elections is higher for children born in more politically competitive regions. In addition, the chapter presents some evidence that health care utilization improves for mothers who give birth before scheduled elections. Children born before scheduled assembly elections are also less likely have low birth weight.

Chapter 3 tests the effect of female labor force participation on fertility rates in India using district level data between the period 1987-2001. I have also computed the effects of female employment in the agricultural and the manufacturing sectors on total fertility rates. The results show that female labor force participation in manufacturing has a significant negative impact on fertility once the endogeneity in female labor force participation is accounted for. However female employment in agriculture and overall female labor force participation has no significant impact on fertility.

Chapter 4 is joint work with Dr. Viktoria Hnatkovska and Dr. Amartya Lahiri. In this chapter we have examined the evolution of gender gaps in India between 1983 and 2010 in education, occupation choices and wages. We find that the gender gaps have shrunk quite sharply in education and choice of occupations. Our analysis also shows that wage gaps have declined across most percentiles of the income distribution. The gaps have narrowed most sharply for the youngest cohorts in the workforce suggesting that measured gaps will continue to decline over the next two decades.

Chapter 2

The Timing of Elections and Infant Mortality: Evidence from India

2.1 Introduction

Politicians are concerned with winning elections and thus they adopt policies to maximize their chances of being elected. Such opportunistic behaviour on the part of politicians often results in the creation of favorable economic conditions before elections (Nordhaus (1975); Rogoff (1990); Alesina and Roubini (1992)). This can have large implications for the welfare of individuals in developing countries since the poor electorate in these countries is highly sensitive to economic fluctuations.

In this chapter I investigate the effect of the timing of state assembly elections on child health in India. I focus on child health, in particular infant mortality, for the following reasons. Firstly, child health is an extremely important issue from the point of view of developing countries, where deaths in childhood typically comprise a significant percentage of all deaths (roughly 30%) as compared to rich countries (less than 1%) (Cutler, Deaton, and Lleras-Muney (2006)). Given that child health is such an acute problem in poor countries, a politician may want to exert higher effort to improve these health conditions before elections in order to secure more votes. Thus public health systems can potentially function more efficiently during election years. Secondly, even if policy makers do not target public health directly, the existence of political cycles implies that overall economic conditions improve during election years and this can show up in child health. Various development schemes (like temporary employment generation schemes) might work more efficiently under pressure from the government which translates into higher family income and improved nutritional status leading to better child health outcomes.

The existing literature has extensively studied opportunistic political cycles. Some studies have examined the impact of the election cycle on government policy. Veiga and Veiga (2007) showed that Portuguese local governments increase total expenditures in the before elections. Other studies have analyzed political cycles in macro level outcomes such as inflation, growth or employment (McCallum (1978); Alesina (1988)). However, very few studies have focused on whether the injection of public services before elections produces better social and economic individual level outcomes.

There is a small but emerging literature on political cycles in India (Cole

(2009), Khemani (2004)). However, their research mostly focused on the effect of political cycles on government policy. In this chapter, instead of looking at government policies, I investigate the effect of state elections on child heath which is often considered an index of welfare in developing countries.

This study also contributes to the literature on the implications of aggregate economic conditions on child health. Previous research has found that political cycles create temporary economic booms. The results obtained in this chapter imply that the improvement in overall conditions during elections contribute positively towards child survival during infancy. The results also seem to suggest that there might be some long run implications of being born before elections on adult outcomes. There has been evidence of factors that jointly determine infant mortality and adult life outcomes. For example birth weight in the short run influences infant mortality while in the long run has significant impact on adult characteristics like height, IQ, earnings and education (Black, Devereux, and Salvanes (2007)). However, further research is required on this topic.

India is a particularly relevant place to analyze the implications of election cycles. It is a developing country with high participation in democratic elections. The states in my sample have an average voter turnout of about 58%. Also, Indian state elections are not perfectly synchronized enabling me to identify the impact of elections separately from time invariant effects. The constitution of India requires state elections to be held every five years. However, there have been some midterm elections where elections were held before the completion of the full five year terms. These elections take place one, two, three and four years after the previous election. Since scheduled elections take place after the completion of full five year terms, the electoral calendar is exogenous and known perfectly in advance by all agents. Hence, opportunistic manipulation by politicians before elections is possible. On the other hand, midterm elections are more likely to be sudden and thus allow politicians much less time to manipulate policies. The identification strategy used in this chapter rests upon comparing the mortality risks of siblings born before scheduled elections and those born in off-election years.

An advantage of this study compared to previous research on political cycles in India is that this study uses a significantly larger sample; more than 150,000 children spanning over 23 years and covering 91 elections, 58 of which are scheduled elections[1]. Moreover, since the data have information on birth histories of mothers over time, I have been able include mother fixed effects in the estimations [2]. Thus, the results here essentially compare across children born to the same mothers at different points of time (those born before scheduled election years and those not born before scheduled elections).

Using data from the 14 major Indian states which have at least some degree of political competition; that is, states where an effective opposition party exists, I find that children born 0-12 months before scheduled state assembly elections have 13.4% lower mortality risks as compared to children not born before scheduled elections. The timing of midterm elections has no influence on infant mor-

1. One problem with Cole (2009) was that it covered only a period of eight years which might be considered insufficient for finding the effect of political cycles.

2. In Cole (2009) the unit of observation was at the district level analysis and in Khemani (2004) the unit of observation was at the state level. Thus Cole (2009) and Khemani (2004) could include only district and state fixed effects respectively

tality.

It can be argued that those children who are born just after scheduled elections have been exposed to improved prenatal care before elections. Thus these children should also experience some improvement in infant mortality. My results show that those children, who are born 0-1 month and 0-2 months after elections, gain from their exposure to improved prenatal care. However, children born 0-6 months after election do not experience any improvement in infant mortality.

It has been emphasized in the literature that political cycles depend on the degree of political competition (Dahlberg and Johansson (2002), Cole (2009)). Thus, we expect the impact of the timing of scheduled elections on infant mortality to be higher in more politically competitive regions. My results provide evidence of such targeting and show that the effect of the timing of scheduled elections is higher for children born in close election districts[3].

Infant mortality is sensitive to a number of conditions at the time of birth such as environment, sanitation, access to clean water, prenatal and neonatal health services, calorie intake and diseases (Ross (2006)). Governments can influence health conditions though public health initiatives like reducing the absenteeism of doctors and nurses in government hospitals, encouraging parents to visit public health facilities more frequently, filtering drinking water supplies, building sani-

3. Close election districts are those districts where incumbents had a narrow margin of victory in the previous election. In India, elections are held at constituency level. However, the data used for generating the infant mortality variable is observed only at the district level and not at the constituency level. A district is composed of a number of constituencies (9 on average) and so the election data has to be aggregated to the district level. Thus, the absolute margin is defined at the district level.

tation systems and draining swamps. Estimating the impact of election timing on the efficiency of the public health system (for example whether the election timing is synchronized with reduced absenteeism of public health workers) is a direct test of whether elections have a positive impact on government health policy. However, in the absence of data on these variables, I check whether there is improved health care utilization by mothers who gave birth before elections. In particular, I test whether the mothers of children born just before elections had more regular antenatal check-ups and had at least one tetanus injection during pregnancy. This chapter provides evidence that both of these things in fact occurred.

Government initiatives can also improve the nutritional status of children. This can be achieved by reducing leakages in the food security network, generating increased temporary employment opportunities via public works program (Schuknecht (1996)), or by providing direct monetary payments to voters (Akhmedov and Zhuravskaya (2004)) before elections. This means that consumption is likely to go up before elections. However, consumption data in available from the National Sample Survey (NSS) dataset and the survey is conducted every five years. Thus yearly consumption data is not available which makes it difficult to compare between election years and non-election years. In order to test the impact of the timing of elections on the nutritional standards of children, I analyze the impact of timing of elections on the incidence of low birth weight.

This chapter is divided into seven sections. The next section provides a brief review of the existing literature related to my work. Section 2.3 briefly outlines the institutional background. Section 2.4 describes the data used in this study.

Section 2.5 outlines the empirical strategy and discusses the results. Section 2.5.1 outlines the main results on the impact of the timing of elections on infant mortality. In section 2.5.2, I have estimated the impact of the timing of scheduled elections on neonatal and 2-12 month mortality separately, since in India most of the deaths during infancy occur in the first month of life. In sections 2.5.3 and 2.5.4, I have tried to identify the effect of the timing of elections on mortality risks of children born just before or after scheduled elections. Section 2.5.5 shows whether the impact of being born before scheduled elections is higher for electorally more competitive districts. Section 2.5.6 discusses some possible mechanisms which might describe the main results. I have done some robustness checks in Section 2.6. Section 2.7 finally concludes the chapter.

2.2 Literature Review

There is substantial research on whether politicians manipulate policy for electoral gains in developed countries. The first models of political cycles were developed by Nordhaus (1975) and Lindbeck (1976). They argue that with myopic voters opportunistic incumbent politicians stimulate the economy before elections. A separate set of models by Persson and Tabellini (1990) and Rogoff and Sibert (1988) predict political budget cycles based on rational expectations on the part of voters and asymmetric information between incumbents and voters. In such cases, policy makers signal their abilities by creating favorable economic situations before elections which lead to the emergence of political cycles.

Empirical evidence on opportunistic political cycles in developed countries is mixed. McCallum (1978), Alesina (1988) and Klein (1996) reject the claim that the timing of elections influences macroeconomic outcomes such as GDP growth and output in the United States. However, Berger and Woitek (1997) and Grier (2008) found that the timing of elections exerts a significant influence on aggregate output for Germany and the United States respectively. Apart from macroeconomic targets, several authors have claimed that politicians target policy instruments just before elections. Veiga and Veiga (2007) evaluated a panel composed of Portuguese municipalities during the 1979-2001 period and identified decreases in budget balances and local taxes and increases in expenditures in election years.

There is also a growing literature documenting the presence of political cycles in developing countries. Gonzalez (2002) showed that the Mexican government systematically used fiscal policy before elections as a means to secure votes. Akhmedov and Zhuravskaya (2004) investigated a panel of local Russian political jurisdictions and found an increase in public expenditures before elections and a decrease right afterwards. Drazen and Eslava (2010) showed that infrastructure spending increases prior to elections in Colombia.

In the Indian context, Cole (2009) shows that bank lending follows the electoral cycle, with agricultural credit increasing by 5-10% points in an election year. His paper also demonstrates that election year credit booms do not affect agricultural output. Khemani (2004) developed a career concerns model and empirically showed that state elections in India has a positive effect on public service delivery [4]. She also showed that elections have a negative effect on some commodity taxes and concluded that fiscal instruments are targeted to provide favors to pivotal groups of voters. My work is similar in spirit to the growing literature on political cycles in India. However, unlike most of the previous work which explores the manipulation of government policy instruments such as expenditure, taxes and credit during election years, my study analyses the effect of elections on individual level health outcomes.

A number of recent papers have highlighted the role of politicians' electoral incentives on service delivery which influences public health. Most of these studies have focused on interventions and institutions[5] that strengthen the electorate's voice leading to better public good provision and improved health outcomes (Fujiwara (2014), Chattopadhyay and Duflo (2004), Besley and Burgess (2001)). This chapter makes an important contribution to this literature by showing how the timing of policy is determined by the electoral incentives of the politicians and that this has a significant impact on health outcomes.

2.3 Institutional Background

The constitution of India requires that elections for state assemblies be held at five year intervals. However, unscheduled elections are possible, when alignments shift within the ruling party or the coalition government breaks down. Politi-

4. She used a specific public service, road construction

5. Interventions include changes in electoral rules like the introduction of new voting technologies (Fujiwara (2014)) and mandated political representations (Chattopadhyay and Duflo (2004)). Besley and Burgess (2001) showed that democratic institutions and mass media play a significant role in increasing the government's responsiveness to the electorate.

cal pressure from the central government is another important reason for midterm elections. The party governing at the center can dissolve a state legislature following the imposition of Presidential rule in a state. In the period 1975-1998, there were 91 state elections. Of these, 33 elections (36%) were unscheduled elections. The presence of midterm elections implies that elections across states do not take place at the same time.

The constitution of India assigns the powers and functions of the center and states[6]. The delivery of public health services is essentially a state responsibility[7] (Berman (1998)). In addition, health care workers are almost always state employees (Singh (2008)).

2.4 Data

The micro-data used in this survey come from the second round of the National Family Health Survey of India (NFHS-2) conducted in 1998[8]. This data-set contains complete fertility histories for ever-married women aged 15-49 in 1998-99, including the retrospective time and incidence of child deaths. The data has information on the district of residence of the household during the time of the survey.

6. The central government is responsible and can pass legislation on the services mentioned in the Union list (like defense and foreign affairs). Similarly, state governments have exclusive powers to pass legislation on services mentioned in the state list (like public order, police, and agriculture). There are also areas of joint jurisdiction of the center and the states like education. These items are mentioned in the concurrent list. The states do have jurisdiction over the concurrent list but in the case of conflict between the center and the states, the former has overriding power.

7. The health-related provisions in the union list relate mostly to research, and scientific and technical education. The concurrent list includes prevention of infectious diseases from spreading over state boundaries and other issues with wider national ramifications (Gupta and Rani (2004))

8. The last round of the NFHS (NFHS III, 2006) does not have district information and so the sample could not be extended beyond 1998.

While it is possible that the district of birth of the child might not be same as the district of the residence of the household in 1998-99, this is unlikely to be an issue in India. Spatial mobility is low in India(Munshi and Rosenzweig (2006); Deshingkar and Anderson (2004); Cutler et al. (2010)) and this is particularly true for women after marriage. Migration at the time of marriage is the main reason for geographical movement among women in India (Rosenzweig and Stark (1989), Deshingkar and Akter (2009)).

Using this dataset, we can construct individual-level indicators of infant mortality across time. The estimation sample contains more than 175,000 children born to more than 56,000 mothers born over the period 1975-1998 across 14 major Indian states. Table 2.1a shows that the average infant mortality over the sample is 89 per 1000 individuals[9]. There is substantial variation in infant mortality across states. Kerala has the lowest incidence of infant deaths at 29 per 1000 while the Uttar Pradesh has the highest rate at 117 per 1000 The sample averages of other individual level controls (listed in Appendix A) are also reported in Table 2.1a.

The election data come from the official website of the Election Commission of India. This data include the identity of the contestant, party affiliation and poll percentage of the electoral unit [10]. Table 2.1b shows the distribution of births across election and non-election years, for both scheduled and all elections. Figure 2.1 captures this cycle, where SE denotes scheduled election and ME denotes midterm election. 0 indicates children born 0-12 months before elections, -1 in-

9. This can be compared with the global average of 63 per 1000 in 1990

10. Assembly elections are held at the constituency level which is typically smaller than a district.

dicates children born 12-24 months before an election, -2 indicates children born more than 24 months before an election, +1 indicates children born 1-12 months after an election, +2 indicates children born 13-24 months before an election. By construction, the proportion of children born in all categories, except those born more than two years before, is higher for all elections as compared to the scheduled elections. The figures shown in Table 2.1b confirm this. Also by construction, the proportion of children born more than 24 months before scheduled elections is much higher than children born in the other categories.

Table 2.1b also shows a relatively higher proportion of children born 0-12 months before scheduled elections. This might imply that the mothers who give birth during election years are different from mothers who give birth in non-election years. However, comparing across children born to the same mother addresses this problem.

I have also tried to test whether the effect of the timing of elections on infant mortality is higher in more politically competitive regions. I define a region to be politically competitive if the incumbent party/coalition had a narrow margin of victory in the previous election in that region. The definition of regions however is a little problematic. In India elections are held at the constituency level and constituency level information is not available in the NFHS data-set. However, the NFHS data report the district of residence. A district is composed of a number of constituencies (usually 9). Thus, I have defined the margin of victory of the incumbent ruling party at the district level. This is given by the absolute difference between the proportion of seats obtained by the ruling party or ruling coalition and the proportion of seats obtained by the biggest opposition. Mathematically, the variable measuring political competition is given by:

$$A_{dst} = |p_{wdst} - p_{odst}| \tag{2.1}$$

where A_{dst} is the variable measuring political competition in the district d at time t. The variable p_{wdst} and p_{odst} measure the proportion of seats obtained by the ruling party (or ruling coalition) and the biggest opposition respectively, in the last assembly election, corresponding to time t in district d of state s.

The Election Commission of India website provides information on party affiliations of individual contestants in an election. However, the name of the ruling party or ruling coalition is not available from the election commission website which is essential for computing the political competition variable. I have used the Times of India database to ascertain the name of the party (or all the parties in case of coalition governments) that ruled a state.

In order to analyze the possible mechanisms behind the fall in infant mortality I have estimated the impact of the timing of elections on the following outcomes: the number of antenatal checkups during pregnancy, whether the mother had a tetanus injection during pregnancy and the incidence of low birth weight. Information on these variables is available only for children born after 1995 in NFHS II data. Three years is an extremely short period for estimating the impact of election cycles. At most one election per state will be covered and some states might not have a single scheduled election during this time. In order to address this problem of a small sample size, I have used NFHS I (1992-93) in addition to NFHS II for estimating these. Thus, the sample in this case contains information on children born between 1987-1992 from NFHS I and 1995-1998 from NFHS II[11].

2.5 Empirical Strategy and Results

2.5.1 Effect of Elections on Infant Mortality

I estimate the effect of being born in an election year on infant mortality. The basic estimating equation is:

$$y_{imdst} = \alpha + \beta E_{ist} + \phi X_{imdst} + \tau_t + \mu_m + \varepsilon_{idst} \quad (2.2)$$

Where y_{imdst} is a dummy variable that indicates whether the index child i, born to mother m, in district d of state s in year t died by the age of 12 months. E_{ist} is a dummy variable equal to 1 if the child i is born between 0 and 12 months before an election. μ_m and τ_t denote mother and year of birth fixed effects. X_{imdst} includes the controls used throughout the chapter. Child specific controls included in X_{imdst} are dummies for the order of birth, month of birth of the child, and a dummy variable indicating whether the child is female. These controls account for the variation in death risk within children born to the same mother. In addition real state domestic product lagged by two years and average voter turnout in districts in the previous election are also included as controls. Real state domestic product

11. The main results are also estimated using both rounds of NFHS as shown in Table A.4 given in Appendix A. The results are consistent with estimation using only NFHS II

controls for the level of prosperity across states[12].

Including mother fixed effects is particularly important. A problem of comparing children born in election years with children born in non-election years is that mothers who give birth just before elections might be different from mothers who give birth in other years. The differences can be due to differential living standards, fertility, contraception preferences and awareness of the availability of health-related technology and services. Thus, health improvements of children born before elections might be due to selection issues rather than changes in government policies. This will overestimate the effects if relatively better off mothers give birth in election years as compared to non-election years. Similarly, if poorer mothers choose to give birth before elections[13], the results will be underestimated. Mother fixed effects take account of the selection issues associated with the type of mothers who give birth before elections.

Here it is important to distinguish between scheduled elections and midterm elections. The scheduled elections are those which are mandated by the Constitution of India and occur five years after the previous election. Whereas midterm elections are those that occur one, two, three or four years after the last election (either scheduled or midterm), that is, before the completion of the full term of the present elected government in office. The timing of midterm elections is less likely to be exogenous. They are also likely to be sudden and so the government has less time to adjust policies. I have estimated the results separately for all elec-

12. The results are also robust to the inclusion of contemporaneous GDP as shown in Table A.2 in Appendix A.

13. This is more likely since these mothers are most in need of resources

tions, midterm elections and scheduled elections. We would expect the coefficient of the election dummy, β in equation (2.2), to be negative and statistically significant for children born before scheduled elections. We also expect smaller effects for children born before midterm elections.

Columns 1, 3 and 5 of Table 2.2 present the estimates of equation (2.2) for all elections, scheduled elections and midterm elections respectively. Column 1 shows that infant mortality is lower for children born between 0-12 months before all elections. The result is significant at the 10% level. The fall is much higher for children born 0-12 months before scheduled elections as shown in Column 3. Children born 0-12 months before scheduled elections have over 13% more survival chances. The estimate for scheduled election is highly significant at the 1% level. Consistent with the fact that midterm elections provide less scope for opportunistic manipulation, the results are insignificant for children born 0-12 months before midterm elections as shown in Column 5.

I have also estimated the effect of the entire election cycle on infant mortality. The estimating equation is:

$$y_{imdst} = \alpha + \beta_{-1}E_{-1ist} + \beta_0 E_{ist} + \beta_{+1}E_{+1ist} + \beta_{+2}E_{+2ist} + \gamma X_{imdst} + \delta_m + \tau_t + \xi_{imdst} \tag{2.3}$$

Where E_{ist} is a dummy variable which is equal to 1 if the child i is born 0-12 months before an election, E_{-1ist} is a dummy variable which is equal to 1 if the child i is born between 13 and 24 months before an election, E_{+1ist} is a dummy variable equal to 1 if the child i is born between 1 and 12 months after an election, E_{+2ist} is a dummy variable equal to 1 if the child i is born between 13 and 24 months after an election[14]. The omitted category includes children born 2 or more years before an election[15].

Figure 2.2 shows the predicted relationship estimated by equation (2.3). Panel (a) shows the relationship for all elections and panel (b) shows the relationship for scheduled elections. While panel (a) shows that infant mortality is more or less flat over the election cycle for all elections, panel (b) shows that infant mortality falls significantly for children born 0-12 months before scheduled elections

Columns 2, 4 and 6 of Table 2.2 show the estimates of equation (2.3) for all elections, scheduled elections and midterm elections respectively. Column 2 shows that children born 0-12 months before all elections have lower mortality risk. The estimates are all statistically insignificant. On the other hand, children born 0-12 months before scheduled elections have significantly lower mortality risk as shown in Column 4. The effect of being born before a midterm election is small and statistically insignificant.

One problem of comparing children born before scheduled election years with children not born before a scheduled election, is that the comparison group consists of children born before midterm elections and those born in off-election years. I have estimated the results dropping all children born 0-12 months before midterm elections so that the control group consists of children born in the

14. Sections 2.5.3 and 2.5.4 will show the results using different time frames.

15. The results obtained when other categories are treated as omitted categories are shown in Table A.1 in Appendix A.

off-election years. These results are presented in Table 2.3. Columns 1 and 2 of Table 2.3 correspond to Columns 3 and 4 of Table 2.2. They present the baseline results. Columns 3 and 4 of Table 2.3 present results from regressions estimated by excluding children born 0-12 months before midterm elections. It can be seen that the results are similar in sign and significance to the baseline results. Columns 5 and 6 of Table 2.3 show estimates of equation (2.3) using the full sample but controlling for midterm elections (that is including a dummy variable equal to 1 if the child i is born 0-12 months before midterm elections.). The estimates are again similar in sign and magnitude to the baseline results.

2.5.2 Neonatal and 2-12 Months Mortality

Infant mortality can be disaggregated into two components: neonatal mortality and mortality during the remaining 2-12 months of an infant's life. Neonatal mortality is mainly influenced by the mother's health and prenatal care. It is also extremely significant for India because most of the deaths during infancy occur in the first month of life. In my data the average neonatal mortality over the sample is 58 per 1000 while average infant mortality is 88.9 per 1000.

I have estimated the results separately for neonatal and 2-12 months mortality. The results are shown in Table 2.4. The first two columns of Table 2.4 shows the baseline results for infant mortality and are the same as Columns 3 and 4 of Table 2.2. Columns 3 and 4 show estimates for neonatal mortality and the last two columns contain estimates for 2-12 months mortality. The results show that children born before scheduled elections gain both from reduced neonatal and 2-12 month mortality. Children born 0-12 months before scheduled election years have a 13% and 14% reduced chance of neonatal and 2-12 month mortality respectively.

2.5.3 Closeness to Election and Infant Mortality

It is plausible that the children born closer to scheduled elections compared to those born earlier are more likely to benefit from policy manipulation before elections. In order to test this, I have divided the children born 0-12 months before scheduled elections into two groups: those who are born 0-6 months before elections and those who are born 6-12 months before elections. I have also regressed infant mortality on the number of months between birth of a child and the next scheduled election. The specification for these regressions are similar to equation (2.2).

Table 2.5 shows the estimates from the above regression. Column 1 shows the effect of being born 0-6 months before a scheduled election. The regression estimates corresponding to Column 2 include a dummy variable indicating whether a child is born 6-12 months before a scheduled election in addition to the dummy variable indicating whether a child is born 0-6 months before a scheduled election. Column 3 is similar to Column 3 of Table 2.2 and shows the effect of being born 0-12 months before a scheduled election. The results show that children who are born 0-6 months before a scheduled election experience a greater fall in infant mortality compared to children born 6-12 months before a scheduled election. The estimates of Column 4 are obtained by regressing the infant mortality variable on the difference in months between the birth of a child and the next scheduled election. Column 4 also shows that children born closer to elections are more likely to survive their infancy.

2.5.4 Infant Mortality Just Before and Just After Scheduled Elections

It might be argued that the mothers of children born just after scheduled elections have been exposed to better prenatal care for the most part of their pregnancy. Thus, these children should also experience better health outcomes.

I have estimated the effect of being born just before and just after scheduled elections. The results are shown in Table 2.6. The first 3 columns show the impact of being born 0-6, 0-2 and 0-1 months before a scheduled election respectively. Column 4, 5 and 6 show the impact of being born 0-1, 0-2 and 0-6 months after a scheduled election. The table shows that the effect of being born in election years is strongest for children born 0-1 months before scheduled elections followed by children born 0-1 months after scheduled elections. However, the effect drops if we consider children born 0-2 months before and 0-2 months after the election. Again compared to children born 0-2 months before an election, the effect is lower for children born 0-2 months after an election since the cohort born 0-2 months after election is less exposed to improved prenatal care. The effect becomes statistically insignificant for children born 0-6 months after a scheduled election.

2.5.5 Margin of Victory as a Determinant of Political Cycle

It is likely that politicians will have an incentive to behave more opportunistically, in terms of manipulating service provision, when their margin of victory is small. To address this, I have examined whether the extent of political cycles depends on the margin of victory enjoyed by the current ruling party or coalition. As mentioned before, elections in India take place at the constituency level which has to be aggregated to the district level to be merged with the individual level NFHS data. The margin of victory is given by the absolute difference between the proportion of seats obtained by the ruling party/coalition and the proportion of seats obtained by the largest opposition in a district.

The simplest test estimating the role of political competition would be to look at the sign and significance of the interaction between the election dummy and the district margin of victory variable. Thus, I have estimated the following equation:

$$Y_{imdst} = \alpha + \beta E_{ist} + \mu E_{ist} * A_{dst} + \theta A_{dst} + \gamma X_{imdst} + \delta_m + \tau_t + \zeta_{imdst} \quad (2.4)$$

If infant mortality falls in election years and the fall is greater in areas of higher political competition, we expect the coefficient on the election dummy, β, to be negative and statistically significant and for μ to be positive and statistically significant.

Figure 2.3 shows the predicted relationship between infant mortality and the absolute margin for children born before a scheduled election and children not born before scheduled elections. While panel (a) shows the relationship between infant mortality and the absolute margin of victory for children born 0-12 months before scheduled elections, panel (b) shows the same relationship for children born 0-6 months before scheduled elections. Figure 2.3 shows that among children born before scheduled elections, infant mortality is lower in districts where the state ruling party had a narrower margin of victory in the previous election. Infant mortality is flat over the absolute margin for children not born before scheduled elections.

Table 2.7 shows the estimates of equation (2.4). Columns 1 and 2 show the results for children born 0-12 months before a scheduled election and Columns 3 and 4 show the results for children born 0-6 months before scheduled elections. The results show that the fall in infant mortality before a scheduled election is higher for children born in districts where the previous election was particularly close. This is true for both children born 0-12 months before an election and children born 0-6 months before an election. However, the effect of targeting is more pronounced for children born 0-6 months before a scheduled election, as shown by the coefficient of the interaction term.

2.5.6 Mechanisms

The government can influence infant mortality in a number of ways. Firstly, The public health system might work more efficiently and so the usage of medical services might go up. I have estimated the impact of being born before scheduled elections on the number of antenatal checkups of the mother during pregnancy and whether the mother had at least one tetanus injection during pregnancy[16].

Secondly children born just before elections are likely to be better nourished. This might be the result of two factors. Firstly, if government job schemes (food work schemes) run more efficiently before elections, employment rates will go up in years preceding elections. The increased income is likely to have an impact on child health and child nutrition. Secondly, the public distribution system which is the food security network in India might function better before scheduled elections. To estimate the impact of the timing of elections on nutritional status of children I estimate the impact of the timing of elections on the incidence of low birth weight.

As pointed out earlier, the information on these variables is not available for the majority of children born to a mother. Thus, I could not include mother fixed effect in these regressions. I have included district fixed effects and some additional controls like parental education, membership in a disadvantaged socioeconomic group and a dummy variable for urban residence in these regressions.

Tables 2.8-2.10 show the estimated results. Table 2.8 shows the results for antenatal visits during pregnancy by mothers of children born 0-6 and 0-12 months before elections. Columns 1 and 2 of Table 2.8 show the estimates for children born 0-6 months before pregnancy while Columns 3 and 4 contain estimates for children born 0-12 months before an election. Columns 1 and 3 show the baseline

16. I have shown the impact of the timing of scheduled elections on the presence of doctors during delivery in Table A.5 of Appendix A. However due to the discrepancies in the definition of this variable between the coding documents of NFHS I, I had to use data from NFHS II only. Thus the sample is further small in this case and consists of children born between 1995-1998.

estimates without interaction effects. Columns 2 and 4 include the interaction term between the election dummy and the absolute margin. The estimates of Columns 1 and 3 show that mothers of children born before scheduled elections made more frequent antenatal visits during pregnancy. Columns 2 and 4 show that the impact is higher in politically more competitive districts. The estimates also show that the impact on antenatal visits is higher for children born 0-6 months before an election as compared to children born 0-12 months before an election.

Table 2.9 shows that results for the probability of having at least one tetanus injection during pregnancy. Column 1 shows that mothers of children born 0-6 months before scheduled elections were more likely to have at least one tetanus injection during pregnancy. The effect is insignificant for children born 0-12 months before an election. Columns 2 and 4 however show evidence of targeting for both 0-6 and 0-12 months.

Table 2.10 shows the impact of being born in election years on the probability of having a low birth weight. The estimates show that the probability of low birth weight falls just before elections. The effect becomes insignificant if we consider children born 0-12 months before an election. The coefficient of the interaction between the election dummy and the margin of victory is however insignificant for both children born 0-12 and 0-6 months before elections.

2.6 Robustness Checks

2.6.1 Placebo Tests

I have done a falsification exercise to check the robustness of my results. Assuming that the election took place 12 months, 24 months and 36 months before the real election, I have estimated equations (2.2) and (2.4). If the previous estimates were driven by pre-existing state-specific trends, then the estimates of these placebo treatment effects on infant mortality would be similar in sign and magnitude to the main estimates and statistically significant. Table 2.11 shows the estimated results. The coefficients on all of the placebo treatment dummies are small and insignificant

2.6.2 Birth of More Preferred Children and the Timing of Elections

I also explore the possibility that my results are driven by the gender composition of births. Given the extent of son preference that exists in India (Pande and Astone (2007); Clark (2000)), the reduction in infant mortality before scheduled elections could be driven by the fact that families have more boys then. I have estimated the impact of being born 0-6 or 0-12 months before an election on the sex of the child. Table 2.12 shows the estimated results. The results are statistically insignificant. This implies that the gender composition remains unchanged for children born close to elections.

2.6.3 Excluding Kerala

The reduction in infant mortality before scheduled elections should be higher in states which have low infant mortality rates compared with states in which there is little scope for reduction. In my sample one state, Kerala has significantly lower infant mortality rates as compared to the others. The infant mortality rate in Kerala is 29 per 1000 compared to the sample average of 89 per 1000. All other states except Kerala have infant mortality rates over of 60 per 1000. Thus, the effect of the timing of elections should be higher if Kerala is excluded from analysis. Table 2.13 shows the results excluding Kerala. It can be seen that the magnitude of the estimates improves with the exclusion of Kerala.

2.6.4 Including Politically Non-competitive States

The main argument for the decline in infant mortality just before elections is that politicians are opportunistic and want to remain in power. Thus, we expect the effect of the timing of elections on infant mortality to be non-existent or weak in states with very little political competition. For the 14 states considered so far, the government changed at least once during the sample period.[17] I have estimated the results including all 15 major states of India. Table 2.14 presents results with all states using specification 2.2 and 2.3. Columns 1 and 2 of Table 2.14 repeat Columns 3 and 4 of Table 2.2. Column 3 and 4 of Table 2.14 shows the results

17. Among the 15 major states in India, West Bengal is the only state where government changed just once during the sample period. The left front came into power in West Bengal in 1977 and remained in power until 2011. Thus, one party ruled for almost the entire sample period (1975-1998). West Bengal has very little political competition and so we expect political cycles to be significantly muted there.

with all states. As expected, the magnitude and the level of significance of the estimates drop if we consider all states.

If it is indeed the lack of political competition that results in the estimates becoming insignificant if we consider all states, then including the interaction term between the election dummy and the political competition variable as in specification (2.4) should return significant estimates. Table 2.15 presents the estimates of equation (3) for all states. The results are statistically significant once again.[18]

2.7 Conclusion

The economics and political science literatures provide evidence that politicians have strong incentives to improve the economic conditions of voters in election years. These incentives to provide special favors can be higher in more politically competitive regions. However, there has been very little empirical research on the welfare implications of these political cycles. The results presented in this chapter show that the impacts of electoral cycles are not confined to economic policies and macroeconomic outcomes alone. Rather, they can have important effects on individual level developmental outcomes.

This chapter shows that infant mortality is significantly lower for children born just before scheduled elections in states with at least some political competition. The results further show that the reduction in infant mortality is higher in politi-

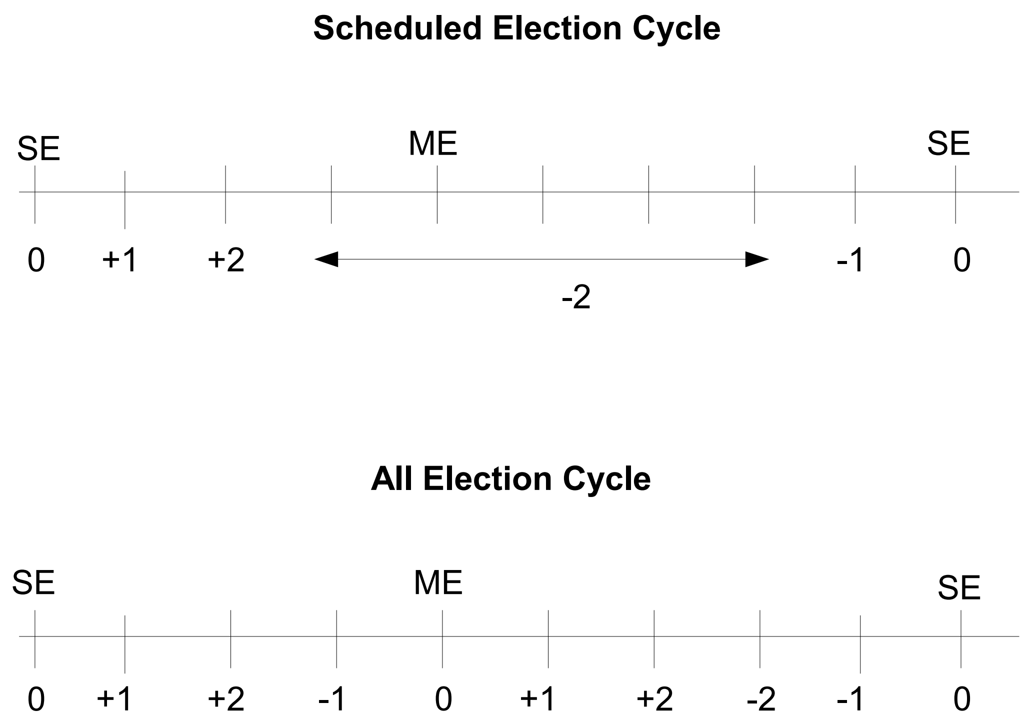
18. The regressions for mechanisms are also estimated using data from all states. The results are presented in Table A.6 in Appendix A and the results are similar to the results with only the politically competitive states.

cally more competitive districts.

My results also provide evidence that medical care utilization goes up before elections. Mothers of children born just before elections are likely to have more regular antenatal checkups and have at least one tetanus injection during pregnancy. Antenatal visits can have significant positive effects on both mother and child health. Kitzman et al. (1997) showed that increased consultation with nurses during pregnancy reduces pregnancy induced hypertension and childhood injuries. Children born just before elections are also less likely to be of low birth weight. Birth weight determines a number of adult life outcomes like educational attainment and earnings. Thus, my results suggest that periods of prosperity created by political cycles can potentially have long-term impacts on the lives of individuals in poor countries.

Health in general and particularly child health is an extremely important issue in developing countries. Child deaths occur due to insufficient health care facilities or inadequate nutrition (Jones et al. (2003)). The availability of health care facilities and nutrition both depend on government policies and thus political variables play an important role in influencing child survival. These variables can be manipulated by politicians to signal their ability to improve the economic conditions of voters before elections, or simply because voters are myopic. My results are consistent with the maximization of political gains by politicians leading to extremely different results for similar children (born to the same mother) separated only by their timing of birth.

Figure 2.1: Election Cycle Dummies



Notes: The figure shows creation of the election dummies. The top figure corresponds to all elections and the bottom figure corresponds to scheduled elections.

Table 2.1a: Summary Statistics (Child Characteristics)

Variable	Mean	(Std. Dev.)	N
Infant Mortality (Scaled 0-100)	8.923	(28.510)	175804
Neonatal Mortality (Scaled 0-100)	5.814	(23.402)	175804
2-12 month Mortality (Scaled 0-100)	3.11	(17.359)	175804
Female Child	0.48	(0.5)	175804
Birth Order 1	0.278	(0.448)	175804
Birth Order 2	0.246	(0.431)	175804
Birth Order 3	0.184	(0.387)	175804
Birth Order 4	0.121	(0.327)	175804
Birth Order 5	0.075	(0.264)	175804
Birth Order 6	0.045	(0.208)	175804
Birth Order 7	0.025	(0.157)	175804
Birth Order 8	0.014	(0.115)	175804
Birth Order 9	0.007	(0.083)	175804
Birth Order 10	0.005	(0.073)	175804
Month of Birth 1	0.068	(0.253)	175804
Month of Birth 2	0.063	(0.243)	175804
Month of Birth 3	0.078	(0.269)	175804
Month of Birth 4	0.076	(0.265)	175804
Month of Birth 5	0.083	(0.276)	175804
Month of Birth 6	0.087	(0.282)	175804
Month of Birth 7	0.087	(0.282)	175804
Month of Birth 8	0.106	(0.308)	175804
Month of Birth 9	0.089	(0.285)	175804
Month of Birth 10	0.097	(0.296)	175804
Month of Birth 11	0.088	(0.284)	175804
Month of Birth 12	0.076	(0.266)	175804

Notes: Standard deviations are in parentheses. Infant mortality, Neo-natal mortality and 2-12 month mortality are defined as percentages. Female denotes the gender of the child. Month of birth, order of birth refer to the month and order of birth of a child. Sample includes children born in the period 1975-1998 from 14 major states in India.

Table 2.1b: Summary Statistics (Electoral Variables)

Variable	Mean	(Std. Dev.)	N
Born 0-12 Months before Election	0.265	(0.441)	175804
Born 13-24 Months before Election	0.182	(0.386)	175804
Born 1-12 Months after Election	0.226	(0.418)	175804
Born 13-24 Months after Election	0.208	(0.406)	175804
Born more than 24 Months before Election	0.120	(0.325)	175804
Born 0-12 Months before Scheduled Election	0.183	(0.387)	175804
Born 13-24 Months before Scheduled Election	0.147	(0.355)	175804
Born more than 24 Months before Scheduled Election	0.434	(0.496)	175804
Born 1-12 Months after Scheduled Election	0.119	(0.324)	175804
Born 13-24 Months after Scheduled Election	0.125	(0.331)	175804
Absolute Margin	0.497	(0.285)	175804
Average District Turnout	0.583	(0.108)	175804

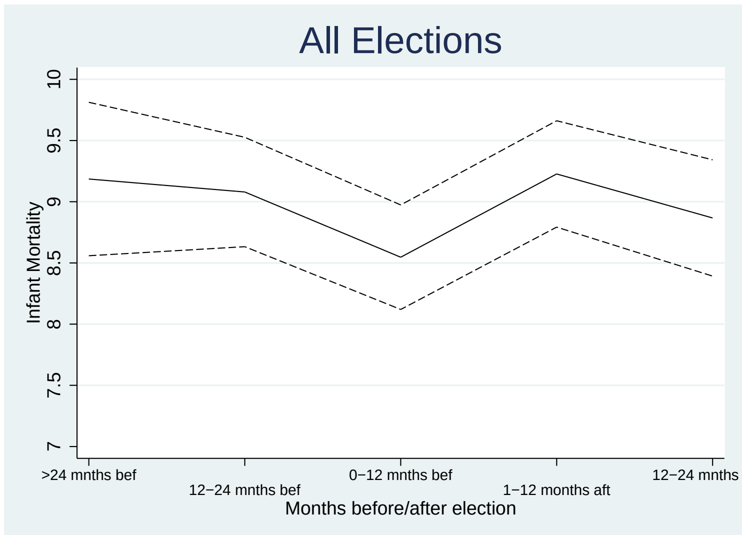
Notes: Standard deviations are in parentheses. Born m to n months before or after election is a dummy indicating whether the child is born m to n months before or after an election. The figures are tabulated for all elections and scheduled elections. Absolute margin of victory is defined as the proportion of seats by which the ruling party/coalition in the state won/lost in the district of birth of the child during the previous election. Sample includes children born in the period 1975-1998 from 14 major states in India.

Table 2.1c: Summary Statistics (Mother's Characteristics)

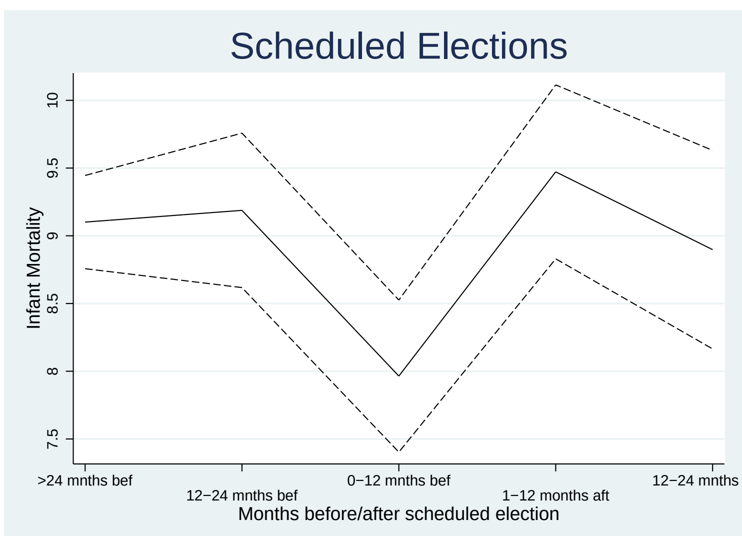
Variable	Mean	(Std. Dev.)	N
Scheduled Caste	.173	(.379)	74580
Scheduled Tribe	0.094	(0.292)	74580
Muslim	0.133	(0.339)	74580
Urban	0.22	(0.414)	74580
Mother's Years of Education	2.932	(4.322)	74580
Father's Years of Education	5.79	(5.04)	74580
Number of Antenatal Visits	1.973	(2.862)	56140
Tetanus during pregnancy	0.651	(.477)	62004

Notes: Standard deviations are in parentheses. Scheduled Caste, Scheduled Tribe and Muslim are dummies indicating whether the mother belonged to historically disadvantaged caste (Scheduled Caste) or tribal groups (Scheduled Tribe) or the second largest religious community in India (Muslim). Tetanus during pregnancy is a dummy equal to 1 if the mother had at least one tetanus injection during pregnancy. The sample consists of mothers of children born in the period 1987-1992 (NFHS I) and 1995-1999 (NFHS II). This sample is used to estimate Tables 2.8-2.10.

Figure 2.2: Election and Infant Mortality



(a)



(b)

Notes: The panels in the figure shows the predicted relationship between infant mortality and years relative to scheduled election and all election years. While Panel (a) graphs the relationship for all elections, panel (b) shows the relationship for scheduled elections.

Table 2.2: Elections and Infant Mortality

	(1) All	(2) All	(3) Scheduled	(4) Scheduled	(5) Midterm	(6) Midterm
Born 0-12 Months before Election	-0.560*	-0.639				
	(0.290)	(0.388)				
Born 13-24 Months before Election		-0.106				
		(0.366)				
Born 1-12 Months after Election		0.0413				
		(0.429)				
Born 13-24 Months after Election		-0.318				
		(0.389)				
Born 0-12 Months before Scheduled Election			-1.194***	-1.137***		
			(0.351)	(0.398)		
Born 12-24 Months before Scheduled Election				0.0866		
				(0.390)		
Born 1-12 Months after Scheduled Election				0.371		
				(0.436)		
Born 12-24 Months after Scheduled Election				-0.203		
				(0.469)		
Born 0-12 Months before Midterm Election					0.267	0.295
					(0.433)	(0.452)
Born 12-24 Months before Midterm Election						0.0667
						(0.471)
Born 1-12 Months after Midterm Election						0.0823
						(0.441)
Born 12-24 Months after Midterm Election						-0.222
						(0.438)
Observations	175804	175804	175804	175804	175804	175804
r2	0.341	0.341	0.341	0.341	0.341	0.341

Notes: Standard errors in parentheses. Each column represents a separate regression. Infant mortality is the dependant variable in all the columns. Columns 1 and 2 report coefficients on dummies for all election, columns 3 and 4 report coefficients on dummies for scheduled elections and columns 5 and 6 report coefficients on dummies for midterm elections. In addition to the reported variables, all regressions include mother's fixed effect, dummies for year of birth, month of birth, order of birth, sex of the child. Other controls include average district turnout, real state domestic product per capita lagged by two years and month of polling dummies. Sample includes children born in the period 1975-1998 from 14 major states in India. Errors are clustered at district level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.3: Accounting for Midterm Elections

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline		Dropping midterm		Including midterm controls	
Born 0-12 Months before Scheduled Election	-1.194***	-1.137***	-1.258***	-1.176***	-1.179***	-1.099***
	(0.351)	(0.398)	(0.364)	(0.427)	(0.353)	(0.411)
Born 12-24 Months before Scheduled Election		0.0866		-0.121		0.120
		(0.390)		(0.451)		(0.407)
Born 1-12 Months after Scheduled Election		0.371		0.517		0.410
		(0.436)		(0.473)		(0.444)
Born 12-24 Months after Scheduled Election		-0.203		0.00429		-0.177
		(0.469)		(0.524)		(0.474)
Born 0-12 Months before Midterm Election					0.111	0.171
					(0.436)	(0.454)
Observations	175804	175804	157442	157442	175804	175804
r2	0.341	0.341	0.370	0.370	0.341	0.341

Notes: Standard errors in parentheses. Each column represents a separate regression. Infant mortality is the dependant variable in all columns. Columns 1 and 2 report coefficients on dummies for children born before or after scheduled elections. The sample here includes children born before midterm election (same as columns 3 and 4 of Table 2.2). Columns 3 and 4 also report coefficients on dummies for children born before and after scheduled elections but the sample now does not include children born 0-12 months before midterm election. Columns 5 and 6 include a dummy for whether a child is born 0-12 months before midterm election in addition to the scheduled election dummies. Apart from the reported variables, all regressions include mother's fixed effect, dummies for year of birth, month of birth, order of birth, sex of the child. Other controls include average district turnout, real state domestic product per capita lagged by two years and month of polling dummies. Errors are clustered at district level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.4: Neonatal and Infant Mortality

	(1)	(2)	(3)	(4)	(5)	(6)
	Infant Mortality		Neonatal Mortality		2-12 Month Mortality	
Born 0-12 Months before Scheduled Election	-1.194***	-1.137***	-0.746**	-0.730**	-0.445**	-0.407*
	(0.351)	(0.398)	(0.289)	(0.322)	(0.210)	(0.237)
Born 12-24 Months before Scheduled Election		0.0866		0.00852		0.0781
		(0.390)		(0.340)		(0.246)
Born 1-12 Months after Scheduled Election		0.371		0.231		0.140
		(0.436)		(0.352)		(0.283)
Born 12-24 Months after Scheduled Election		-0.203		-0.153		-0.0498
		(0.469)		(0.350)		(0.269)
Observations	175804	175804	175804	175804	175804	175804
r2	0.341	0.341	0.341	0.341	0.295	0.295

Notes: Standard errors in parentheses. Each column represents a separate regression. Infant mortality is the dependant variable in column 1 and 2, neonatal mortality in column 3 and 4 and 2-12 month mortality in column 5 and 6. The coefficients reported correspond to dummies for children born before and after scheduled elections. In addition to the reported variables, all regressions include mother's fixed effect, dummies for year of birth, month of birth, order of birth, sex of the child. Other controls include average district turnout, real state domestic product per capita lagged by two years and the dummies for month of polling. Sample includes children born in the period 1975-1998 from 14 major states in India. Errors are clustered at district level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5: Closeness to Election and Infant Mortality

	(1) 0-6 months before	(2) 0-6,6-12 months before	(3) 0-12 months before	(4) Distance Next Sch Elec
Born 0-6 Months before Scheduled Election	-1.035**	-1.227***		
	(0.419)	(0.428)		
Born 6-12 Months before Scheduled Election		-1.145**		
		(0.484)		
Born 0-12 Months before Scheduled Election			-1.194***	
			(0.351)	
Dist of the next Scheduled Election from the MOB				0.010**
				(0.005)
Observations	175804	175804	175804	175804
r2	0.341	0.341	0.341	0.341

Notes: Standard errors in parentheses. Each column represents a separate regression. Infant mortality is the dependant variable. Column 1 reports the coefficient on the dummy indicating whether a child is born 0-6 months before scheduled election. Column 2 reports the coefficients on dummies indicating whether a child is born 0-6 months or 6-12 months before scheduled election. Column 3 reports coefficients on a dummy indicating whether a child is born 0-12 months before election. The coefficient reported in columns 4 corresponds to the distance between the month-year of birth of the child and the month year of next scheduled election. In addition to the reported coefficients, all regressions include mother's fixed effect, dummies for year of birth, month of birth, order of birth, sex of the child. Other controls include average district turnout, real state domestic product per capita and the month of polling dummies. Sample includes children born in the period 1975-1998 from 14 major states in India. Errors are clustered at district level.

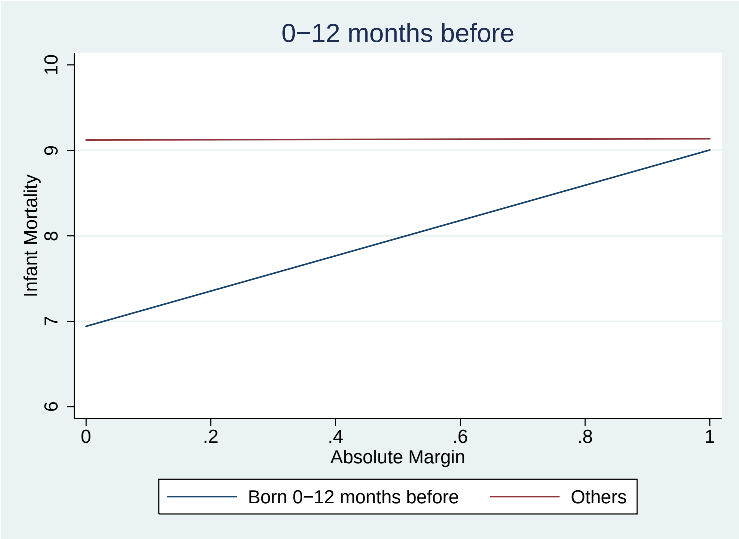
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.6: Slightly Before and After Scheduled Election

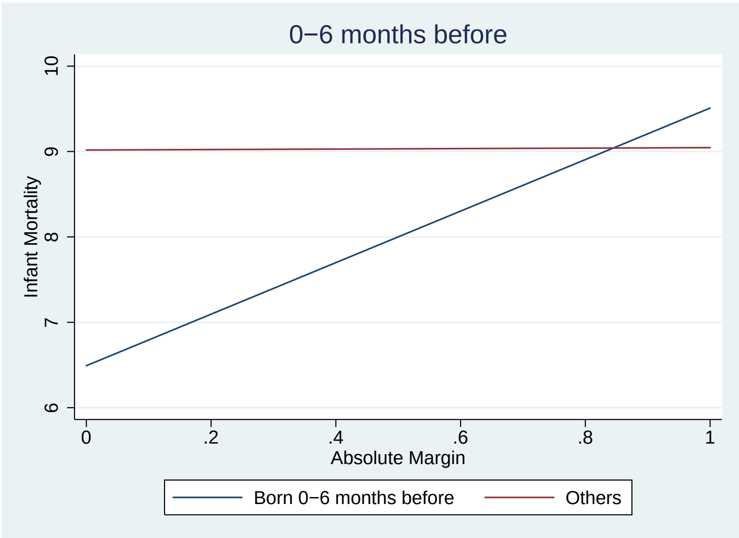
	(1) 0-6 months before	(2) 0-2 months before	(3) 0-1 months before	(4) 0-1 months after	(5) 0-2 months after	(6) 0-6 months after
Born 0-6 Months before Scheduled Election	-1.035**					
	(0.419)					
Born 0-2 Months before Scheduled Election		-1.305**				
		(0.571)				
Born 0-1 Months before Scheduled Election			-1.688**			
			(0.659)			
Born 0-1 Months after Scheduled Election				-1.663**		
				(0.663)		
Born 0-2 Months after Scheduled Election					-1.186**	
					(0.594)	
Born 0-6 Months after Scheduled Election						0.0294
						(0.451)
Observations	175804	175804	175804	175804	175804	175804
r2	0.341	0.341	0.341	0.341	0.341	0.341

Notes: Standard errors in parentheses. Each column represents a separate regression. Infant mortality is the dependant variable. Columns 1 and 6 report coefficients on dummies indicating whether a child is born 0-6 months before and after scheduled election respectively. Columns 2 and 5 report coefficients on dummies for children born 0-2 months before and after scheduled election respectively. Columns 3 and 4 report coefficient on dummies indicating whether a child is born 0-1 months before and after scheduled election respectively. In addition to the reported variables, all regressions include mother's fixed effect, dummies for year of birth, month of birth, order of birth, sex of the child. Other controls include average district turnout, real state domestic product per capita lagged by two years and month of polling dummies. Column 1 includes coefficient of dummy indicating whether the child is born 0-6 Sample includes children born in the period 1975-1998 from 14 major states in India. Errors are clustered at district level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 2.3: Role of Political Competition



(a)



(b)

Notes: The panels in the figure shows the predicted relationship between infant mortality and absolute margin of victory for children born before scheduled election and other years. While panel (a) graphs the relationship for children born 0-12 months before scheduled election, panel (b) shows the relationship for children born 0-6 months before scheduled election.

Table 2.7: Role of Political Competition

	(1)	(2)	(3)	(4)
	0-12 months before		0-6 months before	
	Baseline	With Interactions	Baseline	With Interactions
Born 0-12 Months before Scheduled Election	-1.194***	-2.180***		
	(0.351)	(0.598)		
Absolute Margin x Born 0-12 Months before Scheduled Election		2.048**		
		(1.002)		
Born 0-6 Months before Scheduled Election			-1.035**	-2.526***
			(0.419)	(0.824)
Absolute Margin x Born 0-6 Months before Scheduled Election				2.989**
				(1.380)
Absolute Margin		0.0146		0.0279
		(0.482)		(0.477)
Observations	175804	175804	175804	175804
r2	0.341	0.341	0.341	0.341

Notes: Standard errors in parentheses. Each column represents a separate regression. Infant mortality is the dependant variable. Columns 1 and 3 report the coefficients on dummies for children born 0-6 months and 0-12 months before scheduled elections. Columns 2 and 4 report the coefficients on dummy variables indicating whether a child is born 0-6 or 0-12 months before scheduled elections and interactions between the election dummy and the absolute margin of victory of the ruling party/coalition in the previous election. Columns 2 and 4 also report the coefficient on the absolute margin of victory variable. In addition to the reported variables, all regressions include mother's fixed effect, dummies for year of birth, month of birth, order of birth, sex of the child. Other controls include average district turnout, state domestic product lagged by two years and dummies for the month of polling. Sample includes children born in the period 1975-1998 from 14 major states in India. Errors are clustered at district level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.8: Antenatal Visits

	(1)	(2)	(3)	(4)
	0-6 months before		0-12 months before	
Born 0-6 Months before Scheduled Election	0.126***	0.285***		
	(0.0468)	(0.0864)		
Absolute Margin x Born 0-6 Months before Scheduled Election		-0.317**		
		(0.152)		
Born 0-12 Months before Scheduled Election			0.0693*	0.166**
			(0.0418)	(0.0766)
Absolute Margin x Born 0-12 Months before Scheduled Election				-0.199
				(0.140)
Absolute Margin		-0.0555		-0.0536
		(0.0652)		(0.0669)
Observations	56140	56140	56140	56140
r2	0.493	0.493	0.493	0.493

Notes: Standard errors in parentheses. Each column represents a separate regression. The dependant variable is the number of antenatal visits. Columns 1 and 3 report the coefficients on dummies for children born 0-6 months and 0-12 months before scheduled elections. Columns 2 and 4 report the coefficients on dummy variables indicating whether a child is born 0-6 or 0-12 months before scheduled elections and interactions between the election dummy and the absolute margin of victory of the ruling party/coalition in the previous election. Columns 2 and 4 also report the coefficient on the absolute margin of victory variable. In addition to the reported variables, all regressions include district fixed effect, dummies for year of birth, month of birth, order of birth, sex of the child, mother's and father's year of schooling and dummies for rural residence, membership in SC/ST. Other controls include average district turnout, real state domestic product per capita lagged by two years and month of polling dummies. Sample includes children born in the period 1987-1992 and 1995-1998 from 14 major states in India. Errors are clustered at district level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.9: Tetanus During Pregnancy

	(1)	(2)	(3)	(4)
	0-6 months before		0-12 months before	
Born 0-6 Months before Scheduled Election	0.0184**	0.0511***		
	(0.00844)	(0.0150)		
Absolute Margin x Born 0-6 Months before Scheduled Election		-0.0704**		
		(0.0296)		
Born 0-12 Months before Scheduled Election			0.00504	0.0275**
			(0.00743)	(0.0115)
Absolute Margin x Born 0-12 Months before Scheduled Election				-0.0494**
				(0.0200)
Absolute Margin		0.00327		0.00450
		(0.0146)		(0.0149)
Observations	62004	62004	62004	62004
r2	0.262	0.262	0.262	0.250

Notes: Standard errors in parentheses. Each column represents a separate regression. The dependant variable is a dummy indicating whether the mother had at least one tetanus injection during pregnancy. Columns 1 and 3 report the coefficients on dummies for children born 0-6 months and 0-12 months before scheduled elections. Columns 2 and 4 report the coefficients on dummy variables indicating whether a child is born 0-6 or 0-12 months before scheduled elections and interactions between the election dummy and the absolute margin of victory of the ruling party/coalition in the previous election. Columns 2 and 4 also report the coefficient on the absolute margin of victory variable. In addition to the reported variables, all regressions include district fixed effect, dummies for year of birth, month of birth, order of birth, sex of the child, mother's and father's year of schooling and dummies for rural residence, membership in SC/ST. Other controls include average district turnout, real state domestic product per capita lagged by two years and month of polling dummies. Sample includes children born in the period 1987-1992 and 1995-1998 from 14 major states in India. Errors are clustered at district level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.10: Low Birth Weight

	(1)	(2)	(3)	(4)
	0-6 months before		0-12 months before	
Born 0-6 Months before Scheduled Election	-0.0214**	-0.0312*		
	(0.00848)	(0.0186)		
Absolute Margin x Born 0-6 Months before Scheduled Election		0.0195		
		(0.0313)		
Born 0-12 Months before Scheduled Election			-0.00363	-0.00797
			(0.00783)	(0.0152)
Absolute Margin x Born 0-12 Months before Scheduled Election				0.00891
				(0.0251)
Absolute Margin		-0.00423		-0.00370
		(0.0115)		(0.0118)
Observations	52817	52817	52817	52817
r2	0.0428	0.0429	0.0427	0.0427

Notes: Standard errors in parentheses. Each column represents a separate regression. The dependant variable is a dummy indicating whether a child is of low birth weight is the dependant variable. Columns 1 and 3 report the coefficients on dummies for children born 0-6 months and 0-12 months before scheduled elections. Columns 2 and 4 report the coefficients on dummy variables indicating whether a child is born 0-6 or 0-12 months before scheduled elections and interactions between the election dummy and the absolute margin of victory of the ruling party/coalition in the previous election. Columns 2 and 4 also report the coefficient on the absolute margin of victory variable. In addition to the reported coefficients, all regressions include district fixed effect, dummies for year of birth, month of birth, order of birth, sex of the child, mother's and father's year of schooling and dummies for rural residence, membership in SC/ST. Other controls include average district turnout, real state domestic product per capita lagged by two years and month of polling dummies. Sample includes children born in the period 1987-1992 and 1995-1998 from 14 major states in India. Errors are clustered at district level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.11: Robustness check: Placebo Tests

	(1)	(2)	(3)	(4)	(5)	(6)
	12 months		24 months		36 months	
Born 0-12 Months before Election	-0.450	0.0558	0.427	-0.543	-0.129	0.0317
	(0.468)	(0.687)	(0.483)	(0.752)	(0.476)	(0.714)
Absolute Margin x Born 0-12 Months before Elecion		-1.079		2.113		-0.330
		(1.130)		(1.354)		(1.213)
Absolute Margin		0.812		0.291		0.678
		(0.633)		(0.656)		(0.640)
Observations	136200	136200	136200	136200	136200	136200
r2	0.397	0.397	0.397	0.397	0.397	0.397

Notes: Standard errors in parentheses. Each column represents a separate regression. Infant mortality is the dependant variable. Columns 1, 3 and 5 report the coefficients on dummies for children born 0-12 months before scheduled elections if the scheduled election was held 12 months, 24 months and 36 months before the actual scheduled election respectively. Columns 2, 4 and 6 report the coefficients on dummy variables indicating whether a child is born 0-12 months before scheduled elections and interactions between the election dummy and the absolute margin of victory of the ruling party/coalition in the previous election. Columns 2, 4 and 6 also report the coefficient on the absolute margin of victory variable. In addition to the reported variables, all regressions include mother's fixed effect, dummies for year of birth, month of birth, order of birth, sex of the child. Other controls include average district turnout, real state domestic product per capita lagged by two years and dummies for the month of polling. Sample includes children born in the period 1975-1998 from 14 major states in India, excluding children born 0-12 months before actual scheduled election. Errors are clustered at district level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.12: Probability of Birth of Female Child

	(1)	(2)	(3)	(4)
	0-6 months before		0-12 months before	
Born 0-6 Months before Scheduled Election	-0.00648	-0.0211		
	(0.00786)	(0.0134)		
Absolute Margin x Born 0-6 Months before Scheduled Election		0.0298		
		(0.0207)		
Born 0-12 Months before Scheduled Election			-0.00442	-0.00674
			(0.00665)	(0.0104)
Absolute Margin x Born 0-12 Months before Scheduled Election				0.00507
				(0.0169)
Absolute Margin		-0.0157*		-0.0133
		(0.00866)		(0.00882)
Observations	175804	175804	175804	175804
r2	0.314	0.314	0.314	0.314

Notes: Standard errors in parentheses. Each column represents a separate regression. Dependant variable is a dummy equal to 1 if the child is female. Columns 1 and 3 report the coefficients on dummies for children born 0-6 months and 0-12 months before scheduled elections. Columns 2 and 4 report the coefficients on dummy variables indicating whether a child is born 0-6 or 0-12 months before scheduled elections and interactions between the election dummy and the absolute margin of victory of the ruling party/coalition in the previous election. Columns 2 and 4 also report the coefficient on the absolute margin of victory variable. In addition to the reported variables, all regressions include mother's fixed effect, dummies for year of birth, month of birth, order of birth, sex of the child. Other controls include average district turnout, real state domestic product per capita lagged by two years and dummies for the month of polling. Sample includes children born in the period 1975-1998 from 14 major states in India. Errors are clustered at district level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.13: Excluding Kerala

	(1)	(2)	(3)	(4)
	Including Kerala		Excluding Kerala	
	0-12 months before	0-6 months before	0-12 months before	0-6 months before
Born 0-12 Months before Scheduled Election	-1.194***		-1.284***	
	(0.351)		(0.365)	
Born 0-6 Months before Scheduled Election		-1.035**		-1.081**
		(0.419)		(0.430)
Observations	175804	175804	170391	170391
r2	0.341	0.341	0.340	0.340

Notes: Standard errors in parentheses. Each column represents a separate regression. Infant mortality is the dependant variable. Columns 1 and 2 report results including Kerala, the state where infant mortality is significantly lower than the average infant mortality over the sample. Columns 2 and 4 report results excluding Kerala from the sample. Columns 1 and 3 report coefficients on dummies indicating whether the child is born 0-12 months before scheduled election. Columns 2 and 4 report coefficients on dummies for children born 0-6 months before scheduled election. Apart from the reported variables all regressions include mother's fixed effect, dummies for year of birth, month of birth, order of birth, sex of the child. Other controls include average district turnout, real state domestic product per capita and month of polling dummies. Errors are clustered at district level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.14: Election and Infant Mortality (All States)

	(1)	(2)	(3)	(4)
	Politically Competitive States		All States	
Born 0-12 Months before Scheduled Election	-1.194***	-1.137***	-0.675*	-0.554
	(0.351)	(0.398)	(0.367)	(0.414)
Born 12-24 Months before Scheduled Election		0.0866		0.250
		(0.390)		(0.380)
Born 1-12 Months after Scheduled Election		0.371		0.589
		(0.436)		(0.460)
Born 12-24 Months after Scheduled Election		-0.203		-0.133
		(0.469)		(0.440)
Observations	175804	175804	185976	185976
r2	0.341	0.341	0.343	0.343

Notes: Standard errors in parentheses. Each column represents a separate regression. Infant mortality is the dependant variable. The sample used in regressions corresponding to columns 1 and 2 include data from 14 major politically competitive states in India (details in section 6.4). Columns 3 and 4 include all 15 major states in India. The coefficients reported correspond to dummies for children born before and after scheduled elections. In addition to the reported coefficients, all regressions include mother's fixed effect, dummies for year of birth, month of birth, order of birth, sex of the child. Other controls include average district turnout, real state domestic product per capita lagged by two years and dummies for month of polling. Errors are clustered at district level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.15: Role of Political Competition (All States)

	(1)	(2)	(3)	(4)
	0-12 months before		0-6 months before	
	Baseline	With Interactions	Baseline	With Interactions
Born 0-12 Months before Scheduled Election	-0.675*	-1.532**		
	(0.367)	(0.613)		
Absolute Margin x Born 0-12 Months before Scheduled Election		1.761*		
		(0.967)		
Born 0-6 Months before Scheduled Election			-0.655	-1.958**
			(0.432)	(0.803)
Absolute Margin x Born 0-6 Months before Scheduled Election				2.594*
				(1.326)
Absolute Margin		-0.100		-0.0883
		(0.479)		(0.475)
Observations	185976	185976	185976	185976
r2	0.343	0.343	0.343	0.343

Notes: Standard errors in parentheses. Each column represents a separate regression. Infant mortality is the dependant variable. Columns 1 and 3 report coefficients on dummies for children born 0-6 months and 0-12 months before scheduled elections. Columns 2 and 4 report the coefficients on dummy variables indicating whether a child is born 0-6 or 0-12 months before scheduled elections and interactions between the election dummy and the absolute margin of victory of the ruling party/coalition in the previous election. Columns 2 and 4 also report the coefficient on the absolute margin of victory variable. In addition to the reported variables, all regressions include mother's fixed effect, dummies for year of birth, month of birth, order of birth, sex of the child. Other controls include average district turnout, real state domestic product per capita lagged by two years and dummies for the month of polling. Sample includes children born in the period 1975-1998 from 15 major states in India. Errors are clustered at district level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 3

Fertility Rate and Female Employment in India

3.1 Introduction

Rapid population growth is viewed as one of the major obstacles to development in several developing countries. Incentives for having small families often do not exist in developing countries (Pörtner (2001); Caldwell and Caldwell (1987)), and as a result their population increases at a very fast rate. Population growth reduces the per capita income and lowers the pace of poverty reduction (Eswaran (2006)). Moreover, high population growth has adverse effects on the environment through deforestation and air and water pollution (Eswaran (2006); Cropper and Griffiths (1994)).

This chapter explores whether providing economic incentives to women affects the number of children they choose to have, and whether there are differences across sectors, in the Indian context. In particular, this study estimates the effect of female labor force participation on the total fertility rates. In addition, I compare the impact of female employment in the agricultural and manufacturing sectors since women working in different sectors could have different demands for children (Goh (1999)).

It is generally held that there exists a negative relationship between fertility and female employment due to the incompatibility between child care and labor force participation (Cramer (1980), Felmlee (1993), Smith-Lovin and Tickamyer (1981)). Since child-rearing is intensive in the mother's time, female labor-force participation may decrease the number of desired children. Alternatively with higher income a woman might be able to afford better childcare services and this can increase the demand for children. Thus, the question of how female employment impacts fertility is an empirical one.

When exploring the relationship between fertility and female labor force participation, an endogeneity problem must be accounted for between these two simultaneous decisions. OLS is inconsistent because the employment of women is potentially correlated with unobservable factors affecting fertility decisions like the preference for children and child care costs.

The standard econometric approach to the endogeneity of regressors is instrumental variables. Thus if we want to estimate the impact of employment opportunities on fertility, we need to find some exogenous determinant of female employment which is uncorrelated with the unobservable factors affecting fertility.

Such an exogenous change took place in India during 1991. In response to a severe balance of payments crisis in 1991, India turned to the International Monetary Fund (IMF) for assistance. As a condition of IMF support, India had to drastically reduce tariffs in different sectors over a short period of time. The dispersion in tariffs across sectors was also substantially reduced. This chapter uses variation in the exposure to tariff levels across districts in India as an instrument for analyzing the impact of female labor force participation on fertility. I also separately examine the influence of female employment in different sectors on fertility. Agriculture, manufacturing and mining are the three broad traded good sectors. However, the proportion of women employed in mining is extremely small. Thus I have confined my analysis to the first two sectors. Figure 3.1 compares the average tariff in agriculture and manufacturing in 1987 and 1998. The figure shows that the tariff decline has been quite substantial in both of these sectors.

Reduction in tariffs is likely to lower the prices of tradable goods in the domestic market. Thus the demand for workers employed in these sectors will fall. So, tariff decline is likely to reduce the demand for female labour who are employed in sectors in which tariff decline took place.

The data used for estimating the total fertility rate is obtained from the Census of India. The estimates for fertility are at the district level. However, the tariff data is at the national level. In order to get a district level estimate, I have calculated a district level tariff measure. I have also computed district level tariff measures separately for the agricultural and manufacturing sectors. This is done by interacting the share of the workers in a district who are employed in the various industries in the pre-reform period and then taking the sum across all the subsectors under agriculture and manufacturing separately. This derivation is based on Topalova

(2007). Thus my instrument exploits the variation in the degree of trade liberalization across the various industries and the variation in districts to the degree to which each is affected by the tariff reduction.

The result obtained in this chapter is that female labor force participation on the whole, and female employment in agriculture, has no statistically significant effect on fertility. However, increasing female employment in manufacturing significantly reduces the fertility rate.

The remainder of this chapter is organized as follows. Section 3.2 gives a brief literature review. In section 3.3, I have given a description of the tariff reform that took place in India to see whether it was indeed exogenous and externally imposed. Section 3.4 describes the data used in this study. Section 3.5 outlines the empirical strategy and the results obtained in this chapter. Finally, Section 3.6 concludes the chapter.

3.2 Related Literature

It has been argued that there exists a negative relationship between fertility and female labor force-participation and wages (Becker (1960), Galor and Weil (1996)). Crafts (1989) used data from the 1911 Census of England and Wales and found that fertility is lower in districts which has better female employment opportunities. Using an instrumental variables approach, Schultz (1985) tried to find the causal impact of increasing male wages and female wages relative to male wages on fertility for Sweden. He used output prices as instruments and found that an increase in the female-to-male wage results in a decline in observed fertility. Other studies have found find an insignificant influence of womans employment on female fertility choices (Santow and Bracher (2001)). The evidence of a positive effect of womens employment on fertility is found for East Germany (Kreyenfeld (2004))

There are many papers which have estimated the impact of female labor force participation on fertility rates using cross-country data for the OECD countries. Most of these studies found that the female labor force participation rate changed its sign from a negative value before 1980, to a positive value thereafter for the OECD countries (Ahn and Mira (2002); Rindfuss, Guzzo, and Morgan (2003)).

There has been limited evidence on the impact of female employment on fertility for developing countries. Fang et al. (2010) studied how off-farm employment affects actual and desired fertility in rural China. They used two instrumental variables. The first one is whether there is a bus stop in the village and the second one is the proportion of the labor force in the village that is employed in enterprises having at least 20 employees. They found that female employment significantly reduces both actual and desired fertility levels in rural China. However, they considered only rural China and off-farm employment. As far as the composition of female employment is concerned, Goh (1999) analysed, with the help of a theoretical model, how women working in the manufacturing sector desire fewer children than women working in agricultural sector, since the former group faces a higher time cost.

In Indian context, Drèze and Murthi (2001) examined the role of female literacy as a determinant of fertility. More recently Jensen (2012) provided experimental evidence on the relationship between women's employment opportunities and fertility outcomes. The author conducted an experiment where women in randomly selected rural villages in four Indian states (Haryana, Punjab, Rajasthan, and Uttar Pradesh) were given recruiting services for a period of three years. The author found that women were significantly more likely to work in treated villages and there was substantial delay in marriage and child bearing. Another recent paper by Anukriti and Kumler (2015) has analysed the impact of trade reforms on fertility in India.

3.3 Trade Reform in India

Until the mid 1980s, India pursued inward-looking development strategies. In particular, India had high nominal tariffs and nontariff barriers, and a complex import licensing system. During the mid 1980's, India started to gradually implement some reforms. Import and industrial licensing were eased. Also tariffs replaced some quantitative restrictions (Topalova (2007)). However a rise in macroeconomic imbalances, accompanied with this gradual liberalization policy adopted in India, lead to balance of payments problems. As a result of the Gulf War, India's oil bill increased. There was also a reduction in demand from some of its trading partners and a drop in remittances from the Middle East. This lead to a deterioration of investor confidence and investors started to withdraw money. Political instability during this period exacerbated the situation. The Congress Party led by Rajiv Gandhi lost the 1989 election and a coalition government came into power. However two subsequent coalitions could not survive long and a fresh election was announced in 1991. Political stability was further disrupted by the assassination of the then chairman of the Congress Party, Rajiv Gandhi in 1991. These exogenous events led to large capital outflow.

In order to overcome the crisis, the Indian government secured an emergency loan from the IMF. However, the IMF's support was conditional on macroeconomic stabilization policies and structural reforms. The structural reforms focused on the dismantling of industrial and import licenses, reforms in the financial sector and loosening trade policy. Thus the Indian government was forced to sharply reduce import and export control systems. There were drastic tariff reductions: average tariffs fell from over 90% in 1987 to about 30% in 1997. The standard deviation of tariffs dropped by about 50 percent over the same period. Industries which initially had higher tariffs faced higher tariff reductions and the structure of tariffs across industries changed.

From the perspective of households, such changes were exogenous in nature. Households were unlikely to have anticipated the reforms in the late 1980s. The government had to meet strict compliance deadlines and implemented the tariff reforms abruptly. Thus India drastically reduced tariffs over a short period of time. Topalova and Khandelwal (2011) documents that tariff changes were not correlated with pre-reform industry characteristics, including productivity and skill intensity, at least until 1997.

3.4 Data Sources

The data used in my analysis come from a number of sources. Firstly, the data for estimating the total fertility rate come from two Indian censuses held in 1991 and 2001. In this chapter, I have measured fertility in a district by the total fertility rate (TFR), which represents the number of children that would be born to a woman if she lived to the end of her childbearing years and bore children at each age in accordance with the prevailing age-specific fertility rates. The total fertility rate is a more useful measure of the fertility level than other measures (for example crude birth rate), since it is independent of the age structure of the population. The total fertility rate for the year 1991 are obtained from the census report on district level estimates of fertility published in 1997. In this report, the total fertility rate has been computed using the Arrianga method (described in detail in Appendix B). I have computed the total fertility rate for the year 2001 by this method using the 2001 census data on the number of children ever born to women by 5-year age group. The construction of this variable is explained in Appedix B. Table 3.1 contains the summary statistics of the variables used in this chapter. The average TFR reduced from 4.4 in 1991 to 3.9 in 2001.

The second data set used in this study consists of tariff data. The tariff data was initially collected by Petia Topolova from various publications of the Ministry of Finance. This data was at the 6 digit level of the Indian Trade Classification Harmonized System. Arka Roy Chaudhuri matched the product lines of the HS code to the 3 digit National Industrial Classification (NIC) code using the concordance of Debroy and Santhanam (2001) for the paper Roy Chaudhuri (2012). In this chapter I have used the data-set compiled by him. I have used the tariff data for the years 1987 and 1998 in my analysis.

Using this dataset, I have constructed a district level tariff variable. The variable is also constructed separately for the agricultural and manufacturing sectors. This district level tariff variable is a weighted aggregate of the tariffs faced by each sub sector of the particular sectors in a district. The weights are equal to the proportion of workers in each district who were employed in that industry before the reforms took place. The information about the proportion of workers employed in each industry is obtained from the 43rd (1987-88) round of the Indian National Sample Survey (NSS). Table 3.1 shows that the agricultural tariff used has reduced from 27% to 8%. It is to be noted here that the sector specific tariffs are not scaled by the share of industry employment in that particular sector but by the share of industry employment in the district labor force. Thus the sum of the weights attached to the tariff is less than 1. The manufacturing tariff similarly reduced from 6.5% to 2%.

The district level information on the female labor force participation as well as the proportion of females employed in agriculture and manufacturing comes from the 43rd (1987-88) and 55th (1999-2000) rounds of the NSS. We can see from Table 3.1 that the proportion of females employed in agriculture by district and in age group 16-25, increased on average from 28.5% to 30%. However on average, the proportion of females employed in manufacturing reduced slightly from 3.4% to 3%. Overall female labor force participation also slightly reduced from 40% to

39% during the same period.

I have included controls such as the proportion of people belonging to the Scheduled Caste or Scheduled Tribe[1], female literacy, proportion of population that is urban in the district and proportion of Muslims[2] in the district. The data on these variables are obtained from the 1991 and 2001 censuses.

3.5 Empirical Strategy and Results

3.5.1 Effect of Female Labor Force Participation on Fertility

The trade liberalization in India was externally imposed and comprehensive. Thus the variations in tariff levels are unlikely to be correlated with the unobservable factors that determine the fertility decisions of women. On the other hand, since tariffs affect the productivity of industries; it is likely to influence the labor force participation of women.

In order to find the causal impact of female labor force participation on the fertility rate of a given district, I have used the district level tariffs as instrument. The first stage is given by:

$$P_{dt} = \alpha + \beta X_{dt} + \gamma T_{dt} + \delta_d + \tau_t + \varepsilon_{dt} \tag{3.1}$$

where P_{dt} denotes the labor force participation of women in district d at time t as a percentage of total women in the age group 16-65 in the district d at time t.

1. The constitution of India recognizes some traditionally disadvantaged castes (Scheduled Castes) and certain culturally distinct tribes (Scheduled Tribes) as requiring some additional consideration.

2. Muslims form the largest religious minority in India

X_{dt} denotes other controls like the proportion of Scheduled Castes and Scheduled Tribes, proportion of urban population, proportion of Muslims, female literacy rate and poverty rate. δ_d and τ_t denote the district fixed effects and a time dummy respectively. The district fixed effects capture differences across districts that are fixed over time while the time dummies capture unobserved countrywide changes over the time period. T_{dt} is the instrument used in this study and is given by

$$T_{dt} = \frac{\sum_i \sum_j WF_{jid1987} \times T_{jit}}{\sum_i \sum_j WF_{jid1987}}$$

where $WF_{jid1987}$ denotes the total workforce employed in industry j of sector i in district d in 1987 (pre-reform period) and T_{jit} is the tariff level in industry j of sector i at time t.

The following equation is estimated in the second stage:

$$TFR_{dt} = \lambda + \theta X_{idt} + \Psi P_{dt} + \Delta_d + T_t + \xi_{dt} \tag{3.2}$$

where TFR_{dt} is the total fertility rate in district d at time t. P_{dt} denotes the proportion of females in the age group 16-65 in the district d who participates in the labor force. The relevant coefficients of interest is Ψ.

Table 3.2 shows the impact of female labor force participation on the total fertility rate. Column 1 shows the OLS results. We can see that female labor force participation has no significant effect on the total fertility rate. Column 2 shows the first stage and shows that the instrument is statistically significant. Columns 3 and 4 present the reduced form and the IV results. It can be seen that the instrument has no significant effect on total fertility rate. The IV results given in Column 4 show that female labor force participation has no effect on the total fertility rate once the endogeneity in female labor force participation is accounted for.

3.5.2 Effect of Female Employment in Agriculture and Manufacturing on Fertility

In order to find the causal impact of female employment in the agriculture and manufacturing sectors on the fertility rate of a district, I have used the district level tariffs for agriculture and manufacturing as instruments. The first stage for female labor force participation is given by:

$$\rho_{idt} = \alpha + \beta X_{idt} + \gamma_a T_{adt} + \gamma_m T_{mdt} + \delta_d + \tau_t + \varepsilon_{idt} \tag{3.3}$$

where ρ_{idt} denotes the proportion of women who are employed in sector i (i = agriculture (a) or manufacturing (m)) of district d in state s at time t as a proportion of the total women in the age group 15-65 in the district d at time t. The instruments T_{adt} and T_{mdt} are given by

$$T_{idt} = \frac{\sum_j WF_{jid1987} \times T_{jit}}{\sum_i \sum_j WF_{jid1987}}$$

In the second stage, I have estimated the following equation:

$$TFR_{dt} = \lambda + \theta X_{idt} + \psi_a \rho_{adt} + \psi_m \rho_{mdt} + \Delta_d + T_t + \xi_{dt} \tag{3.4}$$

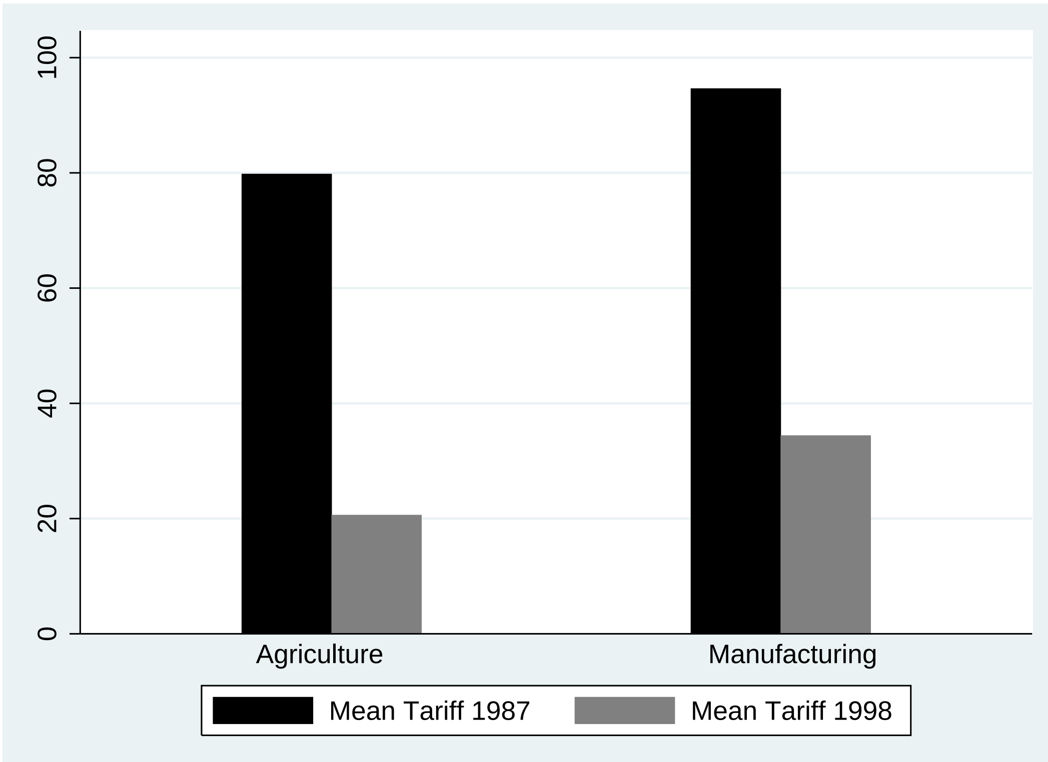
The relevant coefficients of interest are ψ_a and ψ_m.

Table 3.3 shows the results obtained by regressing the proportion of females employed in agriculture and manufacturing in a district on the district total fertility rate. Column 1 presents the OLS results, which do not show any significant relationship between sector wise female employment and fertility. Columns 2 and 3 show the first stage results for the proportion of females employed in agriculture and manufacturing. We can see that the endogenous variables are significantly correlated with the instruments. Columns 4 and 5 show the reduced form and the IV results. The IV results show that increased female employment in manufacturing leads to a lower fertility rate. However, increasing female employment in agriculture has no significant impact on female labor force participation. This might be due to the fact that agricultural jobs can be more easily combined with child rearing.

3.6 Conclusion

This chapter has been devoted to an examination of the hypothesis that there exists a causal link from female labor-force participation, and sector-wise female employment in the agriculture and the manufacturing sectors to the total fertility rate. The key finding is that female employment in manufacturing at the district level reduces the district fertility rate once the endogeneity of female employment is accounted for. However, overall female labor force participation and female employment in agriculture do not have any significant effects on fertility.

Figure 3.1: Decline in the Average Tariff in Agriculture and Manufacturing



Notes: The figure shows the mean tariff in agriculture and manufacturing for the years 1987 and 1998. The left set of bars correspond to agriculture while the right set of bars correspond to manufacturing

Table 3.1: Summary Statistics

Variable	Mean	Std. Dev.	N
Year 1991			
Total Fertility Rate	4.373	0.959	319
Female labor force participation	0.398	0.194	319
Proportion of female in agriculture	0.285	0.183	319
Proportion of female in manufacturing	0.034	0.044	319
Agricultural Tariff	27.201	9.208	319
Manufacturing Tariff	6.426	4.919	319
Proportion of Scheduled Castes	0.166	0.072	319
Proportion of Scheduled Tribes	0.1	0.169	319
Proportion of Muslims	0.107	0.108	319
Proportion of urban population	0.223	0.165	319
Proportion of females literate	0.302	0.162	319
Poverty Rate	0.348	0.174	319
Year 2001			
Total Fertility Rate	3.879	0.733	319
Female labor force participation	0.39	0.186	319
Proportion of female in agriculture	0.298	0.188	319
Proportion of female in manufacturing	0.03	0.045	319
Agricultural Tariff	7.977	3.134	319
Manufacturing Tariff	2.062	1.979	319
Proportion of Scheduled Castes	0.165	0.072	319
Proportion of Scheduled Tribes	0.101	0.167	319
Proportion of Muslims	0.112	0.112	319
Proportion of urban population	0.239	0.174	319
Proportion of females literate	0.521	0.154	319
Poverty rate	0.215	0.123	319

Notes: The table reports the mean and standard deviations of the variables used in this analysis. The top panel corresponds to the year 1991 and the bottom panel corresponds to the year 2001.

Table 3.2: Female Labor Force Participation and Total Fertility Rate

	(1) OLS	(2) First Stage	(3) Reduced Form	(4) IV
Female labor force participation	-0.0227			-0.845
	(0.185)			(0.661)
District Tariff		0.00650***	-0.00549	
		(0.00232)	(0.00586)	
Observations	638	638	638	638
F-stat(First Stage)		8.02		

Notes: The table presents the impact of female labor force participation on total fertility rate. Columns 1, 2, 3 and 4 report the OLS, first stage, reduced form and IV results. The controls used in the regressions are proportion of Scheduled Castes and Scheduled Tribes, proportion of urban population, proportion of Muslims, female literacy rate and poverty rate. The errors are clustered at district level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3: Effect of Female Employment in Agriculture and Manufacturing on Total Fertility Rate

	(1) OLS	(2) First Stage Agriculture	(3) First Stage Manufacturing	(4) Reduced Form	(5) IV
Proportion of female in agriculture	0.127				-0.169
	(0.186)				(0.749)
Proportion of female in manufacturing	-0.940				-4.313**
	(0.754)				(2.065)
Agricultural Tariff		0.00803***	0.00133**	-0.00710	
		(0.00205)	(0.000541)	(0.00597)	
Manufacturing Tariff		0.0144***	0.00631***	-0.0296**	
		(0.00433)	(0.00152)	(0.0124)	
Observations	638	638	638	638	638
F-stat(First Stage)		9.63	15.83		

Notes: The table presents the impact of female employment in agriculture and manufacturing on total fertility rate. Column 1 reports the OLS results. Columns 2 and 3 reports the first stage results for agriculture and manufacturing respectively. Columns 4 and 5 reports the reduced form and the IV results. The controls used in the regressions are proportion of Scheduled Castes and scheduled tribes, proportion of urban population, proportion of Muslims, female literacy rate and poverty rate. The errors are clustered at district level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 4

The Evolution of Gender Gaps in India

4.1 Introduction

The gender gap in employment in India is very large. In 1983, barely 31 percent of Indian women in the working age group of 16-64 years worked in the labor force. By 2005, this number had risen, but barely, to 40 percent. The corresponding numbers for men were around 94 percent. Amongst the Indian workforce that is illiterate, around one-third were women, both in 1983 and in 2005. At the other extreme, in 1983 barely 11 percent of workers with middle school or higher education were women. This number rose to 22 percent by 2005. On the employment side, in 1983 only 10 percent of white collar jobs in India were performed by women. This rose by a bare 5 percentage points to 15 percent in 2005.

To summarize, a large share of working age Indian women choose not to participate in the labor market. When they do, they find themselves very poorly trained with most of them having very little education. Consequently, most women workers end up working in low skill and low return agrarian jobs while the higher skill white collar jobs are typically performed by men. Starting with the basic premise that there are no innate differences between the genders in ability, these statistics tell a rather disheartening overall story of the allocation of talent in the country. They suggest large scale under-utilization of productive resources along with misallocation of labor inputs across occupations that potentially have serious productivity consequences for the country.

While the statistics cited above are disappointing, the period since 1983 has also seen sharp declines in the gender wage gap. The median male wage was 90 percent above the median female wage in 1983. By 2010 this premium had declined to about 50 percent. To put these numbers in perspective, in the US the median gender wage premium declined from 55 percent to 18 percent between 1979 and 2011 (see Kolesnikova and Liu (2011)).[1] In China on the other hand, the gender gap has been reported to be rising over the past two decades. National surveys in China report that the average male-to-female wage mark-up has risen from 28 to 49 percent in urban areas and from 27 to 79 percent in rural areas between 1990 and 2010. The Indian performance is thus quite encouraging when expressed in this relative context.

In this chapter we examine the factors underlying the sharp decline in the gender wage gap. Did the gender wage gap fall across all income groups? Did it decline due to a decline in the gender gaps in the proximate determinants of

1. The OECD average for the median wage premium of full-time male workers over their female counterparts in 2009 was 23 percent. There is a lot of variation though with the male premium varying from 35 percent in Austria and the Czech Republic to just around 5 percent in Italy.

wages such as education attainment rates and occupation choices of the workforce? We examine this using household level survey data from successive rounds of the National Sample Survey (NSS) from 1983 to 2010. The period since 1983 is a particularly interesting phase in India since it has been characterized by sharp macroeconomic changes. Whether such sharp macroeconomic changes have also coincided with better harnessing and allocation of talent in the country is a question of independent interest.

Our primary finding is that there has been broad-based and significant decreases in gender gaps across a number of indicators. Both education attainment rates and occupation choices of men and women have been broadly converging since 1983. Moreover, a large part of the decline in the gender wage gap is accounted for by convergence in these attributes of wages. We also find that the gender wage gap has declined across most of the income distribution. However, while for the 10th and 50th percentiles of the wage distribution, the decline in the gender wage gap was accounted for by convergence in measured attributes (primarily education), the gender wage convergence in the 90th percentile of the wage distribution was mostly due to unmeasured factors. Strikingly, changes in the measured attributes of this group tended to widen the gender wage gap. This effect is particularly strong in urban India which could reflect reductions in gender discrimination in urban areas though this requires more detailed investigation.

Our results on gender gaps suggest a general pattern of declining socioeconomic gaps across a number of different groups in India over the past three decades. In Hnatkovska, Lahiri, and Paul (2012) and Hnatkovska, Lahiri, and

Paul (2013), it has been shown that gaps between Scheduled Castes and Tribes and the rest have narrowed sharply since 1983 along a number of different indicators. Similarly, Hnatkovska and Lahiri (2012) found an even sharper narrowing of socioeconomic gaps between rural and urban workers between 1983 and 2010. Taken together, these results suggest that the period since 1983 which has been marked by rapid economic transformation and growth in India has also been a period that has seen disadvantaged groups sharply reducing their large historical socioeconomic disparities relative to others.

We should note that inequality in society can be measured as within-group inequality or between-group inequality. Our approach in this chapter focuses on between-group inequality. Our finding of declining inequality between groups in these papers is not inconsistent with findings of widening within-group inequality in India during some sub-periods since 1983. It is plausible that there is more inequality within and less inequality across groups. More generally, the results suggest that more work is required to determine the overall pattern of inequality in India during the last 30 years of market oriented reforms and growth take-off.

This chapter is related to some existing literature on the gender difference in labor market outcomes in India. Tilak (1980), used survey data from East Godavari district of Andhra Pradesh analyzed the difference in return to education across gender in India. The paper provides evidence that gender wage gap is relatively less for higher education groups. Using survey data from the Lucknow district of Uttar Pradesh, Kingdon (1998) found that women face significantly lower economic rates of returns to education than men. Kingdon and Unni (2001) found that women face high level of wage discrimination in the Indian labor market using 1987-1988 NSS data on Tamil Nadu and Madhya Pradesh. However, education contributes little to this wage disadvantage of women.

A key limitation of these studies is that they are concentrated in specific districts or states and do not produce national level estimates. Using national level "Employment and Unemployment" surveys of the NSS for the years 1983 and 1993, Duraisamy (2002) found that the return to female post-primary education is higher than that for men in 1983 and also in 1993-94. A study by Bhaumik and Chakrabarty (2008) using 1987 and 1999 rounds of the NSSO employment-unemployment survey found that the gender wage gap narrowed considerably between years 1987 and 1999. The narrowing of the earnings gap was attributed largely to a rapid increase in the returns to the labor market experience of women. Using nationally representative data from India Human Development Survey (IHDS) 2005, Agrawal (2013) found that the wage differential between males and females can largely be attributed to discrimination in the labor market. Differences in endowments plays a more prominent role in explaining wage difference between social groups.

Most of the papers in gender gap literature in Indian context focused on average gap in male-female wages. Khanna (2012) analyzed whether male-female wage gap differs for different wage levels. Using data from the 2009-10 employment-unemployment schedule of the National sample survey, this paper shows that male-female wage gap is higher at the lower end of the wage distribution.

It is important to recognize at the outset that the focus of this chapter is on the evolution of gender gaps amongst full-time workers in the workforce. This has two important consequences. First, the evolution of gender gaps amongst part-time workers is outside the ambit of the chapter. While part-time workers are an important component of the workforce, the measurement issues surrounding this category are too serious to tackle within the confines of this chapter. Second, the chapter is silent about the trends in the labor force participation decisions of women. This is a very important issue, not just for India but for all economies. Indeed, there is a significant amount of work in this area focusing on the USA and other industrial economies that has found evidence of a U-shaped pattern in the evolution of female labor-force participation rates with participation initially declining with development and rising later on in the development process. India too has seen a decline in the labor force participation rates of women over the last ten years. Whether or not this is part of the same syndrome that one has observed elsewhere in the west or is it due to some other India-specific factor is something that deserves a paper on its own right. In this chapter we confine ourselves to summarizing some of this literature in a separate sub-section.

The next section presents our results on education and occupation attainment rates and gender gaps in those indicators. Section 4.3 describes the evolution of gender wage gaps and their decomposition into measured and unmeasured attributes. Section 4.4 analyses the trends in the gender gap of the young workers. Section 4.5 briefly discusses female labor force participation. The last section concludes.

4.2 Empirical Regularities

Our data comes from successive quinquennial rounds of the National Sample Survey (NSS) from 1983 to 2009-10. Specifically, we use rounds 38, 43, 50, 55, 61 and 66 of the Employment and Unemployment surveys of the NSS. Given our interest in labor market characteristics and outcomes, we restrict the sample to working age adults in the age-group 16-64 who belong to households with a male head of household, who are working full-time and for whom we have information on their education and occupation choices.[2] While the overall NSS quinquennial surveys typically sample around 100,000 households (equivalently, around 460,000 individuals on average), our sample restriction reduces the sample to around 160,000 on average. Table 4.1 gives the demographic characteristics of the workforce. Clearly, men and women differ very marginally along these demographic characteristics.

Our primary interest lies in examining the evolution of gender gaps in India since 1983 along three dimensions: education, occupation and wages. Given that education and occupation choices are two fundamental ingredients in wage outcomes, we start with a closer examination of patterns on these two indicators. Before proceeding we would like to address a potential concern regarding our sample selection. Given that we are going to analyze outcomes of those in the labor force, one might have legitimate concerns that our findings may be affected by changes in the gender composition of the labor force. This could occur if there

2. We leave out female-led households from the analysis since these households are likely to be atypical in the generally patriarchal Indian family set-up.

were a differential changes in the proportion of women working full-time relative to men, in the labor force participation rates of women relative to men or in the relative employment rates of women during the sample period. Figure 4.1 shows the ratio of male to female rates in labor force participation, employment, fill-time workers and part-time workers. The key point to note is that there are no clear trends in any of these ratios which suggests that our finding are unlikely to be driven by gender-based differential changes in the participation rates.

The characteristics of the workforce in terms of their labor force participation choices and outcomes may differ across the genders along a number of other margins. One key factor of interest are potential differences between rural and urban workers. With a large majority of workers still living in rural India, it is important to document any differences in labor force behavior between these two sectors. Table 4.2 describes the gender differences in the labor force characteristics of workers broken down by rural and urban workers. The key variables we report are labor force participation rates (LFP), proportion of workers working full time (FULL), proportion working part-time (PART), proportion self employed (SELF), and proportion unemployed (UNMP).

The numbers in the table show that the patterns are similar for rural and urban workers on most measures. The two key features worth noting are: (a) in both rural and urban areas women are more likely to be working part-time relative to their male counterparts; (b) labor force participation rates are higher for rural women relative to urban women. In terms of our focus on full-time workers in the analysis below, the key point that we would like to emphasize is that the composition of full-time and part-time workers has not changed much across gender lines during the sample period.

4.2.1 Education Attainment

Education attainments of sampled individuals in the NSS survey are reported as categories: Illiterate, Primary, Secondary, etc.. While we use the category level information for our analysis below, we also generated statistics on years of education by converting the categories into years of education. This conversion allows us to represent the trends in a more parsimonious manner. The education categories are mapped to years of education following Hnatkovska, Lahiri, and Paul (2012): not literate = 0 years, literate but below primary = 2 years, primary = 5 years, middle = 8 years, secondary and higher secondary =10 years, graduate =15 years, and postgraduate =17 years

Table 4.3 reports the average years of education of the male and female workforce in India across all the rounds. While the overall education level of the workforce was a dismally low 3 years in 1983, the disparity between men and women workers was even more dramatic with men having on average around 3.5 years of education while women had less than a year's schooling. The relative gap in years of education between men and women of the Indian workforce was almost 4. By 2010, the situation had improved, albeit slightly. The relative gap had declined to about 1.7 with men having on average about 6.2 years of schooling while women had 3.6 years. There clearly has been some decline in the education gender gap.

The evidence on years of education does not reveal where and how the catch-up in education levels has been occurring. Did the decline in the gender gap in years of education happen primarily due to women moving out of illiteracy or due to more women moving past middle and secondary school? This question is important to since the addition of a year of education is likely to have very different effects depending on what kind of education is that extra year acquiring. We collect the education levels reported in the NSS survey into five categories: illiterate (Edu1), some education (Edu2), primary (Edu3), middle (Edu4) and secondary and above (Edu5). The last category collects all categories from secondary and above. Given the relatively limited representation of workers in some of the higher education categories at the college and beyond, this allows a relatively even distribution of individuals across categories.

Panel (a) of Figure 4.2 shows the distribution of men by education category on the left and the corresponding distribution of women on the right. The figure illustrates the direness of the education situation in India. In 1983, 70 percent of male workers had primary or below education levels while the corresponding number for women workers was 90 percent. The period since then has witnessed improvements in these with the proportion of men with primary or lower education level declining to 40 percent by 2010 while that for women it fell to around 60 percent. At the other end of the education spectrum, in 1983 around 15 percent of men and 5 percent of women workers had secondary or higher education levels. By 2010 the share of this category had risen to 40 percent for men and 25 percent for women.

Panel (b) of Figure 4.2 looks at the change in the share of women in each education category over time. The figure makes clear that women have been increasing their share in every education category except for Edu1 (illiterate) where the share has stayed unchanged. The fastest rise in the share of women occurred in education categories 2, 3 and 4 (some education, primary and middle school). Overall, the figure suggests that the education catch-up has been fairly uniform across categories.

Are the measured narrowing of the gender education gaps as suggested by the data on years of education as well as categories of education statistically significant? We examine this by estimating an ordered probit regression of education attainment (measured by education category) on a constant and a female dummy. We do this for each sample round. Table 4.4 gives the marginal effect of the female dummy in each round, the changes in the marginal effect across specified rounds as well as the statistical significance of the estimates. The estimates indicate that being female significantly increased the probability of being illiterate and significantly reduced the probability of being in all other education categories in 1983. Over the subsequent 27 years, this over-representation of females amongst illiterate workers and under-representation in other categories declined for all categories except for the secondary and above category. Moreover, the changes over time were statistically significant.[3]

In summary, our review of the education attainment levels of men and women

3. We should note that the marginal effect of the female dummy measures its effect on the absolute gap between the probability of that category between the genders. Hence, this is different from the relative gap numbers reported in Figure 4.2 which reports trends in the relative gap in the probabilities. This explains the difference in our results for the convergence patterns in Edu5 category in Figure 4.2 and Table 4.4.

in the Indian labor force suggests that gender gaps in education have declined significantly over the past three decades though the absolute levels of education in the country remain unacceptably low. Additionally, while more women are joining the labor force with secondary school or higher education, they have been not done this fast enough to consistently raise their share of secondary and above educated workers. This partly also be reflecting the fact that secondary educated women in India are still not joining the labor force at high enough rates.

4.2.2 Occupation Choices

Our next indicator of interest is the occupational choice of the workforce. Specifically, we want to examine differences in the occupational choices between men and women workers in the workforce and how those differences have evolved over time. We use the 3-digit occupation classification reported in NSS and aggregate them into three broad occupational categories: Occ1: *white-collar* occupations like administrators, executives, managers, professionals, technical and clerical workers; Occ2: *blue-collar* occupations such as sales workers, service workers and production workers; and Occ3: *Agrarian* occupations which collects farmers, fishermen, loggers, hunters etc..

Figure 4.3 shows the key features of the occupation distribution patterns of the workforce broken down by gender. Panel (a) shows the distribution of the male workforce across the three occupation categories and the corresponding distribution of female members of the workforce. The two graphs in panel (a) clearly show a robust pattern of occupational churning in the entire labor force: workers of both genders have been switching out of agrarian occupations. The share of agriculture in male full-time employment declined from around 50 percent in 1983 to 30 percent in 2010. Correspondingly, the share of agriculture in female full-time employment also fell, albeit more tepidly, from 70 to 55 percent during the same period. The share of blue-collar employment for males rose from around 40 to 50 percent while that of white-collar employment rose from 10 to around 20 percent. Women, by contrast, saw blue-collar employment's share in their total employment in 2010 rise slightly above its 1983 level of just under 25 percent. White collar employment of women however rose sharply from 5 to just under 20 percent between 1983 and 2010.

Panel (b) of Figure 4.3 shows the share of women in total full-time employment in each occupation. Note that this is in contrast to Panel (a) which showed the share of each occupation in total full-time female employment. The most visible change in the share of women is in Occ1 which is white-collar employment where women's share has increased from 10 to 15 percent between 1983 and 2010. The share of women in total employment in the other two occupations has not changed much during this period.

The trends documented above suggest that women have been changing occupations during this period. Has this resulted in a decline in the gender disparities in the occupation distribution of the labor force? We answer this question by running a multinomial logit regression of occupational choice on a constant and a female dummy for each round. We then compute changes in the effect of the female dummy across the rounds. Table 4.5 shows the results. In a confirmation of the visual suggestion above, in 1983 being female significantly increased the probability of being employed in agriculture while significantly reducing the probability of employment in blue and white collar jobs (Occ2 and Occ1, respectively). While this basic pattern has not changed between 1983 and 2010, the negative marginal effect of the female dummy on the probability of white-collar employment declined significantly during this period indicating that there was statistically significant reduction in the under-representation of women in these occupations during this period. The other two broad occupation categories however, showed a worsening of the initial disparity of representation with the over-representation of women in agricultural employment and under-representation in blue-collar occupations marginally worsening between 1983 and 2010.

In summary, our review of the trends in the disparity between the genders in their occupation distribution suggests a mixed picture. On the positive side, women have been moving out of agricultural jobs into blue and white collar jobs thereby behaving more like their male counterparts in the workforce. However, in terms of the share of women in the different occupations, only white-collar jobs have seen a significant expansion of the share of women while the under-representation in blue-collar jobs and over-representation in agrarian jobs has increased. This latter effect suggests to us that women have been moving out of agricultural jobs and into blue-collar jobs at a slower rate than their male counterparts.

4.3 Wage Outcomes and Gender Differences

We now turn our attention to the third indicator of interest – gender gaps in wages. In terms of background, it is worth reiterating that two key determinants of wages of individual workers are their education levels and the occupations that they choose. In the previous section we have shown that gender gaps in education have tended to narrow for all but the highest education groups. This trend is likely to be a force towards raising the relative wage of women. We have also shown that women's share of employment has only increased in white-collar occupations. In as much as women are getting disproportionately more represented in agricultural jobs, one might expect this force to lower the relative wage of women if agriculture pays relatively lower wages. Clearly, there are offsetting underlying forces here.

The NSS only reports wages from activities undertaken by an individual over the previous week (relative to the survey week). Household members can undertake more than one activity in the reference week. For each activity we know the "weekly" occupation code, number of days spent working in that activity, and wage received from it. We identify the main activity for the individual as the one in which he spent maximum number of days in a week. If there are more than one activities with equal days worked, we consider the one with paid employment (wage is not zero or missing). Workers sometimes change the occupation due to seasonality or for other reasons. To minimize the effect of transitory occupations, we only consider wages for which the weekly occupation code coincides with usual occupation (one year reference). We calculate the daily wage by dividing total wage paid in that activity over the past week by days spent in that activity.

Figure 4.4 shows the evolution of the gender wage gaps since 1983. Panel (a) shows the mean and median wage gaps across the rounds while Panel (b) shows the wage gap across all percentiles for three different years: 1983, 2004-05 and 2009-10. Two points are worth noting from the figure. First, the gender wage gap has shrunk secularly since 1983 for all groups except the very richest groups. In other words, the decline in the gender wage gap has been broad-based and inclusive. Second, there has been a very sharp decrease in the gender wage gap between 2004-05 and 2009-10. Uncovering the reasons behind this phenomenon is interesting in its own right.

Are the measured decreases in the wage gap statistically significant? We test this by running regressions of the log wage on a constant, a female dummy and controls for age and age squared (to control for potential lifecycle differences between men and women related to their labor supply choices). We run the regression for different quantiles as well as for the mean.[4] Table 4.6 shows the results. The regression results show that the decline in the wage gaps were significant for all income groups except the 90th percentile for whom there was no significant change in the wage gap between 1983 and 2010. Moreover, there was also a statistically significant decrease in the wage gap between 2004-05 and 2009-10.

So, what is driving the wage convergence between the genders? Specifically, how much of the decrease in the gender wage gap is due to convergence in mea-

4. We use the Recentered Influence Function (RIF) regressions developed by Firpo, Fortin, and Lemieux (2009) to estimate the effect of the female dummy for different points of the wage distribution.

sured attributes of workers? To understand the time-series evolution of the gender wage gaps we use the Oaxaca-Blinder decomposition technique to decompose the observed changes in the mean and quantile wage gaps between 1983 and 2010 into explained and unexplained components as well as to quantify the contribution of the key individual covariates. We employ Ordinary Least Squares (OLS) regressions for the decomposition at the mean, and Recentered Influence Function (RIF) regressions for decompositions at the 10th, 50th, and 90th quantiles.[5] Our explanatory variables are demographic characteristics such as individual's age, age squared, caste, and geographic region of residence. Additionally, we control for the education level of the individual by including dummies for education categories.[6]

The results of the Oaxaca-Blinder decomposition exercise are reported in Table 4.7. The table shows that all of the gender wage convergence for the median and around 75 percent of it for the mean can be accounted for by measured covariates. For the 10th percentile measured covariates explain around 50 percent of the observed convergence. Encouragingly, convergence in education was a key contributor to the observed wage convergence for all these groups.[7] The convergence

5. The inter-temporal decomposition at the mean is in the spirit of Smith and Welch (1989). All decompositions are performed using a pooled model across men and women as the reference model. Following Fortin (2006) we allow for a group membership indicator in the pooled regressions. We also used 1983 round as the benchmark sample.

6. We do not include occupation amongst the explanatory variables since it is likely to be endogenous to wages.

7. As we show below, adding occupation choices to the list of explanatory variables does not significantly raise the share of the explained component in the observed wage convergence. This is not unusual. Blau and Kahn (2007) report that over 40 percent of the gender wage gap in the USA remains unexplained even after accounting for a rich set of explanatory variables including education, race, occupation, industry, union status, experience, etc..

at the 90th percentile between 1983 and 2010 however cannot be explained by measured covariates. In fact, the observable covariates of wages predict that the gender wage gap should have actually widened rather than narrowed The source of the wage convergence at the 90th percentile is thus a puzzle as it is almost entirely unexplained.

To gain greater perspective on the underlying forces driving the contraction in the gender wage gap, Panel (a) of Figure 4.5 shows the gender wage gaps by education category. Examining panel (a) it is clear that the dispersion in the wage gap by education category has declined perceptibly since 1983. Moreover, gender wage gaps have declined sharply for groups with some education (edu2), primary education (edu3) and those with middle school education (edu4) while increasing slightly for illiterates and those with secondary and above education. Since women have been increasing their representation in education categories 2,3 and 4 while reducing their relative representation in categories 1 and 5, the behavior of the wage gaps by education category in panel (a) of Figure 4.5 suggests why education accounts for a large part of the observed gender wage convergence.

Panel (b) of Figure 4.5 gives the median wage gaps by occupation category. The median wage gaps were the highest in blue-collar jobs (occ2) and used to be the lowest in white collar jobs (occ1) in 1983. By 2010, the wage gaps in these two occupations had converged while the wage gap in agrarian jobs remained relatively unchanged. Recall from Table 4.5 that between 1983 and 2010 women reduced their under-representation in white-collar occupations. At the same time their over-representation in agrarian jobs rose and the under-representation in blue-collar occupations worsened.

The effect of occupation choices on the wage gap is thus ambiguous. On the one hand, the movement of women towards white-collar occupations that had lower average wage gaps would have tended to lower the wage gap. The increased under-representation in blue-collar jobs, typically characterized by high gender wage gaps, would also tend to lower the overall wage gap as would the decline in the wage gap over time in that occupation. However, the increase in the wage gap in white-collar occupation over time would have had the opposite effect of widening the wage gap.

In summary, our results on wage outcomes of the workforce indicate that the gender wage gap has narrowed significantly. Most of this convergence was due to convergence in measured covariates of wages. Additionally, there has been a very sharp convergence in male and female wages between 2004-05 and 2009-10. While the reasons behind this require more careful examination, our preliminary examination of the issue suggest that a narrowing of the gender gap in education was a key contributing factor. It is tempting to attribute the convergence to factors such as the National Rural Employment Guarantee Program (NREGA) which guarantees 100 days of work in the off-season to every rural household. However, we don't believe that our results are driven by NREGA for a couple of reasons. First, as Figure 4.4 illustrates clearly, the convergent trends pre-date the introduction of NREGA (which was only introduced in 2006). Second, the convergent patterns characterize both rural and urban areas whereas NREGA only applied to rural areas. Clearly, some factors that were common to both rural and urban areas are likely to have been at play rather than a rural India specific program like NREGA.

4.4 The Young

The trends documented above do suggest significant narrowing in gender gaps across multiple categories. However, a key reason for examining these trends is to also anticipate what might one expect to see over the next couple of decades in terms of gender disparities. While forecasting such trends are very difficult, one measure which usually provide windows into future trends would be the trends in the gender gaps of the young workers.

To probe this more closely, Figure 4.6 shows that the primary force driving the catch-up in education is the increasing education levels of younger cohorts. Thus, in 1983 the relative gender gap in years of education between men and women workers aged 16-22 was 3. By comparison, in 2005, the education gap was 1.4 for the 17-23 year old cohort who were born between 1982-88. Clearly the gap is lower for younger birth cohorts.

We take a closer look at the gaps amongst younger workers by concentrating on the characteristics of 16-25 year olds in each survey round. We start with education. Figure 4.7 reports the years of education of the 16-25 year olds, broken down by females and males, and by rural and urban. As can be seen from the Figure, young workers in the 16-25 age group have been increasing their years of education in both rural and urban India. Moreover, in both areas the gap between men and women has narrowed sharply. Perhaps, most impressively, in 2010 women workers in urban areas had more years of education on average than their male counterparts. Even in rural India, in 2010 the gap was just above 1 year for this group. These trends suggest that over the next two decades, the gender gap in education should become very small. These trends would get even stronger as more and more educated women begin participating in the labor force.

How have the 16-25 year olds been behaving in terms of their occupation choices? Are there significant differences between the genders on this dimension? Figure 4.8 shows the occupation choices of women (Panel (a)) and men (Panel (b)). The patterns are very similar for the two. The share of agricultural occupation have declined while the share of the other two occupations have risen for both men and women between 1983 and 2010. In terms of comparisons of the occupation distribution, by 2010, the share of the female workforce in the 16-25 age group that was engaged in white-collar jobs was marginally higher than the corresponding proportion for male workforce in the 16-25 age-group. On the other hand, while women in this age group have been switching out of agriculture into blue-collar occupations, their male counterparts in the same age group have been doing so at a faster rate. Consequently, even in 2010 almost 60 percent of young female workers were engaged in agrarian jobs while blue-collar jobs accounted for only 30 percent of their employment. The corresponding numbers for young male workers on the other hand were 50 percent and 40 percent, respectively. The key though is that the gaps have narrowed much faster for these younger workers as compared to their older counterparts.

The rapidly shrinking gender gaps amongst younger workers suggests to us that going forward gender gaps are likely to narrow even faster as more and more of the older cohorts drop out of the labor force and more younger cohorts with similar education and occupation choices) replace them in the workforce.

4.5 Female Labor Force Participation

A number of existing studies found that a U-shaped relationship exists between female labor force participation and economic development (Goldin (1995); Mammen and Paxson (2000); Kottis (1990); Fatima and Sultana (2009)). They argue that in low income societies, women work on family farms or enterprises and thus female labor force participation is high. As society gets richer there is higher focus on industrialization. Thus blue collar jobs becomes more important and woman's participation in the labor market falls accordingly. This can be explained by rising family income, incompatibility of factory work with child care and social stigma associated with working outside home. With further economic development, female labor force participation increases once again due to the expansion of higher education among females and the emergence of a white-collar jobs. The stigmas associated with jobs disappear overtime and at such advanced stages of development, the substitution effect on account of higher female wages dominates the income effect.

Empirical support for the U-hypothesis is primarily based on cross-country analysis (Mammen and Paxson (2000), Çağatay and Özler (1995)). Panel analyses, on the other hand, have produced mixed results. While Luci (2009) and Tam (2011) have argued that the U-shaped LFP hypothesis has support within countries over time, Gaddis and Klasen (2014) found that the evidence of a U-shaped relationship is weak and extremely sensitive to underlying data.

In the Indian context, there is mixed evidence on the U-shaped relationship. On the one hand, Olsen and Mehta (2006) found that a U-shaped relationship exists between female employment and educational status. Using 1999-2000 NSS data, they found that women with low education as well as those with university degrees more likely to work than middle educated women. Using panel data between 1983-2010 from the National Sample survey, Lahoti and Swaminathan (2013) however did not find a significant relationship between level of economic development and woman's participation rates in the labor force. Female labor participation rates tend to also vary between rural and urban areas and across subrounds of the NSS data, as shown by Bardhan (1984).

As the discussion above makes clear, female labor force participation is a complicated subject that requires a separate paper on its own. We hope to return to this issue in future work.

4.6 Conclusion

Allocating talent is one of the major challenges for any country. It is an even bigger issue in rapidly developing economies with their changing economic structure. This chapter has examined one aspect of this talent allocation process by examining the evolution of gender gaps in India since 1983. The absolute differences between males and females in the Indian labor force are huge in a number of different indicators including education attainment rates, labor force participation rates, occupation choices as well as wages. However, the gaps have narrowed along all these indicators in the last 27 years. Most encouragingly, the majority of the wage convergence is accounted for by measured covariates of wages, particularly education.

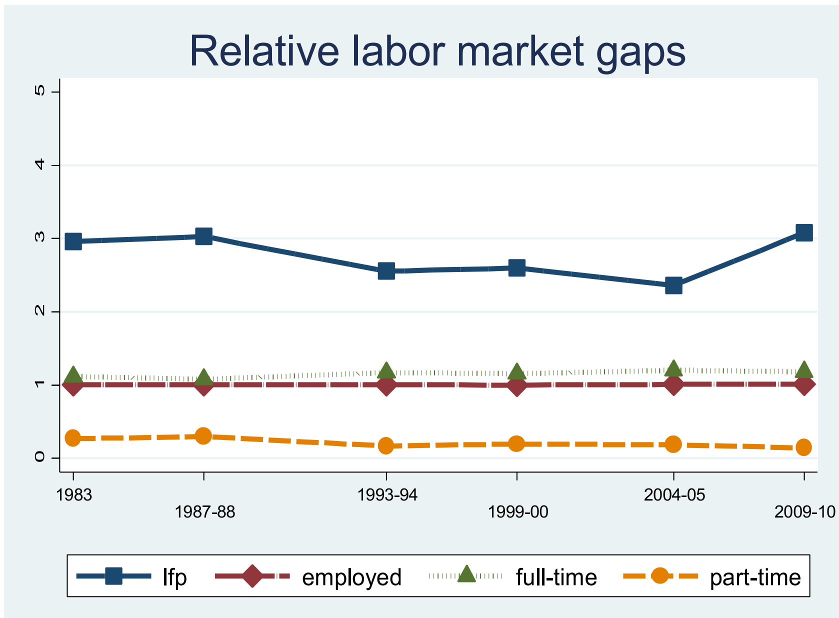
This study has ignored some key areas that can shed greater light on the evolution of gender gaps. First, the study has focused on aggregate India-wide trends. Given the huge variation in policies and outcomes across states in India since 1983, one profitable approach would be to exploit the cross-state differences to better identify the causal channels at work. This left for future research. Second, trends in female labor force participation rates in India need to be explored. This has first-order implications for gender disparities but comes with a host of data and conceptual issues that render a full-scale examination of it difficult in this chapter.

Table 4.1: Sample Summary Statistics

	Male					Female				
	Age	SCST	Married	Sample share	Rural	Age	SCST	Married	Sample share	Rural
1983	35.55	0.25	0.79	0.79	0.75	33.69	0.36	0.85	0.21	0.86
1987-88	35.82	0.26	0.8	0.79	0.77	33.82	0.35	0.87	0.21	0.87
1993-94	36.11	0.27	0.8	0.79	0.75	34.62	0.35	0.86	0.21	0.86
1999-00	36.27	0.28	0.8	0.76	0.74	35.22	0.38	0.88	0.24	0.86
2004-05	36.63	0.27	0.8	0.78	0.73	35.91	0.35	0.86	0.22	0.84
2009-10	37.68	0.28	0.81	0.81	0.71	36.71	0.36	0.86	0.19	0.81

Notes: This table reports summary statistics for the sample. The statistics are reported at the individual level.

Figure 4.1: Gender Gaps: Labor Market Participation Rates



Notes: The figure shows the ratio of male to female rates in labor force participation, employment, filltime workers and part-time workers for the six survey rounds.

Table 4.2: Labor Market Characteristics by Gender: Rural and Urban Workers

	Male					Female				
Round	LFP	FULL	PART	SELF	UNMP	LFP	FULL	PART	SELF	UNEMP
					Panel A: Rural					
1983	0.9365	0.9578	0.0422	0.6131	0.0354	0.3567	0.8557	0.1443	0.6001	0.0438
1987-88	0.9417	0.966	0.034	0.5844	0.0396	0.3449	0.8965	0.1035	0.5692	0.0412
1993-94	0.9512	0.9665	0.0335	0.5836	0.0291	0.4188	0.8246	0.1754	0.614	0.0298
1999-00	0.9439	0.9626	0.0374	0.5561	0.0365	0.4163	0.8323	0.1677	0.5927	0.0351
2004-05	0.9528	0.9567	0.0433	0.5873	0.0354	0.4557	0.7912	0.2088	0.6661	0.0398
2009-10	0.9511	0.97	0.03	0.5361	0.0297	0.3477	0.8127	0.1873	0.5849	0.0357
					Panel B: Urban					
1983	0.9352	0.977	0.023	0.3941	0.06	0.1819	0.8933	0.1067	0.412	0.0808
1987-88	0.9345	0.9834	0.0166	0.4026	0.0614	0.1877	0.9162	0.0838	0.4213	0.0984
1993-94	0.9366	0.9858	0.0142	0.4074	0.0467	0.2173	0.8634	0.1366	0.4515	0.0901
1999-00	0.9275	0.984	0.016	0.4015	0.0518	0.1981	0.8745	0.1255	0.4453	0.0781
2004-05	0.931	0.9808	0.0192	0.4396	0.0475	0.2383	0.8561	0.1439	0.4957	0.092
2009-10	0.9279	0.9876	0.0124	0.4085	0.0302	0.198	0.8804	0.1196	0.4217	0.079

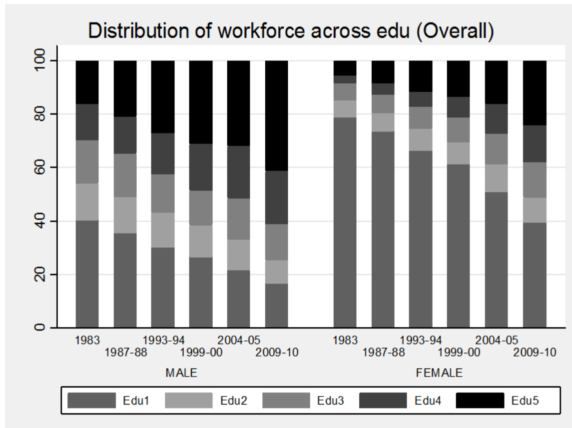
Notes: This table reports the labor force characteristics of men and women separately for rual and urban workers. LFP indicates Labor Force Participation rates, FULL is proportion of workers working full-time, PART are proportions of part-time workers, SELF indicate proportion of self-employment and UNEMP denotes the unemployent rate.

Table 4.3: Education Gaps: Years of Schooling

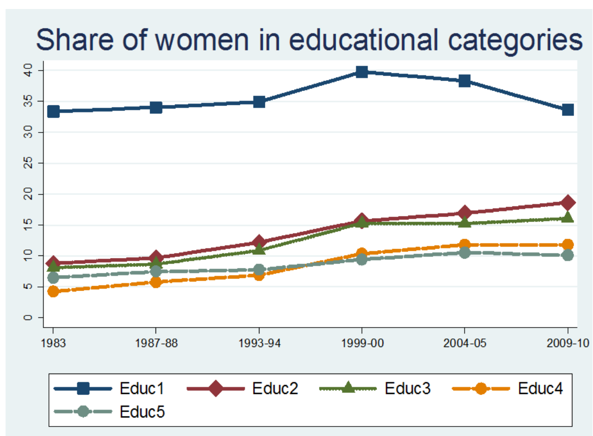
	Average years of education			Relative education gap
	Overall	Male	Female	
1983	2.99	3.54	0.93	3.83***
	(0.01)	(0.01)	(0.02)	(0.08)
1987-88	3.19	3.75	1.15	3.25***
	(0.01)	(0.01)	(0.02)	(0.06)
1993-94	3.82	4.42	1.55	2.86***
	(0.01)	(0.02)	(0.02)	(0.04)
1999-00	4.32	5.05	2	2.53***
	(0.02)	(0.02)	(0.03)	(0.04)
2004-05	4.82	5.44	2.64	2.06***
	(0.02)	(0.02)	(0.03)	(0.02)
2009-10	5.71	6.21	3.59	1.73***
	(0.03)	(0.03)	(0.06)	(0.03)

Notes: This table presents the average years of education for the overall sample and separately for males and females; as well as the gap in the years of education. The reported statistics are obtained for each NSS survey round which is shown in the first column. Standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p<0.01

Figure 4.2: Distribution of Workforce Across Education Categories



(a)



(b)

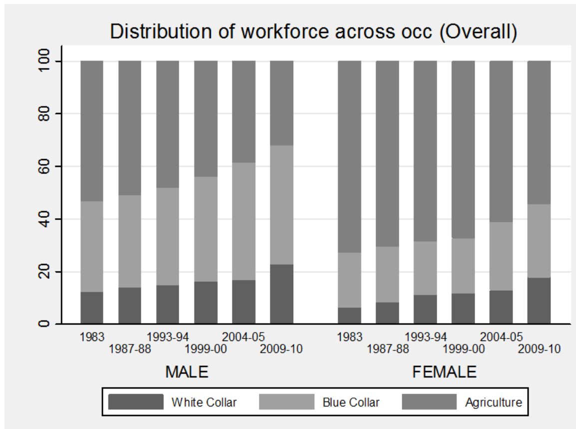
Notes: Panel (a) of this Figure presents the education distribution of each gender into the different education categories. Panel (b) shows the share of women in all workers in each category.

Table 4.4: Marginal Effect of Female Dummy on Education Categories

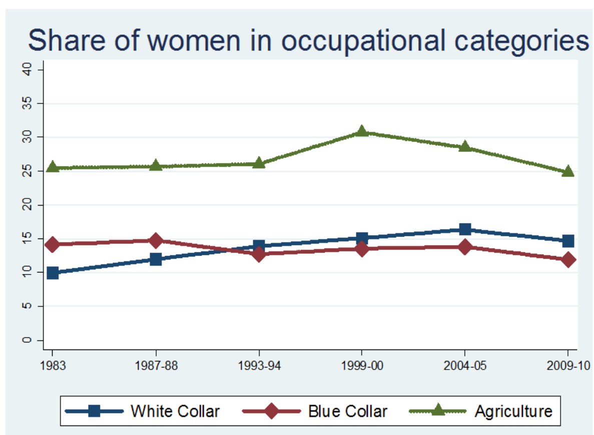
	Panel A. Marginal effects of female dummy						Panel B.Changes	
	1983	1987-88	1993-94	1999-00	2004-05	2009-10	1983-2005	1983-2010
Edu 1	0.3760***	0.3641***	0.3582***	0.3460***	0.3011***	0.2482***	-0.0749***	-0.1278***
	(0.003)	(0.003)	(0.0035)	(0.0036)	(0.004)	(0.0062)	(0.005)	(0.0069)
Edu 2	-0.0607***	-0.0531***	-0.0367***	-0.0180***	0.0008*	0.0165***	0.0615***	0.0772***
	(0.001)	(0.0009)	(0.0008)	(0.0006)	(0.0005)	(0.0006)	(0.0011)	(0.0012)
Edu 3	-0.0971***	-0.0879***	-0.0648***	-0.0460***	-0.0335***	-0.0099***	0.0636***	0.0872***
	(0.0012)	(0.0011)	(0.001)	(0.0009)	(0.0009)	(0.0009)	(0.0015)	(0.0015)
Edu 4	-0.0935***	-0.0851***	-0.0884***	-0.0883***	-0.0790***	-0.0555***	0.0145***	0.038***
	(0.0011)	(0.001)	(0.0011)	(0.0012)	(0.0013)	(0.0018)	(0.0017)	(0.0021)
Edu 5	-0.1247***	-0.1380***	-0.1683***	-0.1937***	-0.1895***	-0.1992***	-0.0648***	-0.0745***
	(0.0011)	(0.0011)	(0.0014)	(0.0018)	(0.0021)	(0.004)	(0.0024)	(0.0041)
N	164979	182384	163126	173309	176968	133926		

Notes: Panel (a) reports the marginal effects of the female dummy in an ordered probit regression of education categories 1 to 5 on a constant and a female dummy for each survey round. Panel (b) of the table reports the change in the marginal effects over stated periods and over the entire sample period. N refers to the number of observations. Standard errors are in parenthesis. * p-value≤0.10, ** p-value≤0.05, *** p-value≤0.01.

Figure 4.3: Distribution of Workforce Across Occupation Categories



(a)



(b)

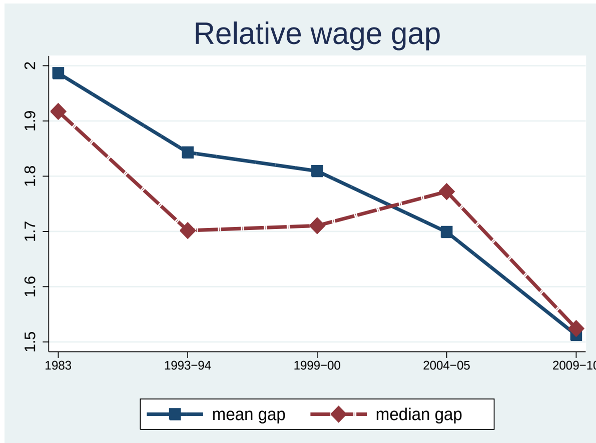
Notes: Panel (a) of this Figure presents the occupation distribution of each gender into the different occupation categories. Panel (b) shows the share of women in each category.

Table 4.5: Marginal Effect of Female Dummy on Occupational Categories

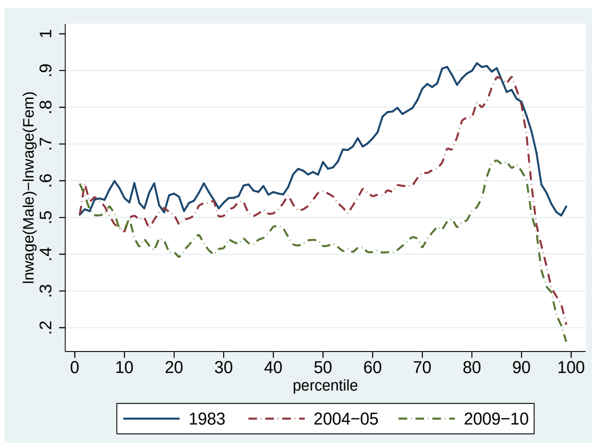
	Panel A. Marginal effects of female dummy						Panel B.Changes	
	1983	1987-88	1993-94	1999-2000	2004-05	2009-10	1983-2005	1983-2010
Occ1	-0.0564***	-0.0488***	-0.0407***	-0.0512***	-0.0370***	-0.0394***	0.0194***	0.017***
	(0.0016)	(0.0015)	(0.002)	(0.0022)	(0.0024)	(0.004)	(0.0029)	(0.0043)
Occ2	-0.1172***	-0.1155***	-0.1481***	-0.1756***	-0.1670***	-0.1592***	-0.0498***	-0.042***
	(0.0031)	(0.0031)	(0.0031)	(0.0034)	(0.0037)	(0.0055)	(0.0048)	(0.0063)
Occ3	0.1736***	0.1644***	0.1888***	0.2268***	0.2040***	0.1986***	0.0304***	0.025***
	(0.0033)	(0.0033)	(0.0035)	(0.0037)	(0.0041)	(0.0064)	(0.0053)	(0.0072)
N	164979	182384	163126	173309	176968	133926		

Notes: Panel (a) of the table presents the marginal effects of the female dummy from a multinomial probit regression of occupation choices on a constant and a female dummy for each survey round. Panel (b) reports the change in the marginal effects of the rural dummy over the relevant time periods. Agrarian jobs is the reference group in the regressions. N refers to the number of observations. Standard errors are in parenthesis. * p-value≤0.10, ** p-value≤0.05, *** p-value≤0.01.

Figure 4.4: Gender Wage Gaps Since 1983



(a)



(b)

Notes: Panel (a) of this Figure presents the relative male to female wage for full-time workers. Panel (b) shows the log ratio of male to female wages for each percentile.

Table 4.6: Changes in the Gender Wage Gap

	Panel A: Female dummy coefficient					Panel B: Changes	
	1983	1993-1994	1999-2000	2004-2005	2009-2010	1983-2005	1983-2010
10th Perc	-0.8851***	-0.6020***	-0.4727***	-0.7737***	-0.6035***	0.1114***	0.2816***
	(0.0193)	(0.0157)	(0.0129)	(0.0199)	(0.0277)	(0.0277)	(0.0338)
50th Perc	-0.6872***	-0.6064***	-0.6115***	-0.5164***	-0.3690***	0.1708***	0.3182***
	(0.0097)	(0.0089)	(0.009)	(0.0086)	(0.0112)	(0.013)	(0.0148)
90th Perc	-0.3543***	-0.3506***	-0.4141***	-0.4073***	-0.3841***	-0.0530***	-0.0298
	(0.01)	(0.0132)	(0.0184)	(0.0235)	(0.0354)	(0.0255)	(0.0368)
Mean	-0.6604***	-0.5641***	-0.5810***	-0.5777***	-0.4622***	0.0827***	0.1982***
	(0.0083)	(0.0095)	(0.0095)	(0.01)	(0.0139)	(0.013)	(0.0162)
N	63981	63364	67322	64359	57339		

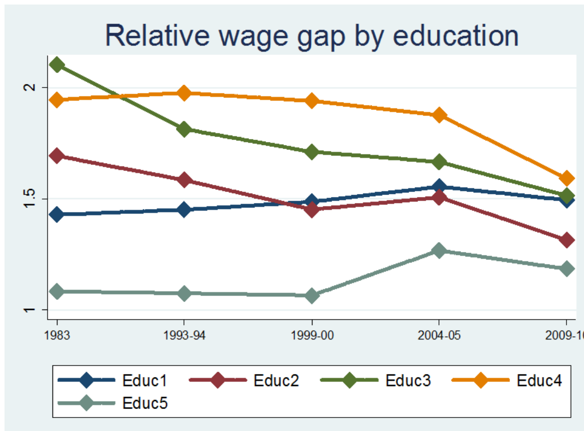
Notes: Panel (a) of this table reports the coefficient on the female dummy in a regression of log wages on a constant, a female dummy and controls for age (age and age squared). Panel (b) reports changes in the coefficient across the relevant rounds. N refers to the number of observations. Standard errors are in parenthesis. * p-value≤0.10, ** p-value≤0.05, *** p-value≤0.01.

Table 4.7: Decomposition of the Changes in the Wage Gap

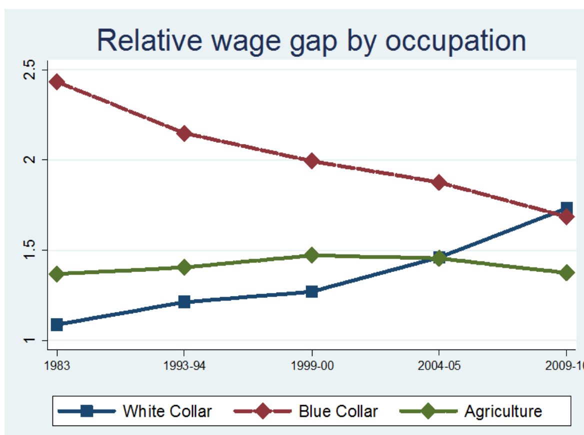
	Measured gap	Explained	Unexplained	Explained by education
	Change (1983 to 2009-10)			
10th Perc	-0.1220***	-0.0638***	-0.0582**	-0.0241***
	(0.0267)	(0.0097)	(0.0273)	(0.0078)
50th Perc	-0.2102***	-0.2452***	0.0349	-0.1378***
	(0.0287)	(0.0143)	(0.0257)	(0.0099)
90th Perc	-0.1665***	0.1484***	-0.3148***	0.0455*
	(0.0569)	(0.0352)	(0.0544)	(0.0259)
Mean	-0.2157***	-0.1512***	-0.0645***	-0.0891***
	(0.0169)	(0.0105)	(0.0158)	(0.0083)

Notes: This table presents the change in the rural-urban wage gap between 1983 and 2009-10 and its decomposition into explained and unexplained components using the RIF regression approach of Firpo, Fortin, and Lemieux 2009 for the 10th, 50th and 90th quantiles and using OLS for the mean. The table also reports the contribution of education to the explained gap (column (iv)). Bootstrapped standard errors are in parenthesis. * p-value$\leq$0.10, ** p-value$\leq$0.05, *** p-value$\leq$0.01.

Figure 4.5: Gender Wage Gaps by Education and Occupation Categories



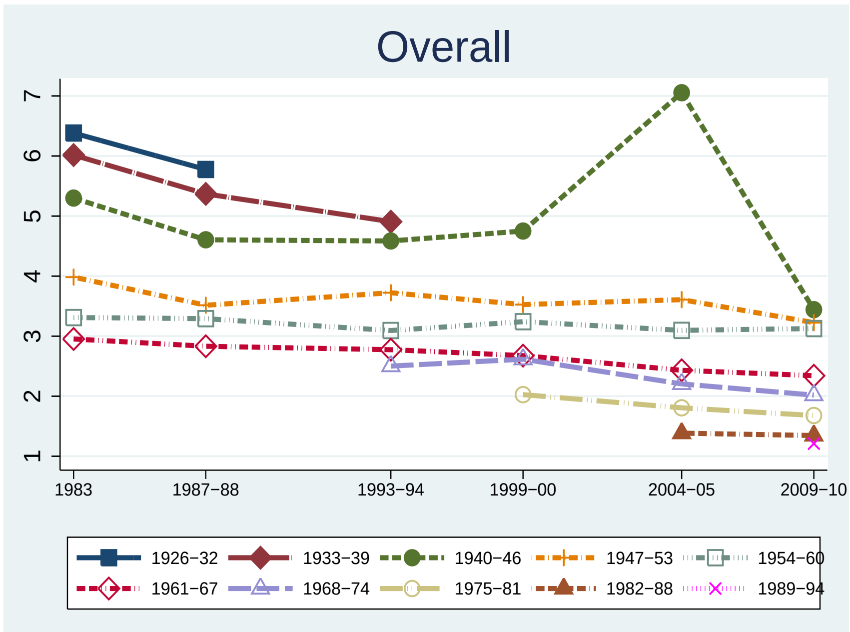
(a)



(b)

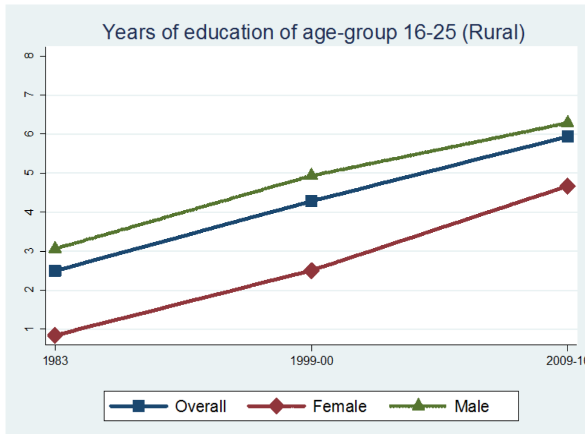
Notes: Panel (a) of this Figure presents the relative male to female median wage gap by education category while Panel (b) shows the median wage gap between men and women in different occupations.

Figure 4.6: Education Gaps in Years by Birth Cohorts

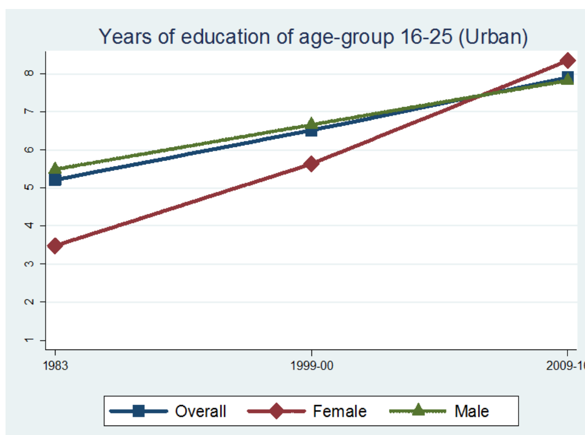


Notes: The figure shows the relative gap in years of education between males and females for the six survey rounds for different birth cohorts.

Figure 4.7: Gap in Years of Education: 16-25 Year Olds



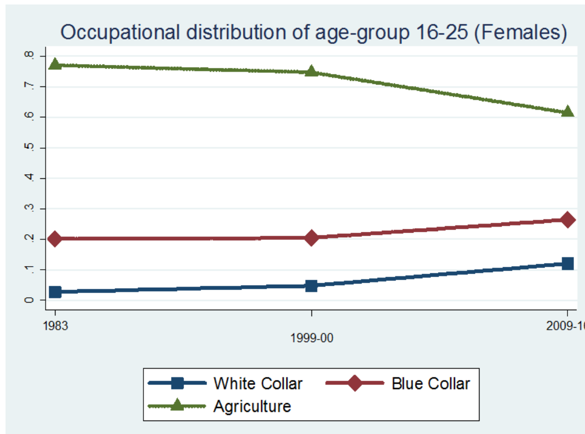
(a)



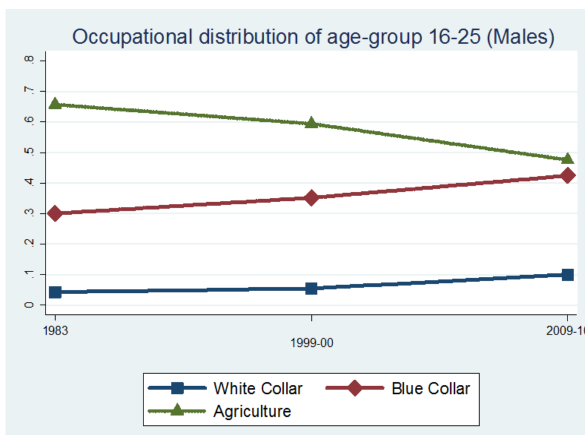
(b)

Notes: The figure reports the overall years of education as well as the years of education of female and male workers in the 16-25 age-age-group. Panel (a) of this Figure corresponds to the rural sector and panel (b) corresponds to the urban sector.

Figure 4.8: Occupational Distribution of 16-25 Year Olds



(a)



(b)

Notes: Panel (a) of this Figure presents the occupation distribution of female workers in the 16-25 age cohort across the six survey rounds. Panel (b) shows the corresponding figures for urban male workers aged 16-25.

Chapter 5

Conclusion

This thesis attempts to understand the factors that influence two major problems in India; high infant mortality and fertility. It also explores the distributional impacts of the rapid rate of growth that India has faced in the last three decades on the labor market characteristics and outcomes of women vis-a-vis men.

In the economics literature, there is substantial evidence that politicians have strong incentives to signal their ability to improve the economic conditions of voters in election years. However, there has been very little research on the welfare implication of these election cycles. In Chapter 2, I attempt to test whether the timing of elections have any impact on child survival in India. In particular, I have analyzed whether children born before scheduled state assembly election years are more likely to survive their infancy as compared to children born in the off-election years and if this impact is higher for districts where the previous election was particularly close. My work shows that children born before the scheduled state assembly election years are less likely to die in infancy as compared to children born in off-election years. Moreover the decline in infant mortality rate is higher in areas where the state ruling party had a narrow margin of victory in the previous election. The results also show that children born before scheduled election years are less likely to suffer from low birth weight and the mothers are likely to have more regular antenatal checkups. The probability that mothers receives tetanus injection during pregnancy is significantly higher for children born in the election years.

It is generally held that there exists a negative relationship between fertility and female employment (Cramer, 1980; Felmlee, 1993; Smith-Lovin and Tickamyer, 1978). The association between fertility and female employment reflects the incompatibility between child care and work force participation. Since child-rearing is intensive in mother's time, female employment decreases the number of children. However evidence on the relationship between female employment and fertility in developing countries is limited. The chapter 3 of my thesis empirically examines the causal impact of female labor force participation on the whole and female employment in different sectors on the fertility rate. The results show that while female labor force participation and female employment in agriculture has no statistically significant effect on fertility, female employment in manufacturing significantly reduces fertility.

Chapter 4 looks at the evolution of male-female gap in India in the last three decades. This is a joint work with Dr. Viktoria Hnatkovska and Dr. Amartya Lahiri. Using data from six consecutive rounds of the employment-unemployment schedule of National Sample Survey covering the period 1983-2010, we have studied the evolution of gaps in education attainment rates, occupation choices, and wages in India across male and female workers. Our primary finding is that there has been significant convergence in these indicators over the last three decades.

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Appendix A

Appendix to Chapter 2

Data Sources

The data used in this chapter come from a number of sources. They cover the 14 main politically competitive states in India and span the period 1975-1998.

The unit of observation in this chapter is an individual child. Since twins have a significantly higher mortality rate as compared to singletons (Buekens and Wilcox (1993)), I have considered only the singleton births for this chapter. The results are however robust to the inclusion of twins as shown in Section A.3.

The infant mortality variable is defined as a dummy variable indicating whether a child died before the age of 12 months. The variable is defined for children born between 1975 and 1998. The data is derived from the second round of National Family Health survey (NFHS II) conducted in 1998-99.

The neonatal mortality variable is defined as a dummy variable indicating whether the child died before the age of 1 month. The variable comes from the NFHS II and is defined for children born during 1975-1998.

The 2-12 months mortality variable is given by a dummy variable indicating whether the child died between 2 and 12 months of their life. This variable also comes from the NFHS II and is defined for children born 1975-1998.

Child gender, birth order and month of birth dummies also come from NFHS II and are defined for the period 1975-1998. These variables are used as controls in sections 2.5.1-2.5.5 and section 2.6.

The number of antenatal visits gives the total number of antenatal visits made by a mother during her pregnancy. The incidence of low birth weight is given by a dummy variable equal to 1 if the mother reported that the child was of low birth weight. Whether the mother had a tetanus injection during pregnancy is also given by a dummy variable indicating whether the mother had at least one tetanus injection during pregnancy. These variables are defined for children born during 1987-1992 whose mothers were surveyed in NFHS I and children born during 1995-1998 whose mothers were surveyed in NFHS II.

The child level and mother level controls used in the mechanisms regressions come from NFHS I and NFHS II. The controls include child gender, birth order dummies, month of birth dummies, a dummy for whether the mother belongs to Scheduled Castes (historically disadvantaged social group in India), a dummy for whether the mother belongs to Scheduled Tribes, a dummy indicating whether the mother is Muslim and a dummy for urban area of residence. The regressions also include mothers' and fathers' years of education. Although the information on controls is available for all mothers, the sample used in this survey is restricted to mothers of children born in the period 1987-1992 (data derived from NFHS I) and

1995-1998 (data derived from NFHS II). This is because the dependent variables in the mechanism regressions are available only for those years.

The dummy variables for being born 0-1 months, 0-2 months, 0-6 months, 0-12 months and 13-24 months before and after elections are derived from official data of the election commission of India and the first and second rounds of NFHS. The election commission of India website gives the month and year of all elections which took place during the sample period. The NFHS data has information on the month and year of birth of a child. Using these two datasets I have created the dummies for being born before and after elections. These variables are defined for the period 1975-1998.

Average district voter turnout is constructed from the constituency level electoral data obtained from the official website of the election commission of India. Since a constituency is smaller than a district, turnout has been aggregated to the district level.

Real GDP per capita and real state GDP per capita lagged by two years are obtained from the publicly available EOPP (Economic Organization and Public Policy Programme) database.

Appendix Tables

Table A.1: Elections and Infant Mortality (Changing Omitted Category)

	(1)	(2)	(3)	(4)
Born 0-12 Months before Scheduled Election	-1.137***	-1.313***	-1.606***	-1.059**
	(0.398)	(0.432)	(0.467)	(0.501)
Born more than 24 Months before Scheduled Election		-0.220	-0.520	0.0395
		(0.376)	(0.424)	(0.456)
Born 12-24 Months before Scheduled Election	0.0866		-0.390	0.160
	(0.390)		(0.424)	(0.520)
Born 1-12 Months after Scheduled Election	0.371	0.198		0.469
	(0.436)	(0.422)		(0.488)
Born 12-24 Months after Scheduled Election	-0.203	-0.376	-0.638	
	(0.469)	(0.521)	(0.494)	
Observations	175804	175804	175804	175804
r2	0.341	0.341	0.341	0.341

Notes: Standard errors in parentheses. Each column represents a separate regression. Infant mortality is the dependant variable. The coefficients reported correspond to dummies for children born before and after scheduled elections. The omitted category in the regression corresponding to Column 1 is a dummy indicating children born more than 24 months before scheduled elections. The omitted category in the regression corresponding to Column 2 is a dummy indicating whether a child is born 12-24 months before scheduled election. The omitted category in the regression corresponding to Column 3 is a dummy indicating whether a child is born 1-12 months after scheduled elections. The omitted category in the regression corresponding to Column 4 is a dummy indicating whether the child is born 12-24 months after scheduled election. Apart from the reported coefficients, all regressions include mother's fixed effect, dummies for year of birth, month of birth, order of birth, sex of the child. Other controls include average district turnout, real state domestic product per capita and month of polling dummies. Sample includes children born in the period 1975-1998 from 14 major states in India. Errors are clustered at district level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Elections and Infant Mortality (With Current GDP as Control)

	(1) Lagged GDP	(2) Lagged GDP	(3) Current GDP	(4) Current GDP
Born 0-12 Months before Scheduled Election	-1.194***	-1.137***	-1.136***	-1.034***
	(0.351)	(0.398)	(0.349)	(0.397)
Born 12-24 Months before Scheduled Election		0.0866		0.227
		(0.390)		(0.394)
Born 0-12 Months after Scheduled Election		0.371		0.429
		(0.436)		(0.434)
Born 12-24 Months after Scheduled Election		-0.203		-0.158
		(0.469)		(0.467)
Observations	175804	175804	175804	175804
r2	0.341	0.341	0.341	0.341

Notes: Standard errors in parentheses. Each column represents a separate regression. Infant mortality is the dependant variable. While the regressions presented in columns 1 and 2 include real state GDP per capita lagged by two years as a control; the regressions presented in columns 3 and 4 include contemporaneous real state GDP per capita as a control. The coefficients reported correspond to dummies for children born before and after scheduled elections. In addition to the reported coefficients, all regressions include mother's fixed effect, dummies for year of birth, month of birth, order of birth, sex of the child. Other controls include average district turnout, and month of polling dummies. Sample includes children born in the period 1975-1998 from 14 major states in India. Errors are clustered at district level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Elections and Infant Mortality (Including Multiple Births)

	(1)	(2)	(3)	(4)
	Only single births		Both single and multiple births	
Born 0-12 Months before Scheduled Election	-1.194***	-1.137***	-1.311***	-1.226***
	(0.351)	(0.398)	(0.354)	(0.404)
Born 12-24 Months before Scheduled Election		0.0866		0.177
		(0.390)		(0.402)
Born 1-12 Months after Scheduled Election		0.371		0.314
		(0.436)		(0.439)
Born 12-24 Months after Scheduled Election		-0.203		-0.0585
		(0.469)		(0.481)
Observations	175804	175804	178169	178169
r2	0.341	0.341	0.339	0.339

Notes: Standard errors in parentheses. Each column represents a separate regression. Infant mortality is the dependant variable. The sample used in regressions corresponding to columns 1 and 2 include only the single births. Columns 3 and 4 include multiple births in addition to single births. The coefficients reported correspond to dummies for children born before and after scheduled elections. In addition to the reported coefficients, regressions include mother's fixed effect, dummies for year of birth, month of birth, order of birth, sex of the child. Other controls include average district turnout, real state domestic product per capita lagged by two years and dummies for month of polling. Errors are clustered at district level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Elections and Infant Mortality (Including NFHS I)

	(1) 0-12 months before	(2) 0-6 months before	(3) 0-12 months before	(4) 0-6 months before
Born 0-12 Months before Scheduled Election	-1.194***		-0.873***	
	(0.351)		(0.277)	
Born 0-6 Months before Scheduled Election		-1.035**		-0.866**
		(0.419)		(0.338)
Observations	175804	175804	318535	318535
r2	0.341	0.341	0.355	0.355

Notes: Standard errors in parentheses. Each column represents a separate regression. Infant mortality is the dependant variable. The individual level data used for estimating regressions corresponding to columns 1 and 2 come from NFHS II. The sample used in columns 2 and 4 report come from both NFHS I and NFHS II. Columns 1 and 3 report coefficients on dummies indicating whether the child is born 0-12 months before scheduled election. Columns 2 and 4 report coefficients on dummies for children born 0-6 months before scheduled election. In addition, all regressions include mother's fixed effect, dummies for year of birth, month of birth, order of birth, sex of the child. Other controls include average district turnout, real state domestic product per capita and month of polling dummies. Sample includes children born in the period 1975-1998 from 14 major states. Errors are clustered at district level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Presence of Doctor During Delivery

	(1)	(2)	(3)	(4)
	0-6 months before		0-12 months before	
Born 0-6 Months before Scheduled Election	0.00190	0.103**		
	(0.0299)	(0.0471)		
Absolute Margin x Born 0-6 Months before Scheduled Election		-0.203**		
		(0.0935)		
Born 0-12 Months before Scheduled Election			-0.0194	-0.0372
			(0.0190)	(0.0295)
Absolute Margin x Born 0-12 Months before Scheduled Election				0.0461
				(0.0542)
Absolute Margin		-0.0341		-0.0358
		(0.0268)		(0.0268)
Observations	13977	13977	13977	13977
r2	0.366	0.366	0.366	0.366

Notes: Standard errors in parentheses. Each column represents a separate regression. The dependant variable is a dummy indicating whether a child is of low birth weight is the dependant variable. Columns 1 and 3 report the coefficients on dummies for children born 0-6 months and 0-12 months before scheduled elections. Columns 2 and 4 report the coefficients on dummy variables indicating whether a child is born 0-6 or 0-12 months before scheduled elections and interactions between the election dummy and the absolute margin of victory of the ruling party/coalition in the previous election. Columns 2 and 4 also report the coefficient on the absolute margin of victory variable. In addition to the reported coefficients, all regressions include district fixed effect, dummies for year of birth, month of birth, order of birth, sex of the child, mother's and father's year of schooling and dummies for rural residence, membership in SC/ST. Other controls include average district turnout, real state domestic product per capita lagged by two years and month of polling dummies. Sample includes children born in the period 1995-1998 from 14 major states in India. Errors are clustered at district level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Mechanisms (All states)

	(1)	(2)	(3)	(4)	(5)	(6)
	Antenatal Visits		Tetanus during Pregnancy		Low Birth Weight	
Born 0-6 Months before Scheduled Election	0.294***		0.0489***		-0.0280	
	(0.0843)		(0.0150)		(0.0181)	
Absolute Margin x Born 0-6 Months before Scheduled Election	-0.318**		-0.0746**		0.0120	
	(0.150)		(0.0292)		(0.0307)	
Born 0-12 Months before Scheduled Election		0.176**		0.0256**		-0.00733
		(0.0748)		(0.0114)		(0.0149)
Absolute Margin x Born 0-12 Months before Scheduled Election		-0.204		-0.0511**		0.00352
		(0.138)		(0.0197)		(0.0247)
Absolute Margin	-0.0464	-0.0441	0.00229	0.00314	-0.00269	-0.00201
	(0.0647)	(0.0663)	(0.0147)	(0.0149)	(0.0114)	(0.0118)
Observations	59337	59337	65660	65660	56013	56013
r2	0.487	0.487	0.265	0.252	0.0413	0.0412

Notes: Standard errors in parentheses. Each column represents a separate regression. The dependant variable in columns 1 and 2 is the number of antenatal visits made by the mother during pregnancy. The dependant variable in columns 3 and 4 is a dummy indicating whether the mother had at least one tetanus injection during pregnancy. The dependant variable in columns 5 and 6 is a dummy indicating whether a child is of low birth weight. The table reports coefficients on dummy variables indicating whether a child is born 0-6 or 0-12 months before scheduled elections and interactions between the election dummy and the absolute margin of victory of the ruling party/coalition in the previous election. The coefficient on the absolute margin of victory variable is also reported. In addition to the reported coefficients, all regressions include district fixed effect, dummies for year of birth, month of birth, order of birth, sex of the child, mother's and father's year of schooling and dummies for rural residence, membership in SC/ST. Other controls include average district turnout, real state domestic product per capita lagged by two years and month of polling dummies. Sample includes children born in the period 1987-1992 and 1995-1998 from 14 major states in India. Errors are clustered at district level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix B

Appendix to Chapter 3

Arriaga Method for calculating the Total Fertility Rate

The data for the total fertility rate for the year 1991 has been collected from the government publication on fertility and child mortality for the year 1991 (Government of India, 1997). This report used the Arriaga method (Arriaga (1983)) of fertility estimation for computing the total fertility rate. The census data provides information regarding the average number of children ever born (P) in a district tabulated by the age-group of the mother. Arriaga suggested transforming the recorded average number of children ever born data into estimates of age specific fertility. The report used data on the average number of children ever born by mothers 5-year age group from the census 1991 and census 1981. Next they obtained the average number of children ever born for women at exact age x at the time of the two censuses by fitting a ninth degree polynomial on the recorded data. Then by linear interpolation, the information on the number of children ever born by the exact age of the mother for one year after the earlier date (1982) and one year before the latter date (1990) is found. Next the single-year age-specific fertility rates for 1991 are calculated as

f_x=P_{x+1}(1991)-P_x(1990)

where f_x denotes the age-specific fertility rates of mothers at the age x. The age specific fertility rates in the conventional five years groups is calculated by taking arithmetic average of the single year age specific fertility rates within each five year group. The total fertility rate is then calculated by summing these age specific fertility rates by 5 year intervals and multiplying this sum by the number of age-groups.

However for calculating the total fertility rate of the year 2001, I have used the data on the average children born from the 2001 census only. Since the data for only one period is used, after fitting the polynomial to the average number of children ever born, the difference between two consecutive exact ages are taken as the single year specific fertility rates. I have next constructed the total fertility rate in the same way as discussed above. I have used the software PASEX obtained from the US Census Bureau for this calculation.