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Sara Oloomi
Louisiana State University and Agricultural and Mechanical College

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Sara Oloomi
B.S., University of Isfahan, 2008
M.S., Louisiana State University, 2014
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ABSTRACT

In this dissertation, I present three distinct essays in health and public economics. In chapter 2, using Vital Statistics data from National Center for Health Statistics (NCHS) and a Difference in Difference methodology, I investigate the impact of the Paid Family Leave (PFL) of California on birth delay, infant health, and labor market outcomes of mothers after first childbirth. I find that PFL of California reduces birth delay by encouraging women to have their first child earlier. Results are more pronounced for older women who are over the age of 35. This policy also improves infant health by reducing incidence of low birth weight (<2500 grams), premature (<37 weeks of gestation), and cesarean-born infants of older mothers. Furthermore, results show that PFL policy improves labor market attachment by increasing the likelihood of employment after childbirth for college educated women who are more likely to exit the labor force after childbirth.

Chapter 3, investigates the impact of the biggest oil spill in the U.S. history in the Gulf of Mexico in 2010 on air quality and health outcomes of newborns. Using Vital Statistics data from National Center for Health Statistics (NCHS), air quality data from the U.S. Environmental Protection Agency, and a Difference in Difference methodology, I find that oil spill of 2010 reduces air quality and increases the incidence of low birth weight and premature newborns. Heterogeneity effects show higher adverse health impacts for black mothers, less educated mothers, unmarried, and mothers less than 20 years old.

Chapter 4 examines whether the party affiliation of governors (Democrat or Republican) has an impact on the allocation of state expenditures. Exploiting gubernatorial election results from 1960 to 2012 and a Regression Discontinuity Design (RDD), we find that Democratic governors allocate a larger share of their budget to health/hospitals and education sectors. We find no significant

impact of the political party of governors on total spending, only on the allocation of funds. The results are robust to a wide range of controls and model specifications.

CHAPTER ONE: INTRODUCTION

This dissertation consists of three distinct essays within the field of health and public economics. In chapter 2, I investigate the impact of the Paid Family Leave (PFL) of California on three main outcome variables including timing of the first birth, infant health outcomes (incidence of low birth weight and premature newborns as well as gestation in weeks, and birth weight in grams), and labor market outcomes (employment, weeks of work, and hours of work) of mothers after their first childbirths. Chapter 3 examines the impact of the Deepwater Horizon oil spill in the Gulf of Mexico in 2010 on air quality and infant health outcomes. In chapter 4, I study whether party affiliation of governors (Democrat or Republican) has an impact on the allocation of state expenditure. Chapter 5, summarizes the findings of these three essays.

1.1 Impact of Paid Family Leave of California on Delayed Childbearing and on Infant Health Outcomes

Delayed childbearing traditionally has been defined as pregnancy for women over the age of 35 and is an increasing phenomenon. Average age at first birth is a key variable of interest to both policy makers and scholars since it plays a strong role in a wide range of birth outcomes (eg., low birth weight, multiple births, and birth defects). Maternal age at first birth also influences total number of births that a woman might have which impacts the size, composition and future growth of the population (NCHS Data Brief, 2009, Johonson and Tough, 2012; NCHS, 2014; Cnattingius et al., 1993; Guendelman et al., 2014).

The U.S. is one of the four nations with the absence or limited maternity leave polices which makes it hard for families specially women to sustain balance between work and family obligations.[1] Having no or limited job and income security at the time of childbirth is one of the main challenges that women have faced in the labor force and has left them with few options including postponing the decision of having a child, exiting the labor force work after childbirth, or returning immediately to the job which is accompanied with limited bonding between mother and newborn as well as absence or limited breastfeeding. Among existing options, delayed childbearing has been more pronounced especially among college educate mothers who have higher desire to first stablish their careers and avoid motherhood wage penalty (Fass, 2009; Buckles, 2008).

In 2004, California introduces a universal Paid Family Leave (PFL) policy which provides up to six weeks paid family leave with 55 percent wage replacement to bond with a newborn child.[2] Findings of this paper provide insights into the implementation of the PFL policy. This paper estimates the causal impact of Paid Family Leave (PFL) act of California on timing of the first births, infant health outcomes, and labor market outcomes of women after first childbirth. Using a Difference in Difference (DID) methodology and Vital Statistics data from National Center for Health Statistics (NCHS), I find that PFL of California reduces birth delay by encouraging women over 35 years old to have their first child 2 years earlier on average. Heterogeneity effects reveal more pronounced effect on college educated women. In general, college educated women show greater tendency to delay or avoid childbearing altogether since they face higher motherhood

[1] Labor force participation of women has increased from 33.9 percent in 1950 to more than 57 percent in 2014 (Bureau of Labor Statistics). However, labor market has not been adjusted to this huge increase in the female labor force participation in terms of maternal leave policies.

[2] Prior to PFL, the U.S. federal government introduced the Family and Medical Leave Act (FMLA) which provides 12 weeks unpaid but job protected leave from work. However, unpaid leave as well as high restricted eligibility criteria in terms of firm size, location, and minimum hours of work make FMLA far from universal coverage.

penalties for exiting the labor force to care for their children. However, results show that providing maternity leave such as the generous PFL of California encourages college educated women to hasten their decision to have their first child.

I also find that PFL of California improves infant health outcomes of new mothers over 35 years old by decreasing incidence of low birth weight (<2500 g), premature (< 37 weeks of gestation), and cesarean-born infants. Improved infant health is one main evidence of reduction in birth delay following implementation of the PFL policy. However, this policy has no significant impact on infant health outcomes of new mothers less than 35 years old who are already in normal childbearing age. I also explore the impact of this policy on labor market outcomes. Not only does PFL of California decrease birth delay for college graduated women over 35 years old, but it also improves labor market attachment by increasing the likelihood of employment after childbirth. This is important because the related literature presents that one salient change after childbirth for college educated women is an increase in the likelihood of absenteeism and exit from labor force. Results are robust to a wide range of controls and robustness checks including different samples and datasets of Integrated Public Use Microdata Series (IPUMS-USA), synthetic control method as well as falsification tests.

1.2 Pollution and Infant Health: Evidence from the Oil Spill of the Gulf of Mexico

In 2010, the Gulf Coast experienced the largest oil spill in the U.S. history. Oil spill poses direct and indirect threats to human health. Direct threats from inhalation of evaporated crude oil chemicals and dermal contact with the oil and indirect threats via seafood safety (Rotkin-Ellman et al, 2012). Vulnerable groups such as pregnant women and infants are at higher risk of adverse health impacts. This paper examines the impact of the oil spill of 2010 in the Gulf of Mexico on air quality and infant health outcomes. The oil spill of 2010 is considered as an exogenous event that affected the coastal counties and parishes of Alabama, Florida, Louisiana, Mississippi, and Texas.

Using a Difference in Difference methodology and US EPA AirData, we compare air quality (concentrations of NO2, PM10, SO2, and CO) of monitoring stations in Gulf of Mexico coastal counties after 2010 to air quality of monitoring stations in the Gulf of Mexico inland counties and non-Gulf states. Next, using Vital Statistics data from National Center for Health Statistics (NCHS) and a Difference in Difference methodology, we investigate the impact of the oil spill on infant health outcomes (incidence of low birth weight, incidence of premature, birth weight in grams and gestation in weeks).

We find that the oil spill of 2010 decreases air quality in affected coastal counties, increases incidence of low birth weight (< 2500 gr) and incidence of premature born infants (< 37 weeks of gestation). Heterogeneity effects reveal more pronounced adverse infant health outcomes for black and Hispanic mothers, less educated mothers, unmarried, and younger mothers. The paper has important policy implications as vulnerable population are more affected by the oil spill. Our results point to avoidance measures that certain mothers can successfully apply against negative impacts of pollution. Results are robust to a wide range of controls, robustness checks, including placebo estimations.

1.3 Party Affiliation and Public Spending: Evidence from U.S. Governors

It is commonly believed that Democrats are more likely than Republicans to support social policies, increase government involvement, and spend a higher share of their budget on key sectors such as education and health. Major cuts of Pennsylvania's Republican governor in 2011 from higher education, Illinois's Republican governor from health system in 2015, and Louisiana's Republican governor from education in 2015 are some examples of higher association of Republicans and budget cuts to health and education sectors. However, literature is ambiguous regarding the impact of the party affiliation of governors (Democrat vs. Republican) on budgetary decisions. Inconsistent results are often due to small sample of years and failure to address the indigeneity issues.

In this study exploiting gubernatorial election results from 1960 to 2012 and a Regression Discontinuity Design (RDD), we examine the impact of party affiliation of governors on total spending and on distributive budgetary decisions over key sectors (education, health/hospital, public safety, social welfare, and we combine the other sectors). We find significant gubernatorial partisan differences over allocation of money and no impact on total spending. Results show that Democratic governors spend higher share of budget on education, health/hospital, and public safety sectors (2.4, 4.9 and 3.8 % respectively). While, Republican governors spend more on other sectors (2.3%). Other sectors are combined as follows: highway, natural resources, park and recreation, interest on general debt, and governmental administration. We find no significant impact of political party of governors on total spending, only on the allocation of funds.

The heterogeneity estimates show that southern states are not statistically different from non-southern states. Both lame-duck and re-electable governors spend a higher share of the budget on education and health/hospital and less on other sectors. However, lame-duck Democratic governors spend significantly more on education and public safety and less on other sectors than re-electable Democratic governors. Dynamic of the spending shows similar impact of Democratic governors within a term. Also there is no significant difference in the allocation of spending of Democratic governors when the president is a Democrat and when the Democrats control both houses. Results are robust to a wide range of controls and robustness tests including nonparametric and parametric estimations using different orders of polynomials (linear, quarter, cubic, and quartic), falsification checks, etc.

CHAPTER TWO: IMPACT OF PAID FAMILY LEAVE OF CALIFORNIA ON DELAYED CHILDBEARING AND ON INFANT HEALTH OUTCOMES

2.1 INTRODUCTION

The occurrence of delayed childbearing is an increasing phenomenon. During the period between 1970 and 2012, first births for women 35 years and older have increased for all races from 1.7 percent to more than 10 percent (NCHS, 2014). Medical literature has well established that higher maternal age at first birth is associated with an increased risk of poor pregnancy outcomes. First births to women aged 35 and over have been associated with an increased likelihood of infertility, miscarriage, spontaneous abortion, stillbirth, medical risks, operative delivery, low birth weight, and pregnancy complications (Johonson and Tough, 2012; NCHS, 2014; Cnattingius et al., 1993; Guendelman et al., 2014). Changes in first birth trends toward older women also result in lower total fertility and family size, which have an important impact on the U.S. population structure in terms of size, composition, and future growth (Mathews and Hamilton, 2009).[3]

Delayed childbearing has been increasing since the end of World War II following a tremendous increase in female labor force participation, improved educational and professional opportunities for women, and a decline in the wage gap concurrent with improved access to the effective contraceptive methods (Happel, Hill and Low, 1984; Kenya, 2009).[4] Although higher female labor force participation has a significant impact on the U.S. economy, it makes it harder for families to

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[3] Average age of mothers at first births has increased by 3.6 years in the U.S. between 1970 and 2006 which provides evidence of delayed childbearing. At the same time, the first birth rate for women below the age of 30 has declined (NCHS, 2014).

[4] Labor force participation of women has increased from 33.9 percent in 1950 to more than 57 percent in 2014 (Bureau of Labor Statistics).

sustain a balance between work and family obligations (Fass, 2009). The U.S. is one of the four nations with the absence or limited work benefits in terms of paid family leave for pregnant women or mothers with newborn children. In 2004, California introduced a universal Paid Family Leave (PFL) policy which provides up to six weeks of paid maternity leave with 55 percent wage replacement to bond with a newborn child.[5]

This paper investigates the impact of the PFL of California on the timing of first births. Using a Difference in Difference (DID) design, this study examines whether PFL of California has been successful in reducing maternal age at first birth by encouraging women to have their first child earlier. Results show that PFL policy causes a reduction in birth delay. Specifically, it reduces 2 years in the timing of first birth for women over 35 years old and consequently this policy changes the age composition of new mothers toward younger ones. The negative causal impact of this policy on maternal age suggests an investigation into the impact of the PFL on infant health outcomes for women at delayed childbearing age. This paper presents evidence that this policy improves infant health outcomes by reducing incidence of low birth weight (<2500 g), premature (< 37 weeks of gestation), and cesarean-born infants. I also investigate the heterogeneity impact of the PFL policy by years of education, race, and marital status of new mothers. The literature shows that women, especially with higher age at first births, reveal more absenteeism from work and reduction in hours worked (Herr, 2008; Buckles 2008; Cristia 2008; Waldfogel, 1997; Waldfogel, 1998; Budig and England, 2001; Loughren and Zissimopolus, 2008; Anderson et al., 2002). This paper also investigates the impact of the PFL of California on labor market outcomes

[5] The only simple to satisfy eligibility criteria for PFL of California is payrolls in excess of 100 $ in a calendar quarter (State of California Employment Development Department).

including employment, weeks of work, and hours of work per week for women over 35 years old. Results show that this policy has encouraged a return to work by increasing the likelihood of employment after childbirth by 5 percent. Results are robust to a wide range of controls and robustness checks.

The rest of the paper is organized as follows: Section 2.2 discusses maternity leave in the U.S. and reviews the literature; Section 2.3 presents the methodology; Section 2.4 discusses the data and descriptive analysis; Section 2.5 presents the main results, heterogeneity, and sensitivity analysis; and Section 2.6 concludes.

2.2 MATERNITY LEAVE IN THE U.S. AND RELATED LITERATURE

2.2.1 Maternity Leave in the U.S.

In 1993, the U.S. federal government introduced the Family and Medical Leave Act (FMLA), which provides 12 weeks unpaid but job protected leave from work.[6] The main down side of FMLA is its restricted eligibility criteria, which made it far from universal accessibility. FMLA only covers certain private and local, state, and federal government employees who have worked for the same employer for at least 12 months prior to the start of the FMLA leave (with at least 1250 hours). Also, the employee has to work for an employer with at least 50 employees within 75 miles of the home.[7] The other down side of the FMLA is unpaid leave, which resulted in the absence of income security for families and is one of the main reasons for not taking family leave

[6] The purpose of the FMLA is providing time off work for certain workers in case of major life crisis and events such as taking care of seriously ill immediate family members including oneself or time off work for mothers to bond with a new born child. In terms of the eligibility, FMLA only covers 50 percent of the workers. But, take up rate is much lower between 20 to a maximum of 50 percent especially for women.

[7] Unites States Department of Labor.

(Unites States Department of Labor; State of California Employment Development Department; Fass, 2009).

California is the first state to enact Paid Family Leave (PFL) on July 2004. PFL in California provides up to six weeks of partially paid family leave with 55 percent wage replacement of one's weekly earnings up to a maximum benefit ($987 per week in 2011) to bond with a newborn child or to take care of a sick family member. Employees who are covered by the State Disability Insurance (SDI) are also covered by the PFL. Nearly all California workers are covered by the SDI program.[8] Eligibility requirements for PFL are simple to satisfy. It does not require a minimum number of hours worked or limitation of firm size at which the employee is working. PFL eligibility requires an individual to be employed or actively looking for work at the time his or her family leave begins. The law requires coverage for employees working for employers with payrolls in excess of $100 in a calendar quarter. Both full-time and part-time workers can be eligible for PFL (State of California Employment Development Department).

2.2.2 Related Literature

Berkowitz et al. (1990) show that women aged 35 and older are at a higher risk of low birth weight and are significantly more likely to have both cesarean sections and infants who were admitted to the newborn intensive care unit. Also, older women have higher rates of complications during

[8]California, Rhode Island, New Jersey, New York and Hawaii are the only states providing temporary disability insurance (TDI) for their workforce during the 1940s but it did not apply to pregnant women until the 1970s, with the passage of the pregnancy discrimination act. Usually, TDI related to pregnancy provides a specific percentage of wage replacement up to a maximum weekly dollar cap for a typical period of six weeks after the delivery of the baby. California's PFL program is an extended version of the state's TDI program (which is called SDI in California). California state disability insurance provides short run disability income replacement and is comprised of two separate wage replacement benefits including disability insurance and paid family leave. PFL does not provide job protection, although job retention rights can be covered using pre-existing laws including FMLA or the California Family Rights Act (CFRA).

pregnancy and delivery (Johnson and Tough, 2012; Heffner et al., 2003; Baghurst et al., 2014). Johnson et al. (2012) find that the medical risks of childbearing including multiple births, preterm delivery, stillbirths, and caesarean section increase with maternal age. The latter has been supported in the Heffner, et al. (2003) study, that women with first births over 35 years old are at a higher risk of cesarean delivery.

Maternity leave policy is suggested as one possible family-friendly solution to address the challenges faced by working mothers and their newborn children. Previous literature has investigated the impact of maternity leave on both labor market outcomes and infant health outcomes. Ruhm (2000) notes that paid leave reduces infant fatalities and low birth weight in European countries. Also, he suggests that parental leave may be a cost effective method by bettering child health. Baker and Milligan (2005) show that maternity leave in Canada decreases the proportion of women quitting their jobs, increases leave taking, and increases the proportion returning to their pre-birth employers. Although, they find no impact of maternity leave on infant health including low birth weight or infant mortality. In another study, Baker and Milligan (2008) support that maternity leave mandates in Canada have been associated with a high likelihood of leave taking and a positive impact on critical breastfeeding duration. The latter also has been highlighted in the study of Huang and Yang (2014) that PFL of California has been accompanied by a higher percentage in both exclusive and inclusive breastfeeding. Rossin (2011), using vital statistics data, finds that the 1993 Family and Medical Leave Act (FMLA) in the United States improves infant health outcomes in terms of birth weight and a decrease in likelihood of a premature birth.

In terms of impact of maternity leave on mothers' labor market outcomes, Waldfogel (1999) shows that FMLA increases leave usage. However, it has no significant negative effects on women's employment or wages. Baum (2003) shows that FMLA has a small and statistically insignificant effect on employment and wages as FMLA maternity leave is short and unpaid. However, Lawrence et al. (2003) show that those in jobs that provided leave coverage under FMLA are more likely to take leave, but return more quickly after the exhaustion of leave. Espinola-Arredondo and Mondel (2010) find a significantly positive effect of FMLA on female employment and a significantly positive effect on the change in female employment for some of the states that expanded the benefits and eligibility criteria of FMLA.

Baum and Ruhm (2013), using the March Current Population Survey (CPS) data from 1999 to 2010 and a Difference in Difference (DID) approach, show that California PFL raised leave-taking by around 2.4 weeks for the average mother. The rights to paid leave are also associated with higher work and employment probabilities for mothers nine to twelve months after birth, possibly by improving labor force attachment. They also find positive effects of California's program on hours and weeks of work during their child's second year of life and possibly also on wages. Rossin-Slater et al. (2013) using CPS data and a DID methodology also show that the California program doubled the overall use of maternity leave and increased the usual weekly work hours of employed mothers of 1 to 3 years old children. Dustmann and Schönberg (2008), show that maternity leave expansions in Germany increase return to work after childbirth. In another study, Schonberg and Ludsteck (2014) show that maternity leave expansions in Germany reduce mothers' post birth employment rates in the short run. However, the long run effects of the expansions on mothers' post birth labor market outcomes are small.

The literature has emphasized the importance of maternity leave on infant health outcomes and labor market outcomes for women. However, the impact of this policy on birth delay has not been investigated yet. Delayed childbearing traditionally has been defined as pregnancy to women aged over 35 years and is the focus of this study. This paper contributes to the literature by examining the impact of the PFL policy on the timing of first births and age composition of women at first births. In particular, I examine whether PFL of California was successful in reducing birth delay by decreasing maternal age at first birth. This paper also looks into the impact of this policy on infant health especially for women over 35 years who are at higher risk of poor pregnancy outcomes. This is important because births to older women have a high social cost in terms of infant and mother health outcomes (Johnson and Tough, 2012; Heffner et al., 2003; Baghurst et al., 2014; Berkowitz et al., 1990). A further contribution is to examine the impact of this policy on employment, weeks of work, and hours of work per week for this targeted group after first childbirth.[9]

2.3 METHODOLOGY

I use a Difference in Difference (DID) methodology to investigate the impact of the PFL of California on different outcome variables including age of mother at first birth, infant health outcomes, and labor market outcomes of women after first childbirth. The main estimation for the impact of the PFL of California on the age of mother at first birth is:

[9] Literature shows that women, especially with higher age at first births, reveal more absenteeism from work and reduction in hours worked (Herr, 2008).

$$Y_{ist} = \beta_0 + \beta_1\, CA_{is} + \beta_2\, post2004_{it} + \beta_3\, CA_{is} \times post2004_{it} + \beta_4\, X_{ist} + T_t\beta_5 + S_s\beta_6 + Trend_s\beta_7 + \varepsilon_{ist} \quad (2.1)$$

Y_{ist} represents the outcome variable which is the age of mother i at state s and year t at first birth. CA_{is} is the dummy variable which takes a value of one if mother lives in California and zero otherwise. $post2004_{it}$ is an indicator variable representing the enactment of the PFL at time t. It takes a value of one for the years post 2004 when the FPL got effective and takes value of zero for the years prior to 2004. $CA_{is} \times post2004_{it}$ is the interaction term identifying the treatment group for whether state s enacted the PFL in year 2004. The treatment group is mothers in California after the year 2004. Accordingly, β_3 is the coefficient of interest, which captures the impact of this policy on the women's decision regarding timing of their first births. Negative values of β_3 indicate that PFL of California encourages women to have their first child earlier and positive values of this coefficient show this policy encourages women to delay first birth timing.

My sample is limited to the new mothers between the ages of 20 to 45 years old having their first live birth.[10] X_{ist} is a vector of individual characteristics of women including: race, education, marital status, 5 years interval age groups, mother's birth year and household income.[11] I control for the mother's birth year using dummy variables for each 10 years' interval to control for

[10] PFL eligibility requires an individual to be employed or actively looking for work at the time his or her family leave begins. I check the robustness of my results to this condition by using IPUMS-USA data set. IPUMS-USA contains information on whether the mother has worked last year. I restrict my sample to women 20 to 45 years old with an eldest child less than one year old who have worked any usual hours last year (during their pregnancy). Result are similar. I restrict my sample to women with the eldest child less than one year old for three reasons. First, it enables me to check whether an individual has worked any usual hours last year which is during pregnancy in order to be potentially eligible of receiving PFL. Second, limiting the sample to mothers experiencing their first birth reduces potential heterogeneity effects among mothers. Third, for these women the childbearing decision is more strategic as this is the first birth for the mother.

[11] I control for the age of mother using dummy variables for each five years intervals including 20 to 25, 26 to 30, 31 to 35, 36 to 40, and 41 to 45.

women's cohort differences.[12] T_t is the year fixed effect and represents common shocks to all women in a particular year. S_s is the state fixed effect which controls differences in the women's decision for the timing of first birth due to the state specific effects. $Trend_s$ represents a vector of linear and quadratic state-specific time trends that account for time-series variation within each state. Standard errors are clustered at the state level. The estimation strategy for other outcome variables for infant health outcomes of new mothers including gestation in weeks, premature (< 37 weeks of gestation), birth weight (g), low birth weight (<2500 g), and C-section method of delivery are similar to the estimation strategy of the timing of first births in equation (2.1). In the estimation of infant health outcomes, I also control for other risk factors of pregnancy such as plurality (multiple births vs. single birth), place of birth (in hospital vs. not in hospital), number of prenatal visits (=1 if mother had minimum of 4 prenatal visits), and sex of infant (=1 if infant is male). The estimation strategy for labor market outcomes of new mothers after first births including employment, weeks, and hours of work per week is similar to the estimation strategy of the timing of first births in equation (2.1).[13]

I also estimate the heterogeneity of the impact of the PFL of California by individual characteristics including race (white, black, and Hispanic), age groups (over 35 years old and under 35 years old), educational attainment (college graduate, some college, high school, and less than high school),

[12] The youngest mother in my sample was born in 1993 and the eldest mother was born in 1955. Birth year intervals are: 1955 to 1965, 1966 to 1975, 1975 to 1985, and 1986 to 1993.

[13] The NCHS data set does not provide labor market outcomes of mothers. In order to investigate the impact of the PFL of California on labor market outcomes including employment, weeks, and hours of work per week I use Integrated Public Use Microdata Series (IPUMS – USA). This data set provides all the control variables in the main estimation (equation 2.1) including: race, education, marital status, 5 years interval age groups, mother's birth year as well as household income.

and marital status (married, and unmarried). β_4 is the additional difference in the timing of first births by binary individual characteristics at time t.

$$Y_{ist} = \beta_0 + \beta_1 CA_{is} + \beta_2 post2004_{it} + \beta_3 CA_{ist} \times post2004_{it} + \beta_4 CA_{is} \times post2004_{it} \times popcharacter_i + \beta_5 X_{ist} + \delta_t + \mu_s + \varepsilon_{it} \quad (2.2)$$

Studying maternal age is more crucial for women with delayed first births to ages over 35 years. Pregnant women aged over 35 years are at a higher risk of infants with low birth weight (<2500 g), premature births (<37 gestations weeks), and complications of pregnancy and delivery (Cnattingius et al., 2004; Heffner, et al. 2003; Gertru S. Berkowitz, et al., 1990). In this regard, this study mainly investigates whether PFL of California has any causal impact on the timing of first births and consequently infant health outcomes for women at delayed childbearing (over 35 years old).

2.4 DATA AND DESCRIPTIVE STATISTICS

2.4.1 Data

I use two data sets in this study: National Vital Statistics data from National Center for Health Statistics (NCHS) and Integrated Public Use Microdata Series (IPUMS – USA) from 2000 to 2010.

Vital Statistics from NCHS provides birth data of all the births registered in the 50 U.S. states. I used this data set to investigate the impact of the PFL of California on the timing of first births for new mothers and infant health outcomes including incidence of premature (< 37 weeks of gestation), low birth weight (<2500 g), and cesarean-born infants as well as gestation in weeks and birth weight. This data set enables to control for the age, years of education, race, marital status, and other risk factors of the pregnancy including plurality, place of the birth, prenatal visits, and sex of the infant.

IPUMS – USA provides a large sample size of mothers with individual characteristics such as age, years of education, race, and marital status. This data set also provides two variables regarding the age of the eldest and youngest child of the mothers. My sample is limited to the mothers with an eldest child less than one year old who have worked any usual hours in previous year (during pregnancy). I also use this data set to investigate the robustness of the results to an alternate data set. This data set provides information regarding the labor market outcomes of the mothers such as employment, weeks, and hours of work per week which enables the study of the impact of the PFL of California on the labor market outcomes of mothers after their first birth.

2.4.2 Descriptive Statistics

Table 2.1 presents summary statistics for selected variables in the National Vital Statistics Data, for the whole sample and split according to the age of mother at first births in two groups of less than 35 and over 35 years old. In the whole sample there are 11,574,452 mothers with first live births at average age of 26.9 years. 11% of first born infants of all mothers aged 20 to 45 years old during 2000 to 2010 are considered premature (<37 gestations weeks), 8% low birth weight (<2500 g), and 30% delivered using the C-section method of delivery.

There are 816,316 mothers over 35 years old with first live births in the sample. These mothers have poorer infant health outcomes with 15% premature, 12% low birth weight, and 48% born using the C-section method of delivery, compared to mothers less than 35 years old (10% premature, 8% low birth weight, and 29% born using C-section method of delivery). Worse infant health outcomes for women over 35 years old highlights the importance of investigating any policy impacting the timing of first birth decision for women. Mothers over 35 are more likely to be married and have more years of education.

Table 2.1: Summary Statistics

	All			Less than 35 years old			Over 35 years old		
Outcome variables	n	mean	sd	n	mean	sd	n	mean	sd
Age of mother at first birth	11,574,452	26.89431	5.208593	10,758,136	26.04318	4.312077	816,316	38.11127	2.061458
Premature (<37 weeks of gestation)	11,574,452	0.110192	0.313129	10,758,136	0.107005	0.30912	816,316	0.152189	0.359204
Gestation in weeks	11,574,452	38.79537	2.572117	10,758,136	38.82785	2.551269	816,316	38.36685	2.79777
LBW (<2500 g)	11,574,452	0.081655	0.273839	10,758,136	0.078845	0.269497	816,316	0.118687	0.32342
LBW (<1500 g)	11,574,452	0.015864	0.124949	10,758,136	0.0152	0.122348	816,316	0.024613	0.154943
BW (gr)	11,574,452	3261.968	596.7469	10,758,136	3266.735	591.0173	816,316	3199.131	664.5053
C-section	11,574,452	0.304788	0.460318	10,758,136	0.291601	0.4545	816,316	0.479537	0.499582
Control variables									
Mom has college	11,574,452	0.299022	0.45783	10,758,136	0.285352	0.451582	816,316	0.479181	0.499567
Mom has some college	11,574,452	0.188817	0.391364	10,758,136	0.192662	0.39439	816,316	0.138152	0.34506
Mom has high school or less	11,574,452	0.277197	0.447614	10,758,136	0.287219	0.452465	816,316	0.145115	0.352217
Mom is white	11,574,452	0.627884	0.483369	10,758,136	0.623347	0.484547	816,316	0.68768	0.46344
Mon is black	11,574,452	0.111112	0.314271	10,758,136	0.113056	0.316661	816,316	0.085489	0.279608
Mon is Hispanic	11,574,452	0.18	0.384187	10,758,136	0.184808	0.388142	816,316	0.116623	0.32097
Mom is married	11,574,452	0.663025	0.472676	10,758,136	0.650455	0.476826	816,316	0.82868	0.376788
Mom is Unmarried	11,574,452	0.336975	0.472676	10,758,136	0.349545	0.476826	816,316	0.17132	0.376788
Mom is 20-25 yrs old	11,574,452	0.358956	0.479694	10,758,136	0.386193	0.486876	-	-	-
Mom is 26-30 yrs old	11,574,452	0.303946	0.459959	10,758,136	0.327009	0.46912	-	-	-
Mom is 31-35 yrs old	11,574,452	0.172163	0.377522	10,758,136	0.185227	0.388481	-	-	-
Mom is 36-40 yrs old	11,574,452	0.060748	0.238868	-	-	-	816,316	0.861344	0.345587
Mom is 41-45 yrs old	11,574,452	0.009779	0.098404	-	-	-	816,316	0.138656	0.345587
Mom had less than 4 Prenatal visit	11,574,452	0.061866	0.240912	10,758,136	0.062845	0.242684	816,316	0.048958	0.21578
Mom not give Birth at hospital	11,574,452	0.007207	0.084589	10,758,136	0.007249	0.084831	816,316	0.006658	0.081324
Multiple Births	11,574,452	0.021136	0.143836	10,758,136	0.018906	0.136194	816,316	0.050516	0.219007
Infant is male	11,574,452	0.512661	0.49984	10,758,136	0.512682	0.499839	816,316	0.512383	0.499847

Note: Sample includes mothers with first live births aged 20 to 45 years, less than 35, and over 35 years old. Year 2004 and SDI states are dropped.
Sources: National Center for Health Statistics (NCHS) and Integrated Public Use Microdata Series (IPUMS – USA).

2.4.3 Graphical Evidence

Figure 2.1 presents the birth rates for women at different age groups during 1990 to 2013, which provides a useful measure for interpreting childbearing patterns. It represents an increasing birth trend for older women, especially for age groups of 35 to 39 and 40 to 44, and a decreasing birth trend for younger women at age groups of 20 to 24 and 25 to 29, as well as a sharp decrease for women less than 20 years old.

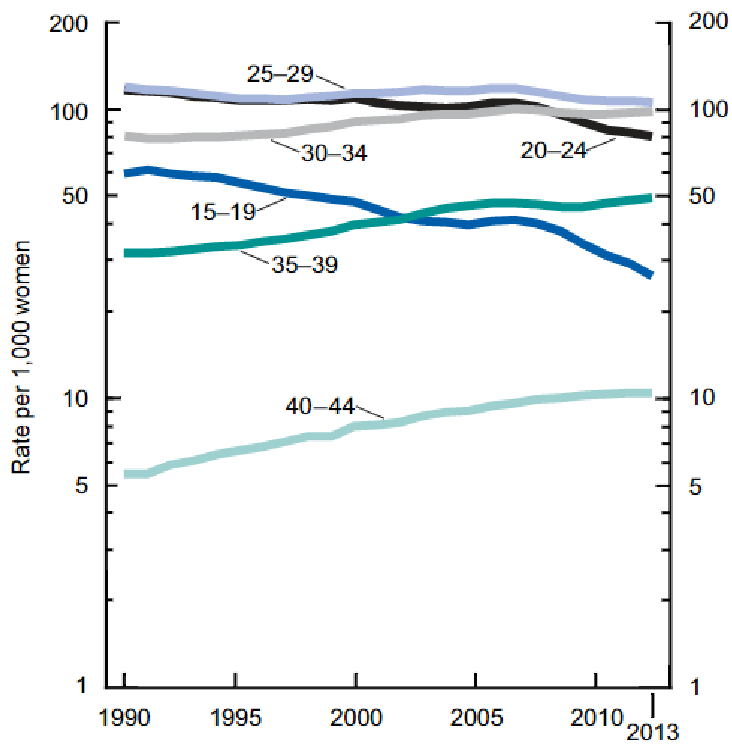


Figure 2.1: Birth rates by selected age groups of mothers (Rates are plotted on a logarithmic scale). Source: CDC/NCHS, National Vital Statistics System.

Appendix A Figure A.1 presents a summary of the main findings using comparison of California and a synthetic control group. Appendix A Figure A.1 shows that implementation of the PFL policy changes the composition of the women with first births by increasing the fraction of births for women aged 30 to 34 and decreasing proportion of births for women aged 40 to 44. There are no change for the age groups of 20 to 29 and 35 to 39. Absence of changes for the age group of 35 to 39 can be justified through a counterbalance of decrease for the age groups of 40 to 45 and 35 to 39. Figure 2.2 illustrates that PFL policy reduces birth delay by changing the age composition of women with first births toward younger ones.

2.5 RESULTS

2.5.1 Main Results

Table 2.2 presents coefficients from the estimation of the main equation (2.1) for the age of mother at first birth using different specifications. Column (1) presents result without controls and column (2) with controls. Results are robust to the inclusion of the individual control variables, which is a sign of an unbiased estimate.[14] Column (3) presents the result after excluding the states with Temporary Disability Insurance (TDI) from the sample. Finally, column (4) shows the estimated coefficient using synthetic control states.[15] Results are similar across these four columns and show that PFL of California decreases the age at first birth equivalent to .06 years (≅ 1 month).[16]

Table 2.3 presents results when the dependent variable measures age at first births for women at either delayed (over 35 years old) or normal (between 20 to 35 years old) childbearing age.

[14] Results are also robust to the smaller time frame of 2000 to 2008.
[15] There are 4 TDI states, including Rhode Island, New Jersey, New York and Hawaii. Synthetic control states are all states except Alaska, Idaho, Indiana, Louisiana, Mississippi, Oklahoma, South Dakota, Utah, West Virginia, and Wyoming.
[16] A key assumption in the DID analysis is that the underlying trends of the treatment and control groups being considered are similar. I include state and year fixed effects and state-specific time trends in the DID specifications to partially address this issue. I also address this issue by using the synthetic control method and a series of robustness checks.

Interestingly, the impact of the PFL of California on the timing of first births for women less than 35 years old is small and not significant (.01 year equivalent to .12 months). However, women with first births delayed to ages over 35 years respond significantly to this policy by reducing the timing of their first births by two years. This result shows that maternity leave policies are effective in reducing birth delay.

Table 2.2: DID Estimates for Age of Mother at First Birth

	(1)	(2)	(3)	(4)
CA*Post 2004	-0.0501**	-0.0655***	-0.0637***	-0.0644**
	(0.0202)	(0.0208)	(0.0225)	(0.0240)
Pre-Treatment Mean	27.5589	27.5589	27.5589	27.5589
Individual Controls	n	y	y	y
No TDI states	n	n	y	y
Synthetic Control	n	n	n	y
Time and State FE	y	y	y	y
State time trends	y	y	y	y

Note: Outcome variable is age of mother at first birth. Year 2004 is dropped from the sample as the PFL of California was enacted in July 2004. Column one, shows estimate without including individual characteristics. There are 12602784 number of observations. In column two, I include individual control (race, years of education, marital status, age groups, and mother's birth year) variables. In column three, I have dropped states with Temporary Disability Insurance (TDI) including; Rhode Island, New Jersey, New York and Hawaii with 11574452 number of observations. Finally, column 4 presents result using synthetic control states. All regressions include time and state fixed effects and State time trends. Standard errors are clustered at the state level and are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$.
Sources: National Center for Health Statistics (NCHS).

Table 2.3: DID Estimates for Age of Mother at First Birth (Women <35 and >35 years old)

	(1)	(2)	(3)
	All	<35 years old	>35 years old
CA*Post 2004	-0.0637***	-0.0143	-2.0319***
	(0.0225)	(0.0132)	(0.2227)
Pre-Treatment Mean	27.5589	26.4495	38.2108

Note: Outcome variable is age of mother at first birth. Year 2004 and TDI states are dropped. Also, sample is limited to mothers with the first live births. Column 1 shows estimate for all women, column 2 for women less than 35 years old and column 3 for women over 35 years old. Number of observations is 11574452 mothers with first live births. All estimates include individual control variables. All regressions include time and state fix effects and State time trends. Standard errors are clustered at the state level and are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$.
Sources: National Center for Health Statistics (NCHS).

Appendix A, Table A.1 shows the results for the proportion of women with first live births at different 5 years interval age groups when aggregating data at the county level. It shows that implementation of the PFL policy causes reduction of 5 and 12 percent in the proportion of first time mothers for 35-39 and 40-44 age groups respectively, whereas the fraction of new mothers for 30-34 age group increased by 7 percent. It provides evidence of a hastening in the timing of first births through the change in the age composition of women with first births toward younger ones. There is no statistically significant impact on the fraction of women less than 30 years old.

Table 2.4 presents results when the dependent variable measures infant health outcomes including incidence of premature (<37 weeks of gestation), low birth weight (<2500 g), extremely low birth weight (<1500g), and cesarean-born infants as well as gestation in weeks and birth weight. Results show that the PFL policy only improves infant health outcomes of women over 35 years old by reducing 1.5 percent in the likelihood of premature born infant, 1 and .5 percent in the incidence of low birth weight, and extremely low birth weight respectively, and 3 percent in infants born using the C-section method of delivery. Also, this policy was successful in causing a 1 percent increase in birth weight.[17]

Table 2.4: DID Estimates for Infant Health Outcomes

	(1)	(2)	(3)
	All	<35 years old	>35 years old
Premature	-0.0013	0.0003	-0.0155***
	(0.0013)	(0.0013)	(0.0017)
Pre-Treatment Mean	0.0877	0.0845	0.1183
Gestation in weeks	0.0001	0.0000	0.0005***
	(0.0001)	(0.0001)	(0.0001)
Pre-Treatment Mean	39.0511	39.0876	38.7030
LBW (<2500 g)	-0.0020*	-0.0009	-0.0114***
	(0.0011)	(0.0011)	(0.0013)
Pre-Treatment Mean	0.0677	0.0643	0.0999
LBW (<1500 g)	-0.0005	-0.0000	-0.0047***
	(0.0003)	(0.0003)	(0.0005)
Pre-Treatment Mean	0.0124	0.01179	0.0192
BW	0.0048	0.0037	0.0145***
	(0.0029)	(0.0029)	(0.0028)
Pre-Treatment Mean	3303.778	3309.048	3253.171
C-section	0.0008	0.0044*	-0.0314***
	(0.0023)	(0.0024)	(0.0032)
Pre-Treatment Mean	0.2787	0.2616	0.4420

Note: Outcome variables are premature (<37 weeks of gestation), gestation in weeks, low birth weight (<2500 g), extreme low birth weight (<1500 g), birth weight (gr), and C-section method of delivery for all mothers aged 20 to 45, mothers over 35 years old, and mothers less than 35 years old. Number of observations is 11574452 mothers with first live births. Year 2004 and TDI states are dropped. Also, sample is limited to mothers with the first live birth. All estimates include individual control variables. All regressions include time and state fixed effects and State time trends. Standard errors are clustered at the state level and are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$.
Sources: National Center for Health Statistics (NCHS).

[17] One possible reason for these improvements is effectiveness of PFL of California in reducing age at first births. Cnattingius et al. (1992) show that women over 35 years reveal significantly higher odds ratios of fetal deaths, low birth weight, and premature births. In another study, Cnattingius et al. (1993) find that rates of adverse pregnancy outcomes are substantially higher in first than second births. Guendelman et al. (2014) also find that maternity leave in late pregnancy shows promise for reducing cesarean deliveries in working women.

Table 2.5 presents results for the labor market outcomes, including employment, weeks and hours of work per week for college graduated mothers over 35 years following their first childbirth.[18] I focus on this group of women, because the related literature presents that one salient change after childbirth for college educated women is an increase in the likelihood of absenteeism and exit from labor force which induce general and firm-specific skills depreciation and consequently wage reduction (Buckles, 2008; Cristia, 2008; Waldfogel, 1997; Waldfogel, 1998; Budig and England, 2001; Loughren and Zissimopolus, 2008; Anderson et al. 2002). Not only does PFL of California decrease birth delay for college graduated women over 35 years old (presented in Table 2.6), but it also improves labor market attachment by increasing the likelihood of employment after childbirth. Conditional on working, Table 2.5 shows that PFL reduces the weeks of work after childbirth until one year. Part of this decrease is because of an increase in leave taking, which has been well documented in the related literature (e.g. Berger and Waldfogel, 2003; Baum and Ruhm, 2013; Rossin et al, 2013; Espinola-Arredondo and Mondel, 2010). College educated women over 35 years old who are more likely to exit from the labor force, under PFL policy prefer to stay in the labor market but work fewer weeks (10%) until one year after childbirth. This result is important, because it shows that the California maternity leave policy reduces the speed of human capital depreciation of these mothers after childbirth by increasing their attachment to the labor force. However, Table 2.5 shows that there is no impact on the labor market outcomes in a longer time period of two years after childbirth.

[18] The limitation of this part of the study is the inability to see if women with eldest child of two years old had worked any usual hours during pregnancy. In table A.3, I show that results for age of mother at first birth for different specifications are robust to removing this condition.

Table 2.5: DID Estimates for Labor Market Outcomes for Women Over 35 with College Degree

	(1)	(2)	(3)
	Employed	Weeks worked	Hours worked
A. Mothers with babies of 1 month to 5 years old			
CA*Post 2004	0.0559***	0.0424	0.00401
	(0.00423)	(0.0271)	(0.00758)
Pre-Treatment Mean	0.7090	43.2181	35.2017
B. Mothers with babies of less than 1 year old			
CA*Post 2004	0.0259**	-0.0994***	0.0135
	(0.0107)	(0.0268)	(0.00989)
Pre-Treatment Mean	0.74251	42.7983	37.0967
C. Mothers with babies of 1 year old			
CA*Post 2004	0.0962***	0.0473	-0.00837
	(0.00750)	(0.0346)	(0.0129)
Pre-Treatment Mean	0.7518	43.3098	35.0925
D. Mothers with babies of 2 years old			
CA*Post 2004	0.0151	-0.0194	-0.0135
	(0.00980	(0.0280)	(0.0144)
Pre-Treatment Mean	0.7039	43.3699	35.9242

Note: Outcome variables are employment, logarithm of hours and weeks worked conditional on employment for mothers over 35 years old who have college degree. Year 2004 and TDI states are dropped. Panel A presents labor market outcomes of mothers with eldest child one month to 5 years old who have been eligible for PFL. Panels B, C, and D show the dynamic of labor market outcomes for mothers with babies less than one year old, one year old, and two years old who have been eligible for receiving PFL. All regressions include individual control variables, time and state fixed effects and State time trends. Number of employed women in panels A, B, C, and D are 719913, 100539, 116240, and 124975 respectively. Standard errors are clustered at the state level and are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$.
Sources: Integrated Public Use Microdata Series (IPUMS – USA).

2.5.2 Heterogeneity and Robustness

Table 2.6 shows the heterogeneity of the impact of the PFL policy of California on the timing of first births for all women (aged 20 to 45 years) and women over 35 by years of education, race, and marital status. Panel A of Table 2.6 shows a slight higher impact of the PFL policy in reducing age at first birth for college educated, black, and married women aged 20 to 45 years. Panel B of

Table 2.6 indicates that college educated women over the age of 35 show a higher response to PFL policy by reducing 2.5 years in timing of their first births compared to women with some college (1.3 years) and high school or less than high school (1.1 years). This suggests that the decrease in birth delay under the PFL policy of California is highly driven by the change in the timing of first births for college educated women. Wilde et al. (2010) and Anderson et al. (2002) show that high-skilled women experience the largest motherhood penalties with a sharper wage diverge which tends to persist over time for exiting the labor force to care for their children. In comparison, low-skilled workers are less vulnerable to such earnings erosion, since they have less human capital and will escape a motherhood wage penalty.[19] These differential costs of childbearing account for the far greater tendency of high-skilled women to delay or avoid childbearing altogether (Buckles, 2008). However, results show that providing maternity leave such as the generous PFL of California encourages college educated women to hasten their decision to have their first child. Table 2.6 also shows that white women compared to black and Hispanic women, and married women in comparison to unmarried women show higher responses to this policy by reducing respectively 1.9 and 2.1 years in timing of their first births. Other heterogeneities regarding infant health outcomes of women over 35 years old including incidence of premature (<37 weeks of gestation), low birth weight (<2500 g and <1500 g), and cesarean-born infants as well as gestation and birth weight by education, race, and marital status of mothers are shown in Table A.2.

[19] Miller (2008) and Herr (2007) note that motherhood delay leads to a substantial increase in earning, wages and work hours per year delay. Supporting a human capital story, the advantage is largest for the college-educated women and those in professional and managerial occupations.

Table 2.6: DID Estimates for Heterogeneity of all Women and Women Over 35 Years Old

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Education			Race			Marital Status	
	College	Some College	High School & less	White	Black	Hispanic	Married	Unmarried
Panel A								
CA*Post 2004 (all)	-.1594***	-0.0511***	-0.0708***	-0.0624**	-0.1243***	-0.0561*	-0.1132***	0.0469
	(0.0375)	(0.0161)	(0.0197)	(0.0240)	(0.0287)	(0.0311)	(0.0217)	(0.0285)
Pre-Treatment Mean	30.9347	26.8310	25.0468	29.1126	26.0681	25.3566	28.7249	24.6904
Panel B								
CA*Post 2004	-2.5082***	-1.2995***	-1.1481***	-1.8949***	-1.4533***	-1.4895***	-2.1359***	-1.0612***
(+35 years old)	(0.1360)	(0.0763)	(0.0858)	(0.0919)	(0.0903)	(0.0808)	(0.1719)	(0.0858)
Pre-Treatment Mean	38.2192	38.2218	38.1565	38.2838	38.3229	38.0770	38.1648	38.4626

Note: Outcome variable is age of mother at first birth for all women aged 20 to 45 years old. Year 2004 and TDI states are dropped. Also, sample is limited to mothers with first live births. Number of observations is 11,574,452 mothers with first live births. All estimates include individual control variables. All regressions include time and state fixed effects and State time trends. Standard errors are clustered at the state level and are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$.
Sources: Sources: National Center for Health Statistics (NCHS).

Appendix A, Table A.2 shows that PFL increases gestation in weeks and birth weight of black infants more that white and Hispanic infants. This is important because there is a big gap between rates of premature births among mothers from different racial groups. The National Center for Health Statistics (2014) reports that non-Hispanic black infants are about 50 percent more likely to be born premature than non-Hispanic white, and Hispanic infants. Risk of low birth weight among non-Hispanic black infants is also more than twice that of non-Hispanic white and Hispanic infants (NCHS, 2005). The higher impact of this policy on black infants helps to reduce the existing racial gap in gestation and birth weight of infants.[20]

Appendix A, Table A.3 shows the robustness of the results to using different samples and datasets. Using the Integrated Public Use Microdata Series (IPUMS – USA) data set, I check the robustness of the impact of the PFL of California on the timing of first births. PFL eligibility criteria requires women to have worked any usual hours during previous year (during pregnancy) to be qualified for receiving PFL benefits. The first row of Table A.3 shows the results for mothers with eldest child less than one year old who have worked any usual hours during the previous year. The second row of Appendix A, Table A.3 shows the results without limiting the sample to mothers with working any usual hours during previous year. Results from both samples are the same and verify the main estimates.

Appendix A, Table A.4 presents the results using IPUMS-USA data set and sample of mothers with youngest child less than one year old who have worked any usual hours during previous year. This sample includes mothers with eldest child less than one year old and also mothers with more than

[20] Higher educated women and white women also show higher response to PFL by reducing delivery using C-section method.

one child but with youngest child less than one year old. In order to avoid high potential heterogeneity among larger families, I limit this sample to mothers with at most three children. I also include a control variable for number of children.[21] Table A.4 also verifies the robustness of the main results.

Appendix A, Table A.5 presents robustness tests for differential time trends in the DID analysis. I checked for the placebo interactions between indicators of years 2001, 2002, 2006, and 2007 and an indicator for treatment state into the DID model. If there are any differential time trends between treatment and control states, then we may see spurious effects in the years prior or after the PFL enactment of California. Appendix A, Table A.5, presents the results for this specification check for women over 35 years old as this is the sample for which I find the strongest impact. Results suggest that for most of the cases there is no spurious effect prior or after the enactment of PFL, which strengthens the validity of the findings for age of mother at first births and other outcome variables including; infant health outcomes and employment. Appendix A, Table A.6 presents the robustness check using synthetic control states as the control group. Results shows, once again, that PFL of California has a significant causal effect on women over 35 years old by reducing the timing of first births, improving infant health outcomes, and finally increasing likelihood of attachment to the labor force.

2.6 CONCLUSION

This paper investigates the impact of the Paid Family Leave (PFL) of California on the timing of first births and infant health outcomes. During the period of 1970 and 2012, the first births for

[21] Results are robust not limiting the sample by number of children.

women 35 years and older have increased for all races from 1.7 percent to more than 10 percent (NCHS, 2014). This paper provides evidence that PFL policy causes a reduction in the birth delay. This reduction happens through the change in the age composition of women with first births toward younger ones. Specifically, women over 35 years old respond significantly to the PFL policy by reducing 2 years in the timing of their first births. The occurrence of delayed childbearing is an increasing phenomenon and has been associated with an increased risk of poor pregnancy outcomes (Cnattingius et al., 1992; Cnattingius et al., 1993). Using a Difference in Difference (DID) methodology and Vital Statistics data from National Center for Health Statistics (NCHS), this paper also shows that PFL improves infant health outcomes of women at delayed childbearing by reducing incidence of low birth weight (<2500 g), premature (<37 weeks of gestation), and cesarean-born infants by 1.5%, 1.1%, and 3.1% respectively. The literature shows that women, especially with higher age at first birth, reveal more absenteeism from work and reduction in hours worked (Herr, 2008). I investigate the impact of this policy on labor market outcomes of new mothers. Results show that this policy has encouraged a return to work with a 5% increase in the likelihood of employment after childbirth for women over 35 years old. This result is important, because it shows that PFL policy reduces the speed of human capital depreciation of these women by increasing their attachment to the labor force after childbirth. The results are robust to a wide range of controls and robustness checks.

CHAPTER THREE: POLLUTION AND INFANT HEALTH: EVIDENCE FROM THE OIL SPILL OF THE GULF OF MEXICO

3.1 INTRODUCTION

In 2010, the Gulf Coast experienced the largest oil spill in U.S. history. With an estimated release of about 5 million barrels of oil over nearly three months, the Deepwater Horizon Spill was almost 50 times larger than the second biggest spill in U.S. history, the 1969 Santa Barbara spill. The oil spill in the Gulf of Mexico poses direct threats to human health from inhalation or dermal contact with the oil and dispersant chemicals, and indirect threats via seafood safety (Rotkin-Ellman et al, 2012). The oil spill of 2010 in the Gulf of Mexico is considered an exogenous event that affected the coastal counties in the Gulf region. Coastal counties and parishes of Alabama, Florida, Louisiana, Mississippi, and Texas have been negatively affected by the oil spill.

Pregnant women and infants can be at higher risk of adverse health impacts of the oil spill. Using air quality data from the US Environmental Protection Agency, infant health data from the National Center for Health Statistics (NCHS) dataset and a Difference in Difference methodology, this study aims to investigate the impact of the oil spill on air quality and on infant health outcomes. We compare air quality in monitoring stations close to the oil spill to other air monitoring stations and infant health outcomes of mothers in coastal counties in the Gulf of Mexico after 2010 to mothers in inland counties and non-Gulf of Mexico counties. This paper aims to investigate the causal impact of the oil spill on air quality (NO2, PM10, SO2, and C0) and on health outcomes of infants (birth weight, low birth weight incidence, gestation in weeks and premature newborn incidence).

Those health outcomes have been documented as good measures of infant health and are important predictors of outcomes during childhood (e.g. Figlio et al., 2014) and adulthood (e.g. Black et al., 2007).

We find that the oil spill of 2010 decreases the air quality and increases incidence of low birth weight (below 2500 gr) and premature born infants (below 37 weeks of gestation). Heterogeneity effects reveal more pronounced adverse infant health outcomes for black mothers, less educated mothers, unmarried, and mothers less than 20 years old. The paper has important policy implications as certain mothers are more affected by the oil spill. Our results point to avoidance measures that certain mothers can successfully apply against negative impacts of pollution. Our results are robust to a wide range of controls and robustness checks, including placebo estimations. The rest of the paper is organized as follows: Section 3.2 reviews the literature; Section 3.3 discusses the oil spill, data and descriptive analysis; Section 3.4 presents the methodology; Section 3.5 presents the results and section 3.6 concludes.

3.2 LITERATURE REVIEW

The paper joins a growing body of literature that documents negative impacts of pollution on health and economic outcomes.[22] Recent papers document the negative impact of pollution on infant health outcomes in the U.S. By example, Currie et al (2013) find negative impact for water contamination and Currie (2009A, 2009B) for air quality. Research in several countries also provide evidence of adverse impact of the air pollution on infant health outcomes; in Mexico (Arceo-Gomez

[22] The literature of pollution on health and economic outcomes is vast. Zivin and Neidell (2013) offer a good survey of the literature.

et al., 2012; Foster et al, 2009), India (Greenstone and Hanna, 2011; Brainerd and Menon, 2012), and United Kingdom (Janke et al., 2009).

Certain papers have also documented the negative impacts of oil on pollution and health. Burning oil has been shown to generate particulate matter, which is associated with cardiac and respiratory symptoms and premature mortality (Solomon and Janssen, 2010; Rotkin-Ellman, Wong, Solomon, 2011; D'Andrea & Reddy, 2014). Lavaine and Neidell (2013) find that temporary reduction in oil refineries, due to a strike, leads to a significant reduction in sulfur dioxide (SO2) concentrations and increases in birth weight and gestational age of newborns, particularly for those exposed to the strike during the third trimester of pregnancy. DNA damage also has been documented in the prestige oil spill of 2002 in Spain (Laffon et al, 2006). Other papers have argued that adverse impact of pollution on human health calls for avoidance activities to reduce negative impacts of pollution. Some optimizing individuals may compensate for increases in pollution by reducing their exposure. Zivin et al (2011), by example, find that following water contaminations, there is an increase in bottled water sales (see also Moretti and Neidell, 2011 and Janke (2014)).

Prenatal exposure to pollution has also been found to have long term impacts. Figlio et al. (2014) study the relation between birth weight and cognitive development. They find that the effects of infant health on cognitive development are important and constant through the school career. They find that the effect is invariant to school quality and similar across different family background. Black et al. (2007), using twins data from Norway, find that birth weight is an important predictor of both short term and long run outcomes. In particular, they find that low birth weight negatively affects educational attainment and earnings. Persico et al. (2016) and Aizer and Currie (2015) have found that prenatal exposure to environmental toxicants reduce later developmental outcomes of children by reducing test scores and increasing the likelihood of repeating a grade and getting suspended from school (see also, Almond et al., 2009 and Lavy et al., 2015).

This paper's contribution is to study the impact of the largest oil spill in U.S. history, an exogenous shock to the coastal regions, on air quality and infant health outcomes. We investigate the impact on women already pregnant at the moment of the oil spill. Our study does not suffer from selection bias. We also contribute to the literature by distinguishing the impact of the oil spill by mother characteristics: race, education, marital status and age.

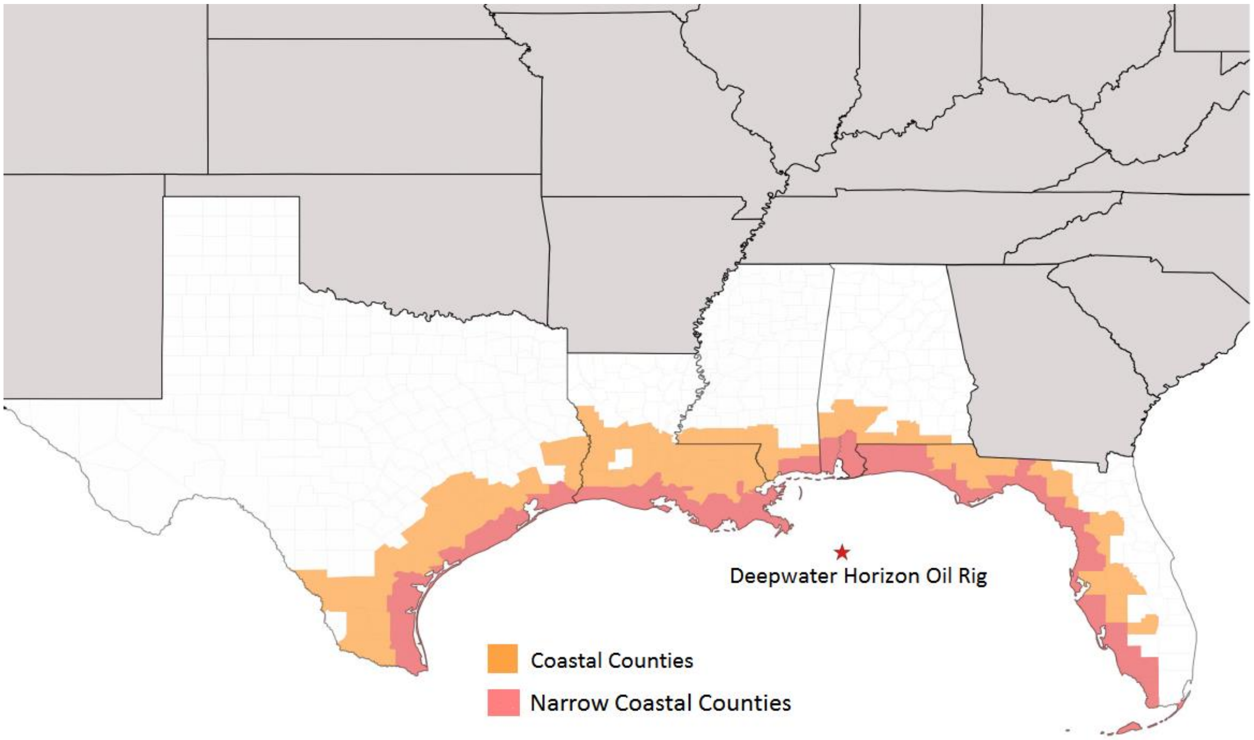
3.3 DEEPWATER HORIZON OIL SPILL DESCRIPTION, DATA SOURCES AND DESCRPTIVE STATISTICS

3.3.1 Deepwater Horizon Oil Spill

The Deepwater horizon Oil spill (also called Gulf of Mexico oil spill or BP oil spill) is recognized as the worst oil spill in U.S. history and one of the worst environmental disaster.[23] The Deepwater Horizon rig was situated in the Gulf of Mexico, approximately 40 miles off the coast of Louisiana. On April 20, 2010, a final cement seal of an oil well failed, causing the disaster. Of the 126 workers aboard the oil rig, 11 were killed. The well was capped on July 15, 2010 (87 days later). The U.S. Government estimates than 4.9 million barrels of oil were released into the Gulf of Mexico over that 87-day period. By early June 2010, oil had washed up on Louisiana's coast and along the Mississippi, Florida, Texas and Alabama coastlines. In December 2012, several miles of coastline remained subject to evaluation and/or cleanup operations. Figure 3.1 presents the map of coastal

[23] For more details, see National Commission on the BP Deepwater Horizon Oil Spill, (2011), Reddy et al, (2012), Michael et al (2013) and On Scene Coordinator Report: Deepwater Horizon Oil Spill (2011).

counties and narrow coastal counties.[24] The oil spill, along with the response and cleanup activities, caused extensive damage to marine and wildlife habitats and fishing and tourism industries. In July 2015, British Petroleum (BP) agreed to pay nearly 19 billion dollars to settle liabilities related to the oil spill.



States	Counties/ Parishes
Florida	Bay*, Calhoun, Charlotte*, Citrus*, Collier*, De Soto, Dixie*, Escambia*, Franklin*, Gadsden, Gilchrist, Glades, Gulf*, Hardee, Hernando*, Hillsborough, Holmes, Jackson, Jefferson*, Lafayette, Lee*, Leon, Levy*, Liberty, Madison, Manatee*, Marion, Monroe*, Okaloosa*, Pasco*, Pinellas*, Polk, Santa Rosa*, Sarasota*, Sumter, Suwannee, Taylor*, Wakulla*, Walton*, Washington.
Alabama	Baldwin*, Clarke, Covington, Escambia, Geneva, Mobile*, Monroe, Washington.
Louisiana	Acadia, Ascension, Assumption, Avoyelles, Beauregard, Calcasieu, Cameron*, East Baton Rouge, East Feliciana, Evangeline, Iberia*, Iberville, Jefferson*, Jefferson Davis, Lafayette*, Lafourche*, Livingston, Orleans, Plaquemines*, Pointe Coupee, Rapides, Sabine, St. Bernard, St. Charles, St. Helena, St. James, St. John the Baptist, St. Landry, St. Martin, St. Mary*, St. Tammany, Tangipahoa, Terrebonne*, Vermilion*, Vernon, Washington, West Baton Rouge, West Feliciana.

[24] We use the National Oceanic and Atmospheric Administration's List of Coastal Counties for the Bureau of the Census Statistical Abstract Series. Coastal counties represent our treatment group. Narrow coastal counties are used as our treatment group in Table A.4. List of coastal counties and narrow coastal counties are available in Figure 3.1.

Texas	Aransas*, Austin, Bee, Brazoria*, Brooks, Calhoun*, Cameron*, Chambers*, Colorado, De Witt, Duval, Fayette, Fort Bend, Galveston*, Goliad, Harris, Hidalgo, Jackson, Jasper, Jefferson*, Jim Hogg, Jim Wells, Kenedy*, Kleberg*, Lavaca, Liberty, Live Oak, Matagorda*, Newton, Nueces*, Orange, Refugio, San Patricio*, Starr, Tyler, Victoria, Waller, Washington, Webb, Wharton, Willacy*.
Mississippi	Amite, George, Hancock, Harrison*, Jackson*, Lamar, Marion, Pearl River, Pike, Stone, Walthall, Wilkinson.

Figure 3.1: Coastal counties and narrow coastal counties of Gulf of Mexico. * Refers to narrow coastal counties and parishes.
Source: NOAA's List of Coastal Counties for the Bureau of the Census Statistical Abstract Series.

3.3.2 Data Sources and Descriptive Statistics

We use pollution data from the U.S. EPA AirData.[25] We have information on daily average concentrations for major pollutants: carbon monoxide (CO), nitrogen dioxide (NO2), particulate matter (Particulates), and sulfur dioxide (SO2). Nitrogen dioxide (NO2) is 1-hour daily data (standard of NO2 1-hour) measured in .01 parts per million (ppm). Particle pollution (PM10) is 24-hour daily data (standard of PM10 24-hour 2006) measured in microgram per cubic meter (µg/m3). Sulfur dioxide (SO2) is 1-hour daily data (standard of SO2 1-hour 2010) measured in .01 parts per million (ppm). Carbon monoxide (CO) is 1-hour daily data (pollutant standard of CO 1-hour 1971) measured in parts per million (ppm). The pollutants are covered by the Clean Air Act and are targeted by the EPA for their negative impacts on health, on the environment, as well as on properties. Of those pollutants, Particulates have the strongest impacts on health and can lead to, or exacerbate respiratory problems, especially for people with asthma. NO2 and SO2 also contribute to the formation of Particulates. We use monitoring stations near the oil spill as our treatment and use the other monitoring stations as our control group.

[25] See www.epa.gov/air/urbanair/ for details. Similar data is used in Beland and Boucher, 2015.

Table 3.1: Summary Statistics

	Treatment Group		Control Group	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Mother characteristics				
Mother has college degree	0.1829	[0.3866]	0.2316	[0.4219]
Mother has some college	0.1447	[0.3518]	0.1413	[0.3483]
Mother has high school or less	0.4038	[0.4907]	0.3117	[0.4632]
Mother is white	0.4060	[0.4911]	0.5486	[0.4976]
Mother is black	0.1929	[0.3946]	0.1418	[0.3488]
Mother is Hispanic	0.3621	[0.4806]	0.2316	[0.4218]
Mother's age	26.6552	[6.0803]	27.6541	[6.1099]
Mother is less than 20 year old	0.1240	[0.3296]	0.0936	[0.2912]
Mother is 20 to 35 years old	0.7870	[0.4094]	0.7942	[0.4043]
Mother is over 35 year old	0.0890	[0.2848]	0.1122	[0.3156]
Risk factors of pregnancy				
Fewer than 4 prenatal visits	0.1331	[0.3397]	0.0951	[0.2934]
Mother is married	0.5356	[0.4987]	0.6026	[0.4894]
Infant is male	0.5107	[0.4999]	0.5118	[0.4999]
First in birth order	0.3892	[0.4876]	0.4007	[0.4900]
Second in birth order	0.3092	[0.4622]	0.3149	[0.4645]
Third in birth order	0.1755	[0.3804]	0.1649	[0.3711]
Fourth or higher in birth order	0.1243	[0.3299]	0.1135	[0.3171]
Multiple Births	0.0311	[0.1737]	0.0344	[0.1823]
Father characteristics				
Father is less than 20 years old	0.0408	[0.1977]	0.0301	[0.1708]
Father is 20 to 35 years old	0.7209	[0.4486]	0.7439	[0.4365]
Father is over 35 years old	0.0783	[0.2686]	0.0904	[0.2867]
Father is white	0.3479	[0.4763]	0.4812	[0.4996]
Father is black	0.1438	[0.3509]	0.1056	[0.3073]
Father is Hispanic	0.3065	[0.4610]	0.2026	[0.4019]

Note: This table shows summary statistics. Time period is 2006 to 2012.
Observations for treatment group: 2,007,345; Observations for control group: 26,430,611
Source: National Center for Health Statistics (NCHS).

The main dataset used in this paper is the National Vital Statistics data from National Center for Health Statistics (NCHS). Vital Statistics from NCHS provides birth data of all the births registered in the fifty U.S. states. We use data from 2006 to 2012. We have access to millions of birth observations and we have counties identifiers.[26] We use this dataset to investigate the impact of the oil spill on infant health outcomes including premature births (<37 weeks of gestation), low birth weight (<2500 grams), gestation in weeks, and birth weight in grams. The mean gestation in our sample is 38.6 weeks and the mean birth weight is 3270.96 grams. The incidence of premature and low birth weight are 11.9% and 8.01%, respectively. This dataset also enables us to control for the age, education, race, marital status, and other risk factors of the pregnancy including plurality, place of the birth, prenatal visits, sex of the infant, and characteristics of fathers. We also use this dataset to investigate the impact of the oil spill by identifying characteristics of the mother.

We present in Table 3.1 descriptive statistics for outcome and control variables, including characteristics of mothers and fathers over our sample of years (2006 to 2012) for our treatment and control group. Table 3.1 shows the two are similar but our treatment group has a higher fraction of blacks and Hispanics.

3.4 METHODOLOGY

We first estimate the impact of the Deep Horizon oil spill on air quality. We use a Difference in Difference strategy. We estimate the following:

$$Airpollutants_{ct} = \beta_0 + \beta_1 OSC_{ct} + \beta_2 OSC_{ct} * AfterApril_{2010} + AfterApril_{2010} + \beta_4 X_{ct} + \beta_M + \beta_Y + \beta_S + \gamma_t + \gamma_t^2 + \varepsilon_{ct} \quad (3.1)$$

$Airpollutants_{ct}$ measures the air quality for the air monitoring stations close to county c at time t. We use information on daily average concentrations for major pollutants: NO2, PM10, SO2, and CO. OSC_{ct} is a dummy variable that takes a value of one for Oil Spill County (OSC) and zero

[26] We made a request and got access to the restricted data from National Center for Health Statistics (NCHS) for this project. The restricted data gives access to county identifiers.

otherwise. $AfterApril_{2010}$ is a variable indicating that the oil spill occurred at time t. It takes value of one for the years post 2010 (after the oil spill of the Gulf of Mexico) and takes value of zero for the years prior to 2010. We use data from 2006 to 2012. $OSC_{ct} * AfterApril_{2010}$ is the interaction term identifying the treatment group for whether the county c is affected by the oil spill in years post 2010. β_2 is the coefficient of interest which captures the impact of the oil spill on air quality in the nearest monitoring stations.

Our comparison group is other monitoring stations in non-Gulf states. There is potential spillover for pollution to other monitoring stations, therefore our estimates will be a lower bound. β_M, β_Y, and β_S represents month, year and state fixed effects and γ_t and γ_t^2 are state time trends (linear and quadratic).

Similarly, we estimate the impact of the oil spill in the Gulf of Mexico on infant health outcomes. We estimate the following equation:

$$Healthoutcome_{ict} = \beta_0 + \beta_1 OSC_{ict} + \beta_2 OSC_{ict} * AfterApril_{2010} + AfterApril_{2010} + \beta_4 X_{ict} + \beta_M + \beta_Y + \beta_S + \gamma_t + \gamma_t^2 + \varepsilon_{ict} \quad (3.2)$$

$Healthoutcome_{ict}$ represents the outcome variable for mother i at county c and year t. We consider the following infant health outcomes: gestation in weeks, premature birth (< 37 weeks of gestation), birth weight (in grams) and low birth weight (< 2500 grams). OSC_{ict} is a dummy variable that takes value of one if mother lives in an Oil Spill county (OSC) and zero otherwise. $AfterApril_{2010}$ and $OSC_{ict} * AfterApril_{2010}$ are defined as above. β_2 is the coefficient of interest which captures the impact of the oil spill on infant health outcomes.

Our comparison group is other infants born in the same period in states and counties that did not get affected by the oil spill. X_{ict} is a vector of characteristics of mothers with information on race, age, marital status and education, as well as risk factors of the pregnancy. β_M, β_Y, and β_S represents month, year and state fixed effects and γ_t and γ_t^2 are state time trends (linear and quadratic).

In the heterogeneity and robustness sections, we investigate if results are robust to several different control groups, robustness checks and placebo tests. We also present results by mother characteristics. Standard errors are clustered at the county level. The sample is limited to mothers between the ages of 20 to 45 years old.

3.5 RESULTS

3.5.1 Main Results

We first look at the impact of the oil spill on air pollution in coastal counties, using air monitoring stations. Table 3.2 presents results for major pollutants: PM10, NO2, SO2, and C0. Table 3.2 shows that the concentrations of NO2, PM10 and SO2 increased significantly in monitoring stations close to the oil spill and therefore the air quality is negatively affected.

We next investigate the impact of the oil spill on infant health outcomes. Table 3.3 shows the impact of the oil spill for several infant health outcomes. Column (1) of Table 3.3 investigates if the oil spill has an impact on the incidence of having a premature baby, column (2) investigates the impact of the oil spill on incidence of low birth weight (< 2500g). Column (3) and (4) study the impact of the oil spill on the gestation (in weeks) and the birthweight (in grams). Table 3.3 shows that the oil spill significantly increases the incidence of premature and low birth weight babies. It also significantly decreases the gestation in weeks and birth weight in grams. The coefficients are small but precisely estimated. Table 3.3 shows that the oil spill of the Gulf of Mexico has significant negative impact on infant health outcomes.

Table 3.2: Impact of oil spill on air pollutants

	(1) PM10	(2) NO2	(3) SO2	(6) CO
Oil spill	2.8945**	5.3285**	2.5391**	0.0162
	(1.1203)	(2.2072)	(1.2415)	(0.0178)
N	966687	827971	1013119	747828

Note: This table shows the impact of oil spill shock in April 20 2010 on air pollutants. All the regressions include month, year and state fixed effects and state linear and quadratic time trends. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$
Source: US EPA AirData.

Table 3.3: impact of the oil spill on infant health outcomes.

	(1) Premature	(2) lbw2500	(3) Gestation (weeks)	(4) BW (gr)
Oil Sill	0.0075***	0.0030***	-0.0752***	-9.5735***
	(0.0025)	(0.0012)	(0.0206)	(2.3829)
N	24755728	24755728	24755728	24755728

Note: This table shows the main results. Control variables consist of mother characteristics including mother's age, mother's education, mother's race, whether mother is married, and risk factors of the pregnancy including birth order, an indicator for whether it is a multiple birth, and whether the child is male as well as father's age group and father's race. All the regressions include month, year and state fixed effects and state linear and quadratic time trends. Time period is 2006 to 2012. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$
Source: National Center for Health Statistics (NCHS).

3.5.2Heterogeneity and Robustness

We next investigate several heterogeneity and robustness checks. Table 3.4 studies the impact of the oil spill separately for women already pregnant at the moment of the oil spill and women who got pregnant subsequently. Table 3.4 shows that both women already pregnant and women who got subsequently pregnant are both affected. Infants health outcomes are affected for both groups.

Table 3.4: impact of the oil spill on infant health outcomes by pregnancy status at time of oil spill

	(1) Premature	(2) lbw2500	(3) Gestation (weeks)	(4) BW (gr)
Oil spill * pregnant	0.0073***	0.0031***	-0.0747***	-9.4905***
	(0.0025)	(0.0012)	(0.0206)	(2.3964)
Oil spill * not pregnant	0.0146**	0.0057**	-0.0904***	-11.5580***
	(0.0064)	(0.0026)	(0.0314)	(3.4212)
N	24755728	24755728	24755728	24755728

Note: This table shows the results by pregnancy status at the moment of the oil spill, using interaction terms. Control variables consist of mother characteristics including mother's age, mother's education, mother's race, whether mother is married, and risk factors of the pregnancy including birth order, an indicator for whether it is a multiple birth, and whether the child is male as well as father's age group and father's race. All the regressions include month, year and state fixed effects and state linear and quadratic time trends. Time period is 2006 to 2012. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$
Source: National Center for Health Statistics (NCHS).

Table 3.5 studies the impact of the oil spill on health outcomes by trimesters for women already pregnant at the moment of the oil spill, using interaction terms. It shows that the negative impact is significantly more pronounced for mothers in the third trimester when the oil spill occurs, but the negative impact is present in the other trimesters which is consistent with the literature.

Table 3.5: The effect of the oil spill on infant health outcomes at different trimesters

	(1) Premature	(2) lbw2500	(3) Gestation (weeks)	(4) BW (gr)
Oil spill * 3rd Trimester	0.0070***	0.0037***	-0.0659***	-8.6037***
	(0.0020)	(0.0013)	(0.0247)	(2.9036)
Oil spill * 2nd Trimester	0.0030	0.0001	-0.0545**	-4.4341*
	(0.0025)	(0.0015)	(0.0250)	(2.5838)
Oil spill * 1st Trimester	0.0054**	-0.0013	-0.0755***	5.0466
	(0.0026)	(0.0012)	(0.0233)	(3.6516)
N	18171420	18171420	18171420	18171420

Note: This table shows the results for the impact of the oil spill on infant health outcomes for different trimesters for mother's already pregnant, using interaction terms. Time spans have been limited to include women who have been exposed to the oil spill shock either at first, second or third trimesters of pregnancy. Control variables consist of mother characteristics including mother's age, mother's education, mother's race, whether mother is married, and risk factors of the pregnancy including birth order, an indicator for whether it is a multiple birth, and whether the child is male as well as father's age group and father's race. All the regressions include month, year and state fixed effects and state linear and quadratic time trends. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$
Source: National Center for Health Statistics (NCHS).

Table 3.6 presents heterogeneity estimates by individual characteristics of mothers including race (white, black, and Hispanic), age groups (age is less than 25, age 26 to 35 and above 35), educational attainment (college graduate, some college, and high school and less than high school), and marital status (married, unmarried). Table 3.6 shows higher adverse infant health outcomes for blacks, less educated, unmarried, and younger mothers. This suggests important policy implications as certain mothers are more affected by the oil spill. Results of Table 3.6 point to avoidance measures that certain mothers can successfully apply against negative impacts of pollution.

Table 3.6: Heterogeneity effect of oil spill on infant health outcome for all women

	(1) all	(2) College	(3) Some college	(4) High School Or less	(5) Age over 35	(6) Age 26-35
Panel A						
premature	0.0075***	-0.0015	0.0032	0.0100***	0.0012	0.0085***
	(0.0025)	(0.0028)	(0.0034)	(0.0036)	(0.0045)	(0.0024)
LBW	0.0032***	-0.0015	-0.0009	0.0054***	0.0014	0.0025**
	(0.0012)	(0.0018)	(0.0021)	(0.0016)	(0.0020)	(0.0013)
Gestation (weeks)	-0.0752***	-0.0021	-0.0111	-0.1150***	-0.0355	-0.0839***
	(0.0206)	(0.0265)	(0.0191)	(0.0331)	(0.0329)	(0.0229)
BW (gr)	-9.5735***	-0.0329	-4.1539	-13.6900***	-4.5680	-10.4136***
	(2.3829)	(2.9940)	(2.9571)	(3.4004)	(5.3159)	(3.2329)
N	24755728	5747765	3494949	7782129	2789663	12414069
Panel B						
	(7) Age below 25	(8) White	(9) Black	(10) Hispanic	(11) Married	(12) Unmarried
premature	0.0063**	-0.0002	0.0105***	0.0133***	0.0053**	0.0087***
	(0.0028)	(0.0023)	(0.0035)	(0.0043)	(0.0024)	(0.0028)
LBW	0.0033**	0.0004	0.0037	0.0050***	0.0010	0.0049***
	(0.0013)	(0.0012)	(0.0037)	(0.0019)	(0.0011)	(0.0016)
Gestation (weeks)	-0.0680***	-0.0154	-0.0568*	-0.1481***	-0.0674***	-0.0771***
	(0.0201)	(0.0218)	(0.0293)	(0.0366)	(0.0218)	(0.0217)
BW (gr)	-8.1875***	-0.6945	-5.6555	-18.8441***	-6.8995**	-11.6754***
	(2.6482)	(2.8394)	(5.5135)	(4.4416)	(2.8677)	(3.0754)
N	9551996	13760277	3423073	5657582	14899952	9855776

Note: This table shows the results for the impact of the oil spill on infant health outcomes for mothers who have been exposed to the oil spill shock in their third trimester of pregnancy. Control variables consist of mother characteristics including mother's age, mother's education, mother's race, whether mother is married, and risk factors of the pregnancy including birth order, an indicator for whether it is a multiple birth, and whether the child is male as well as father's age group and father's race. All the regressions include month, year and state fixed effects and state linear and quadratic time trends. Time period is 2006 to 2012. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Source: National Center for Health Statistics (NCHS).

We next implement placebo tests in Tables 3.7 and 3.8 which presents robustness tests for differential time trends in the DID analysis. These placebo interactions between indicators of years 2007, 2008, and 2009 and an indicator for treatment group should have no significant impact on air quality and infant health outcomes. If there is a positive significant relationship, then there are correlations between the trend and the oil spill. Tables 3.7 and 3.8 show that placebo treatments do not produce significant effect on air quality and infant health outcomes. We take this as further evidence that prior trends are not generating these results. This gives confidence in our main results of Tables 3.2 and 3.3.

Table 3.7: Placebo test for the impact of the oil spill on infant health outcomes

	(1) Premature	(2) lbw2500	(3) Gestation (weeks)	(4) BW (gr)
Oil spill * April 2007	-0.0119	-0.0006	-0.0170	-1.7491
	(0.0439)	(0.0006)	(0.0107)	(1.6999)
Oil spill * April 2008	-0.0074	0.0008	-0.0212	-2.9668
	(0.0286)	(0.0012)	(0.0151)	(2.4524)
Oil spill * April 2009	-0.0067	-0.0010	0.0123	2.2950
	(0.0174)	(0.0007)	(0.0121)	(1.6768)

Note: This table shows the results for the placebo effect of oil spill on April 2007, April 2009, and April 2012 on infant health outcomes. Control variables consist of mother characteristics including mother's age, mother's education, mother's race, whether mother is married, and risk factors of the pregnancy including birth order, an indicator for whether it is a multiple birth, and whether the child is male as well as father's age group and father's race. All the regressions include month, year and state fixed effects and state linear and quadratic time trends. Time period is 2006 to 2012. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$
Source: National Center for Health Statistics (NCHS).

Table 3.8: Placebo test for the impact of the oil spill on pollutants

	(1) PM10	(2) NO2	(3) SO2	(4) CO
Oil spill * April 2007	-1.4095	3.2934	1.0743	0.0101
	(0.9567)	(3.5050)	(2.9726)	(0.0231)
Oil spill * April 2008	0.9379	-1.3850	1.4761	-0.0123
	(0.8206)	(3.8463)	(1.6238)	(0.0216)
Oil spill * April 2009	-1.1607	3.3182	2.7348	-0.0019
	(0.8958)	(3.3040)	(1.7159)	(0.0149)

Note: This table shows the results for the placebo effect of oil spill on April 2007, April 2009, and April 2012 on air pollution. All the regressions include month, year and state fixed effects and state linear and quadratic time trends. Standard errors are clustered at the county level. * p < 0.10, ** p < 0.05, *** p < .01
Source: US EPA AirData.

Appendix B Table B.1 presents the impact of the Oil spill on air quality using different persistence of the impact. Results are robust to different time frames. Appendix B Table B.2 presents a similar exercise for infant health outcomes. Results are once again robust to different time frames.

Appendix B Table B.3 investigates the impact of the oil spill on infant health outcomes for pregnant women at the moment of the oil spill and distinguished by trimester. It shows the effect is more pronounced in the third trimester. Appendix B Table B.4 investigates different definitions of the treatment group. It shows that when the treatment group is defined as narrow coastal counties (most exposed to the oil spill) or the whole gulf states (to consider possible spill over), the results on infant health outcomes are similar. It shows that oil spill in all alternate definitions of the treatment group significantly increases the incidence of premature babies and low birth weight babies and significantly decreases the gestation in weeks and birth weight in grams. Appendix B Table B.5 investigates heterogeneity of the impact for different coastal states (Alabama, Florida, Louisiana, Mississippi and Texas).

It shows that infant health outcomes are affected in coastal counties in all Gulf coast states.[27] Appendix B Table B.6 reproduces the heterogeneity table (table 3.6) for mothers during the third trimester during the oil spill. These mothers were in the last trimester of their pregnancy at the moment of the oil spill. Results are similar to Table 3.6, it shows once again higher adverse infant health outcomes for blacks, less educated, unmarried, and younger mothers. Appendix B Table B.7 investigates if the oil spill has impact on mother's decision to have a child. Table B.7 studies the propensity of having a new baby in coastal counties by birth order. It shows no statistically significant effect on propensity of having a (or anther) baby. In other words, Table B.7 shows that mothers did not decide to postpone having a (or another) child because of the oil spill incident.

Overall, results are robust to alternative specifications and robustness checks. These numerous robustness checks provide confidence that oil spill increases air pollution and has negative impact on infant health outcomes.

3.6 CONCLUSION

This paper examines the impact of the oil spill of 2010 in the Gulf of Mexico on air pollution and health outcomes of newborns. Using a Difference in Difference methodology, air data from EPA and Vital Statistics data from National Center for Health Statistics (NCHS), we find that the oil spill of 2010 decreases the air quality in coastal counties and has significant negative impact on infant health outcomes. Particularly, we find that the oil spill increases incidence of low birth weight (< 2500 gr) and incidence of premature births (< 37 weeks of gestation). We also find that the oil spill significantly decreases the gestation in weeks and birth weight in grams of babies born in

[27] However, Mississippi shows significant negative impact only on birth weight.

coastal counties. Heterogeneity effects reveal higher adverse infant health outcomes for black mothers, less educated mothers, unmarried, and mothers less than 20 years old. The results have important policy implications because it suggests that vulnerable groups are more affected by pollution shock. Our results point to avoidance measures that certain mothers can successfully apply against negative impacts of pollution. Results are robust to a wide range of controls and robustness checks.

CHAPTER FOUR: PARTY AFFILIATION AND PUBLIC SPENDING: EVIDENCE FROM U.S. GOVERNORS

4.1 INTRODUCTION

Some major cuts to state education and health budgets have been widely discussed in the news. For example, in 2011, Pennsylvania's Republican governor proposed slashing the state's higher education funding by hundreds of millions of dollars. In 2015, Illinois' Republican governor decided to cut $300 million from the health care system. Louisiana's Republican governor's 2015 budget plan proposed offsetting a $1.6 billion funding shortfall largely through budget cuts to education. These cuts are generally associated with Republican governors. It is commonly believed that Democrats are more likely than Republicans to support social policies, increase government involvement, and spend a higher share of their budget on key sectors such as education and health.

Despite the above anecdotal evidence, the literature is ambiguous as to whether party affiliation of governors (Democratic vs. Republican) matters regarding allocation of public expenditures. Inconsistent results regarding the impact of party affiliation on budgetary decisions are often due to a failure to address endogeneity concerns or small sample of years, which yields imprecise estimates. In this paper, we use a Regression Discontinuity Design (RDD) to investigate the causal impact of the party affiliation of governors on distributive budgetary decisions over key sectors (education, health/hospitals, public safety, social welfare and we combine the other sectors). We match gubernatorial election data with state government finance data from the U.S. Census Bureau for 1960–2012.

Our results support the existence of gubernatorial partisan differences over budgetary decisions. We find that under Democratic governors, the share of spending on education, health/hospitals, and public safety sectors is, respectively 2.4, 4.9 and 3.8% higher and there is a decrease in the other sectors (−2.3%). Other sectors are combined as follow: highway, natural resources, parks and recreation, interest on general debt, and governmental administration. We find no significant impact of political party of governors on total spending, only on the allocation of funds. This is important because the literature documents benefits to higher funding to education and health (e.g., Barro 1991; Cellini, Ferreira, and Rothstein 2010; Gupta, Verhoeven, and Tiongson 2002; Martin et al. 2012). Results are robust to different RD specifications, controls, and robust-ness checks.

The rest of the paper is organized as follows: Section 4.2 discusses the role of governors and reviews the literature; Section 4.3 presents the methodology; Section 4.4 discusses the data and descriptive analysis; Section 4.5 presents the main results, heterogeneity, and sensitivity analysis; and Section 4.6 concludes.

4.2 ROLE OF GOVERNORS AND RELATED LITERATURE

4.2.1 Role of Governors

Governors have a high degree of autonomy in the administration of their state. As head of the executive branch the governor prepares and administers the budget, sets policies, recommends legislation, signs laws, and appoints department heads. Governors can veto bills, which gives them considerable control over policies. In all but seven states, governors have the power to use a line-item veto on appropriations bills; this gives the governor the authority to reject part of a bill passed by the legislature that involves taxing or spending. In some states, the governor has additional roles, such as commander-in-chief of the National Guard, and has partial or absolute power to commute or pardon criminal sentences.

4.2.2. Related Literature

Our paper contributes to a growing literature on the impact of partisan allegiance (Democratic vs. Republican) on economic outcomes at the state level. Besley and Case (1995) find a positive and significant impact of Democratic lame duck governors on income taxes, workers' compensation benefits and spending during 1950–1986.[28] In another study, they show that the unified effect of a Democratic governor and Democrats controlling both the upper and lower houses of the legislature has a positive impact on total taxes, income taxes, total spending, and family assistance (Besley and Case 2003). Ansolabehere and Snyder (2006) find that the party in power allocates more funds towards counties that provide them with the strongest electoral support. Leigh (2008) investigates the gubernatorial partisan impact on numerous policy settings, economic and social outcomes during the period 1941–2001. He finds few differences between Democratic and Republican governors' out-comes and no impact on state spending. He finds a slightly higher minimum wage, lower post-tax inequality, and unemployment rate under Democratic governors. Joshi (2015), using an RDD, finds no impact of gubernatorial partisanship on health expenditures during the 1991–2009 period. Fredriksson, Wang, and Warren (2013), using an RDD, investigate the effect of gubernatorial party affiliation on tax policies from 1970 to 2007; they find that the impact is dependent on whether the governor is a lame duck or eligible for re-election. While re-electable Democrats tend to increase income taxes, lame duck Democrats tend to decrease them. Beland

[28] Lame duck governors are those who are in their last term and are facing binding term limits. In other words, lame duck governors cannot run for another term.

(2015) and Beland and Unel (2015a), using RDD, find that minorities such as blacks and immigrants have better labor-market outcomes under Democratic rather than Republican governors.[29]

There are other studies investigating the partisan impact at other levels of government in the United States and in other countries. By example, Ferreira and Gyourko (2009), using an RDD, find no significant party affiliation impact of the mayor on th e size of city government, spending, and crime rate. Lee, Moretti, and Butler (2004), using an RDD, find that party affiliation has a large impact on a legislator's voting behavior. Berry, Burden, and Howell (2010) study the impact of the President on the distribution of federal funds. They find that districts and counties receive more federal outlays when legislators in the president's party represent them. Albouy (2013) studies the impact of partisan allegiance in Congress on allocation of funds. He finds that members of Congress in the majority receive greater federal grants. Pettersson-Lidbom (2008), using an RDD, finds a positive party effect of left-wing government on spending and taxation using Swedish local government data.

Our paper contributes to the literature by investigating the causal impact of party affiliation of the governor on distributive budgetary decisions over key sectors using RDD and the long time period of 1960–2012.

[29] Other studies at the U.S. gubernatorial level study the impact of political parties on tax code reform (Ash 2015), on unionized workers (Beland and Unel 2015b), and on pollution (Beland and Boucher 2015).

4.3 RD METHODOLOGY

Following Lee (2001, 2008), we use an RDD to investigate whether the party affiliation of the governor (Democratic vs. Republican) has a causal impact on the allocation of state spending. Endogeneity concerns surrounding election outcomes come from factors such as labor-market conditions, voter characteristics, quality of candidates, the resources available for campaigns, and other unmeasured characteristics of states and candidates that would bias estimates of the impact of the party allegiance of governors. These factors can influence who wins the election. Lee (2001, 2008) demonstrates that looking at close elections provides quasi-random variation in winners and allows for the identification of causal effects of political parties. Similar methodology is used in papers such as Lee, Moretti, and Butler (2004), Pettersson-Lidbom (2008), Ferreira and Gyourko (2009, 2014), and Beland (2015). We use a parametric RDD approach as our primary specification. We estimate:

$$Y_{st} = \beta_0 + \beta_1 D_{st} + f(MOV_{st}) + T_t\beta_2 + S_s\beta_3 + Trend_s\beta_4 + \varepsilon_{st} \qquad (4.1)$$

Y_{st} represents the share of state spending on different budgetary sectors at state s and year t. We use the share of expenditure as our outcome variable to reflect policy choices of governors over the allocation of the state government budget. We consider the following sectors: education, health/hospital, public safety, social welfare, and we combine the other sectors.[30] We also present results for outcome: log of total expenditures in the state. D_{st} takes value of one if the winner of the election at state s and year t is a Democrat and zero if the winner is a Republican. β1 is the

[30] Other sectors group as follow: Highway, natural resources, parks and recreation, interest on general debt, and governmental administration. We combine them under Other sectors for brevity, all have individually non-positive coefficients. A description of those sectors is available here: http:// www.census.gov/govs/state/definitions.html

coefficient of interest which shows the effect of the Democratic governor on the share of state spending in the above sectors. MOV_{st} represents the margin of victory of the elected governor at the most recent election. Elections are held in November and the elected governor takes office the following January. Considering a term length of 4 years, political affiliation and margin of victory of the elected governor are used for the consecutive 4 years after taking the office. Margin of victory is the difference between the percentage of the vote cast for the winner and the candidate who finished second. Zero defines the cutoff point of the margin of victory and it takes positive values if the winner is a Democrat and negative values if the winner is a Republican. We estimate the party affiliation impact of the governor on the state spending controlling for the margin of victory, using a second order polynomial: $f(MOV_{st})$. Separate polynomials are being fit to separate sides of the equation. X_{st} represents time-varying controls used in some specifications regarding states' demographic and political characteristics. Demographic characteristics include population, and whether the state is located in the south. Political characteristics include majority of Democrats in the state legislature (House and Senate), re-electability and gender of the governor.[31] T_t and S_s are state and year fixed effects and $Trend_s$ represents a vector of linear and quadratic state-specific time trends. Standard errors are clustered at the state level to account for potential serial correlation within a state over time. Following Lee and Lemieux (2014), we also present different polynomials (linear, cubic and quartic polynomials) and local-linear RDD.

[31] Upper house and lower house majority are two dummies illustrating whether the majority of the state legislators in the senate or house are Democrat or Republican. Values of one indicate that the majority of the state legislators is Demo-crat and values of zero show that the majority is Republican. Both majority is a dummy variable getting value of one if the majority of both upper house and lower house are Democrats and zero otherwise.

4.4 DATA AND DESCRIPTIVE STATISTICS

4.4.1 Data

The U.S. Census Bureau provides a data set called State Government Finances which presents a comprehensive annual summary of state governments expenditures; data are available from 1960 to 2012. We use variables of state government spending on education, health/hospitals, public safety, social welfare, and group all others. Other sectors group as follow: highway, natural resources and parks and recreation, interest on general debt, and governmental administration.

Gubernatorial election data come from two main sources: Inter-university Consortium for Political and Social Research (ICPSR) 7757 (1995) files called Candidate and Constituency Statistics of Elections in the United States for elections prior to 1990, and the Atlas of U.S. Presidential Elections (Leip 2015) for post-1990 elections. We only keep elections where the political party of the elected governor is either a Democrat or Republican.[32] Variables taken from these sources are the political party of the winner and the margin of victory. As described above, the margin of victory is the difference between the percentage of vote cast for the winner and the candidate who finished second. It takes positive values if a Democrat won and negative values otherwise. We also include other characteristics of elections and other level of government. As mentioned above, we control in

[32] There are 40 observations in our sample where the elected governors are neither Democrat nor Republican. We exclude these observations from the sample. There are some cases in which the governor changed mid-term. It can happen in three conditions including: death, resignation, or impeachment of the governor. In these cases, the lieutenant governor or the executive officer of a state who is next in rank to a governor takes the governor's place. We kept observations where the new governor has the same political party as the previous one using the margin of victory of the previous governor as they are usually elected on the same ticket. We dropped observations where the new governor is from a different political party than the previous one.

some specifications, for which party controls the state house and senate, gender of the governor, and re-electability. These data come from Klarner's political data site at Indiana State University.[33]

4.4.2 Descriptive Statistics

In our sample, there are 2,343 years in office which includes 1,269 years (54%) governed by Democrats. Table 4.1 shows the number of years governed by either a Republican or Democratic governor and the number of elections where either a Democratic or Republican governor was elected by a sub-interval of years. It shows that Democratic governors are slightly more frequently in power than Republicans over this period.

Table 4.1: Number of Gubernatorial Elections and Years in Office

Years in Office	1960-2012	1960-1979	1980-2000	2001-2012
All governors	2343	865	930	548
Democratic governor	1269	514	481	274
Republican governor	1074	351	449	274
Percentage Democratic governor	54	59	51	50
Number of Elections				
All elections	660	268	247	145
Democratic governor elected	365	157	136	72
Republican governor elected	295	111	111	73
Percentage Democratic governor	52	56	50	50

Note: Years in office and number of elections won for Democrats and Republicans by sub-intervals of years.
Sources: ICPSR 7757 (1995) and Atlas of U.S. Presidential Elections (2011).

Table 4.2 shows the number of elected governors by margin of victory (5%, 10%, and 15%). There are 1,025 years in office at the margin of victory of 10%, 519 of which are governed by Democrats. At the margin of victory of 5 percentage points there are 540 years in office and Democratic governors are in office for 257 of them. Table 4.2 provides evidence that the number of Democratic

[33] Data are available at: http://klarnerpolitics.com/kp-dataset-page.html

and Republican governors are balanced for close elections. We discuss this more formally in the Sensitivity/Validity of RDD section. Table 4.2 also presents the probability of switching party in power for close elections (i.e., p(Rt + 1|Dt) and (Dt + 1|Rt)). Table 4.2 shows that for close elections, those probabilities are very close to 50% in both cases.

Table 4.2: Numbers of Years in Office at Different Values of Margin of Victory

Years in Office	Margin of Victory 5 %	Margin of Victory 10 %	Margin of Victory 15 %
All governors	540	1025	1425
Democratic governor	257	519	706
Republican governor	283	506	719
$p(R_{t+1}\|D_t)$	0.52	0.52	0.50
$p(D_{t+1}\|R_t)$	0.48	0.48	0.50

Note: Margin of victory is the difference between the percentage of vote cast for the winner and the candidate who finished second. Small values of margin of victory are representative of close elections. This table shows the balance of the number of Democratic and Republican governors at different values of margin of victory.
Source: ICPSR 7757 (1995), Atlas of U.S. Presidential Elections (2011) and U.S. Census Bureau.

Appendix C, Table C.1 shows summary statistics regarding the share of spending on education, health/hospitals, public safety, social welfare and other sectors and reports that the average spending is respectively 33, 6, 3, 15, and 42% of the state budget.[34]

4.4.3 Graphical Evidence

As is customary in RDD analysis, we next turn to graphical evidence. Figure 4.1 presents the discontinuity at 0% of the margin of victory. Each dot in these graphs represents the average of the outcome variable at state s and year t, grouped by margin of victory intervals. The vertical axis

[34] Table C.2 presents descriptive statistics by political party break-up (Democrats vs Republicans). It shows a higher share of spending on education and health/hospital when Democratic governors are in power.

measures share of state spending and horizontal axis indicates margin of victory. The solid line shows the fitted values. Figure 4.1 shows a higher share of state government expenditure on education, health/hospitals, and public safety when Democratic governors are in office. There is no discontinuity on the share of spending on social welfare and the share of spending is lower for the other sectors. The graphs suggest that some money is shifted from the other sectors to the education, health/hospitals, and public safety sectors under Democratic governors. The following section estimates these effects precisely (Figure 4.2).[35]

[35] Figure 4.2 presents RD graphs for margin of victory for highly contested elections (−5% to +5%). It presents observations, predicted values, and fitted polynomials. Figure 4.2 also points to the same conclusion as Figure 4.1. There is an increase in the share of spending on education and health/hospital and a decrease in other sectors.

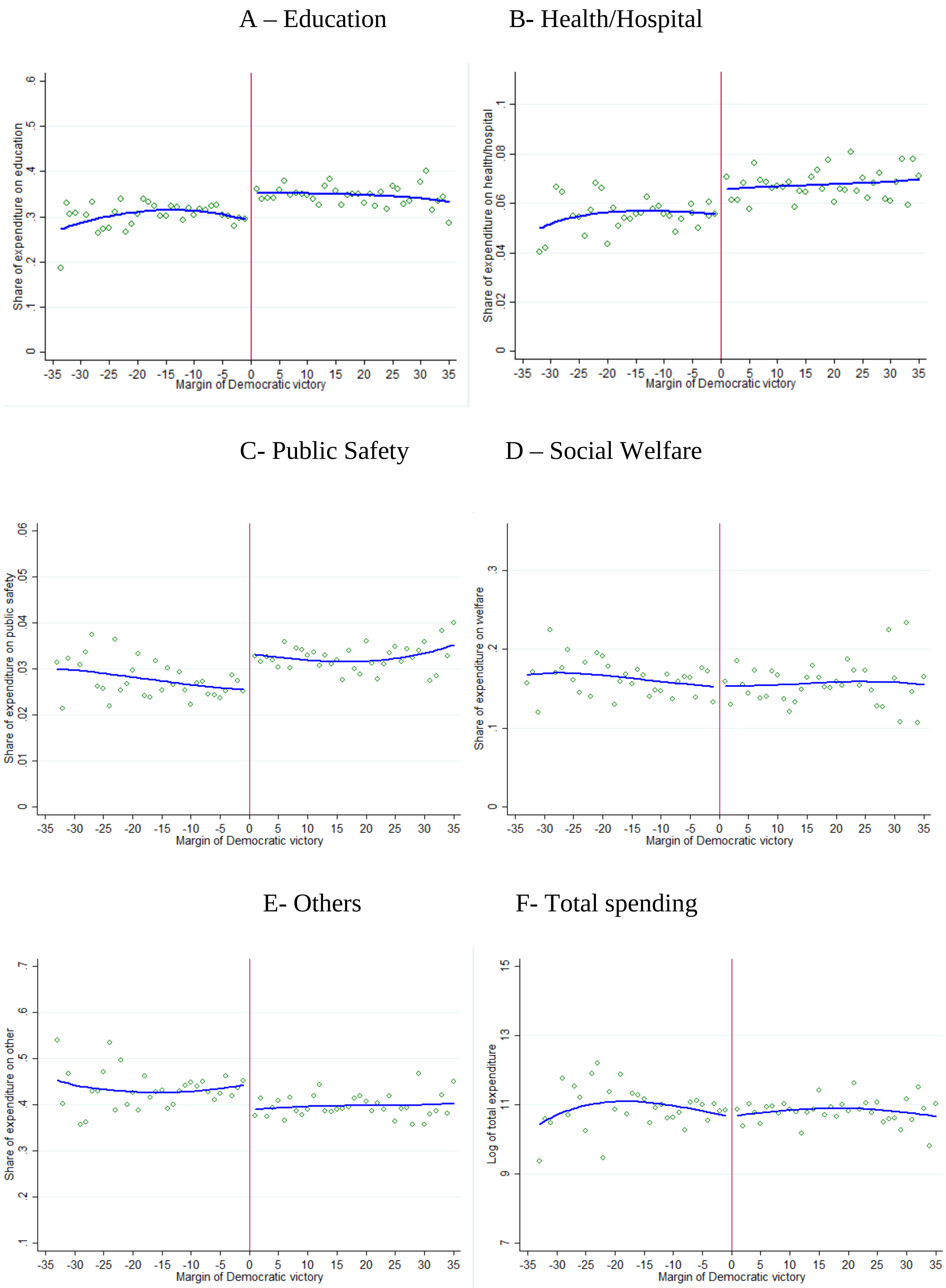


Figure 4.1: Margin of Victory and share of Spending on Education (A), Health/Hospital (B), share of Spending on Public Safety (C), share of Spending on Social Welfare (D), share of Spending on Others (E), and log of total spending (F).

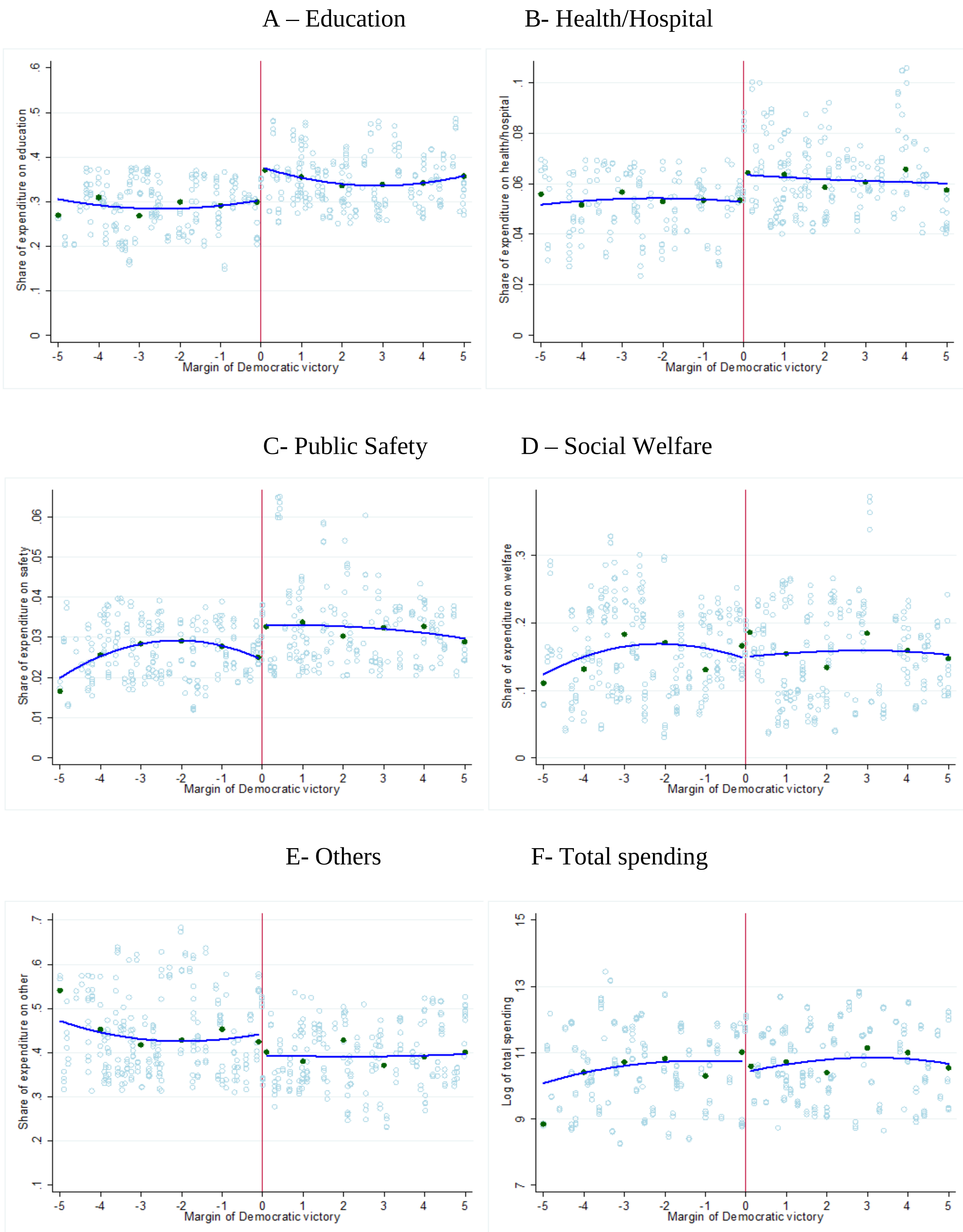


Figure 4.2: Margin of Victory (-5% to +5%) and share of Spending on Education (A), Health/Hospital (B), share of Spending on Public Safety (C), share of Spending on Social Welfare (D), share of Spending on Others (E), and log of total spending (F). %). It presents observations, predicted values and fitted polynomials.

4.5 RESULTS

4.5.1 Main Results

Table 4.3 presents results using the RDD specification. The first row shows the party affiliation impact of the governor using a quadratic polynomial without inclusion of any control variables. Table 4.3 shows that shares of spending on education and health/hospitals are significantly higher under Democratic governors by 2.6% and 4.3%, respectively. Public safety spending is also significantly higher by 3.6%. Table 4.3 shows that there is no difference over the budgetary decision on social welfare between Democrats and Republicans, and the share of spending on the other sectors is 2.1% lower under Democratic governors.

The second row of Table 4.3 investigates the sensitivity of the results to the inclusion of control variables. In a valid RDD, the estimated party affiliation impact of the governor should not be sensitive to adding control variables. Results are robust to adding different control variables. These results also show that Democratic governors spend a significantly higher share of the budget on education (+2.4%), health/hospitals (+4.9%), and public safety sectors (+3.8%); and less on the other sectors (−2.3%).[36]

[36] Tables also present multiple hypothesis testing à la Benjamini and Hochberg (1995) and the results hold.

Table 4.3: Regression Discontinuity Estimates for Total spending & Share of Spending by sectors

	(1) Total Spending	(2) Education	(3) Health/ Hospital	(4) Public Safety	(5) Social Welfare	(6) Other
Democratic Governor (no control)	0.0004	0.0264**	0.0434**	0.0360*	-0.0157	-0.0217**
	(0.0034)	(0.0108)	(0.0206)	(0.0187)	(0.0217)	(0.009)
Single Hypothesis P-value	0.911	0.015	0.036	0.061	0.470	0.019
Multiple Hypothesis P-value	0.911	0.057	0.072	0.092	0.564	0.057
Democratic Governor (with controls)	-0.0014	0.0235**	0.0488**	0.0384*	-0.0177	-0.0233**
	(0.0036)	(0.0109)	(0.0218)	(0.0193)	(0.0211)	(0.0096)
Single Hypothesis P-value	0.694	0.033	0.026	0.053	0.400	0.019
Multiple Hypothesis P-value	0.694	0.066	0.066	0.080	0.480	0.066

Note: Outcome variables are the share of spending on education, health/hospitals, public safety, social welfare, and other sectors as well as log of total spending. The number of observations is 2343. Control variables are the population and personal income of the states, dummy whether the majority of the state legislators in the Senate or House are Democrats or Republicans. We also add a dummy for governors being lame duck or female. We also include a dummy for south, if the state is located in the south region. Standard errors are in parentheses and are clustered at the state level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$. Benjamini and Hochberg (1995) multiple hypothesis testing is presented.
Sources: ICPSR 7757 (1995), Atlas of U.S. Presidential Elections (2011) and U.S. Census Bureau.

4.5.2 Sensitivity/ Validity of RDD

We next undertake several sensitivity checks to examine the validity of our RDD estimates. The main idea behind the RDD is that states with margin of victory just below the cutoff are good comparisons to those just above. In other words, states where Democrats barely win are similar to states where Republicans barely win. In a valid RDD, all variables determined prior to the assignment variable are independent of the treatment status (Lee and Lemieux 2014). In other words, political party of the governor does not have any effect on predetermined demographic and political characteristics of the states and governors. This is investigated in Appendix C, Table C.3 by regressing the political party of the governor using specification (1) on the control variables:

population, majority of Democrats in the upper and lower houses, whether the governor is female. Results show that party affiliation of the governor has no effect on these variables. Appendix C, Table C.4 presents mean and standard deviation of the control variables for each party affiliation. Appendix C, Table C.4 shows they are in most cases similar and not statistically different. Appendix C, Table C.5 shows that the means of the control variables under close election datasets are statistically indifferent from the means of the control variables for the entire dataset. This suggests that close elections represent fairly well the entire dataset.

Another central assumption for a valid RDD is continuity of the assignment variable around the cutoff point. The most common way to verify this assumption is the McCrary test (2008). The density should be smooth around the cutoff point indicating the balance of the number of Democratic and Republican governors. Random variation around the cutoff point is due to the agents' inability to precisely control the assignment variable near the cutoff point (Lee 2008). Figure 4.3 exhibits the McCrary test and verifies the balance of the assignment variable around the threshold; there is no unusual jump.[37]

[37] We also investigate whether campaign spending is different for close elections. It could be that the winning party is the one who spent the most, even for close elections (Caughey and Sekhon 2011). Using campaign data from Jensen and Beyle (2003), we find no evidence for this.

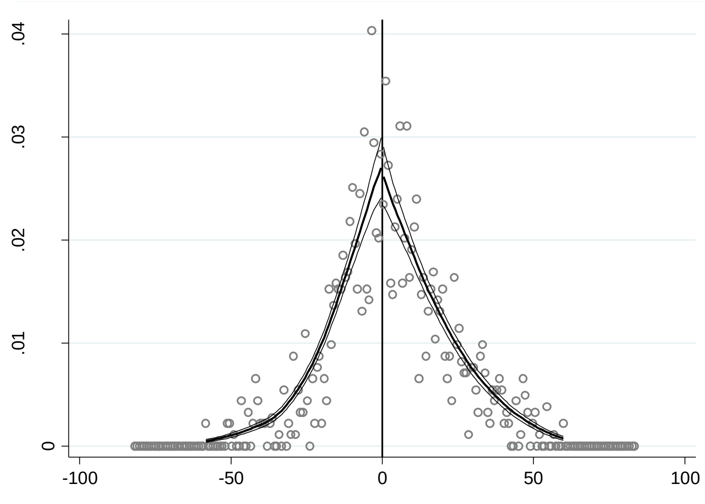


Figure 4.3: McCrary Density of Margin of Victory

Following Lee and Lemieux (2014), we explore the sensitivity of the results to using different orders of polynomial. Panel A of Table C.6 presents results for linear, cubic, and quartic polynomials. Results using different polynomials are qualitatively the same as Table 4.3.

Panel B of Appendix C, Table C.6 shows nonparametric estimations for the party effect of the governor on different sectors of the state budget using optimal bandwidth procedures of Calonico, Cattaneo, and Titiunik (2014) and Imbens and Kalyanaraman (2012). Results are qualitatively the same as Table 4.3. The similarity of the estimates across parametric and nonparametric methods is a sign of the unbiased estimate. Appendix C, Table C.7 presents results for parametric regression discontinuity for different close elections (bandwidths of 3, 5, 10, 12, and 15 are included). Results are once again robust.[38]

[38] The precision is better for larger bandwidths as expected given the optimal bandwidth by IK and CCT are rather large.

One possible concern regarding the discontinuity of the outcome variable is that the jump in the shares of spending across sectors is a phenomenon independent from the political party of the governor. In other words, it could be the case that states with higher preference for education and health/hospitals are more likely to elect a Democratic governor, even for close elections, which could bias the estimated impact. In order to address this issue, we run a placebo RDD test to investigate the party effect on previous term spending, which is presented in Appendix C, Table C.8. Results do not show any significant results for outcomes in the term before the election. This imbues confidence that the results are not due to long term trends.

These numerous robustness checks provide confidence in the RDD and that party allegiance of governors does indeed play a role in allocating state spending. It presents evidence that Democratic governors increase state spending on education, health/hospitals, and public safety.

4.5.3 Potential Heterogeneity of the Effect

We next investigate the heterogeneity of the impact. The Democratic Party has some conservative members whose political views are similar to their Republican counterparts, and they are generally from southern states. Results presented in Table 4.4 show that southern states are not statistically different from nonsouthern states. Tables 4.5 present RD estimates for lame-duck and re-electable governors, respectively. Table 4.5 shows that both re-electable governors and lame-duck governors spend a higher share of the budget on education, health/hospitals and less on other sectors. Table 4.5 also shows that lame-duck Democratic governors spend significantly more on education and public safety and less on other sectors than re-electable Democratic governors. Table 4.6 investigates the dynamics of spending within a term. Table 4.6 points out that the impact of Democratic governors is similar in a term. Appendix C, Table C.9 presents results for the heterogeneity of the effect if Democrats hold other office. Panel A presents RD estimates for an interaction term for Democratic governors and Democrats being president, Panel B presents RD estimates for an interaction term for Democratic governors and Democrats controlling both houses, panel C presents RD estimates using both the interaction terms of panel A and B in the same specification. Appendix C, Table C.9 shows that there is no significant difference in the allocation of spending of Democratic governors when the president is a Democrat (Panel A) and when the Democrats control both houses (Panel B). This holds also when both interactions are included in Panel C. The total spending is however significantly higher for Democratic governors when the president is Democrat (Panel A and C).

Table 4.4: Regression Discontinuity Estimates for Total spending & Share of Spending by Sectors: Southern vs Non-Southern Governors

	(1) Total Spending	(2) Education	(3) Health/ Hospital	(4) Public Safety	(5) Social Welfare	(6) Other
Democratic Governor	-0.0006	0.0187**	0.0521**	0.0359**	-0.0201	-0.0213**
	(0.0041)	(0.0092)	(0.0254)	(0.0178)	(0.0230)	(0.0101)
Single Hypothesis P-value	0.876	0.043	0.041	0.044	0.382	0.041
Multiple Hypothesis P-value	0.876	0.066	0.066	0.066	0.458	0.066
Democratic Governor×	-0.0027	0.0166	-0.0205	0.0086	0.0082	-0.0069
Southern states	(0.0046)	(0.0106)	(0.0322)	(0.0278)	(0.0361)	(0.0128)
Single Hypothesis P-value	0.558	0.117	0.525	0.758	0.821	0.595
Multiple Hypothesis P-value	0.821	0.702	0.821	0.821	0.821	0.821

Note: Outcome variables are the share of spending on education, health/hospitals, public safety, social welfare, and other sectors as well as log of total spending. The number of observations is 2343. Non-Southern states are the states that are not located in the south region. Standard errors are in parentheses and are clustered at the state level. Control variables are the same as Table 4.3. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$. Benjamini and Hochberg (1995) multiple hypothesis testing is presented.
Sources: ICPSR 7757 (1995), Atlas of U.S. Presidential Elections (2011) and U.S. Census Bureau.

Table 4.5: Regression Discontinuity Estimates for Total spending & Share of Spending by sectors: Lame-duck vs Re-electable governors

	(1) Total Spending	(2) Education	(3) Health/ Hospital	(4) Public Safety	(5) Social Welfare	(6) Other
Democratic Governor	-0.0022	0.0198**	0.0425**	0.0284**	-0.0172	-0.0175*
	(0.0038)	(0.0096)	(0.0201)	(0.0128)	(0.0217)	(0.0072)
Single Hypothesis P-value	0.579	0.045	0.035	0.027	0.428	0.016
Multiple Hypothesis P-value	0.579	0.068	0.068	0.068	0.514	0.068
Democratic Governor×	0.0033	0.0289***	-0.0034	0.0388**	0.0069	-0.0182**
Lame duck	(0.0048)	(0.0107)	(0.0266)	(0.0193)	(0.0275)	(0.0088)
Single Hypothesis P-value	0.491	0.01	0.898	0.045	0.803	0.039
Multiple Hypothesis P-value	0.737	0.06	0.898	0.09	0.898	0.09

Note: Outcome variables are the share of spending on education, health/hospitals, public safety, social welfare, and other sectors as well as log of total spending. The number of observations is 2343. Lame-duck governors are the governors who are in their last term and are not eligible for re-election. Standard errors are in parentheses and are clustered at the state level. Control variables are the same as Table 4.3. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$. Benjamini and Hochberg (1995) multiple hypothesis testing is presented.
Sources: ICPSR 7757 (1995), Atlas of U.S. Presidential Elections (2011) and U.S. Census Bureau.

Table 4.6: Regression Discontinuity Estimates for Total spending & Share of Spending by sectors: First 2 years in office vs Last 2 years in office

	(1) Total Spending	(2) Education	(3) Health/ Hospital	(4) Public Safety	(5) Social Welfare	(6) Other
Democratic Governor	-0.0034	0.0233**	0.0543**	0.0430*	-0.0218	-0.0242**
	(0.0043)	(0.0094)	(0.0229)	(0.0218)	(0.0225)	(0.0105)
Single Hypothesis P-value	0.426	0.013	0.018	0.055	0.334	0.026
Multiple Hypothesis P-value	0.426	0.052	0.052	0.083	0.401	0.052
Democratic Governor×	0.0042	0.0003	-0.0174	-0.0097	0.0090	0.0017
Last two years	(0.0036)	(0.0089)	(0.0168)	(0.0120)	(0.0181)	(0.0067)
Single Hypothesis P-value	0.247	0.977	0.303	0.422	0.620	0.797
Multiple Hypothesis P-value	0.844	0.977	0.844	0.844	0.93	0.956

Note: Outcome variables are the share of spending on education, health/hospitals, public safety, social welfare, and other sectors as well as log of total spending. The number of observations is 2343. Last two years is a dummy variable taking value of one if the governor is in his or her last two years in the office. Standard errors are in parentheses and are clustered at the state level. Control variables are the same as Table 4.3. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$. Benjamini and Hochberg (1995) multiple hypothesis testing is presented.
Sources: ICPSR 7757 (1995), Atlas of U.S. Presidential Elections (2011) and U.S. Census Bureau.

4.6 CONCLUSION

This paper investigates the partisan impact of the governor on budgetary spending. The importance of this paper lies in using RDD and the long period from 1960 to 2012 to investigate partisan differences in budgetary decisions at the state level. Using an RDD, we overcome the endogeneity problem due to voters' preferences, state economic and demographic characteristics. We find that shares of spending on education and health/hospitals are respectively about 2.4 and 4.9 percentage points higher under Democratic governors. We find no significant impact of political party of governors on total spending, only on the allocation of funds.

Our analysis suggests that party affiliation has a significant impact on allocation of spend-ing. Our results support political difference between political parties and reject the median voter theorem for allocation of spending. The results on allocation of funds are important because higher spending on education and health/hospitals can have considerable benefits (e.g., Barro 1991; Cellini, Ferreira, and Rothstein 2010; Gupta, Verhoeven, and Tiongson 2002; Martin et al. 2012). Our results are consistent and robust to using a wide range of controls and RD specifications. Future research should investigate if the additional money for health and education has further implications for the state.

CHAPTER FIVE: CONCLUSION

5.1 Impact of Paid Family Leave of California on Delayed Childbearing and on Infant Health Outcomes

This paper investigates the impact of the Paid Family Leave (PFL) of California on the timing of first births, infant health as well as labor market outcomes of mothers after their first childbirths. Delayed childbearing traditionally has been defined as pregnancy to women over the age of 35 and is an increasing phenomenon. During the period of 1970 and 2012, the first births for women 35 years and older have increased for all races from 1.7 percent to more than 10 percent (NCHS, 2014). Absence of generous maternity leave policies increased birth delay for all women especially for women with higher years of education who face higher motherhood wage penalty for exiting the labor force to take care of their children (Buckles, 2008). California introduces PFL in 2004 which provides paid leave with 55 percent wage replacement. Using a Difference in Difference (DID) methodology and Vital Statistics data from National Center for Health Statistics (NCHS), this paper provides policy implications regarding the influential impact of the PFL policy in reducing birth delay by changing the age composition of new mothers toward younger ones. Women over 35 years respond significantly to this policy by reducing 2 years in the timing of their first births on average. However, this policy has no significant impact on the decision to have first child earlier for women under the age of 35 who are already in normal childbearing age.

Medical literature has well stablished that higher maternal age at first birth increases the risk of poor pregnancy outcomes (low birth weight, birth defects, pregnancy complications, etc) (Johonson and Tough, 2012; NCHS, 2014; Cnattingius et al., 1993; Guendelman et al., 2014).

Next, I examine the impact of the PFL policy on infant health. Results show that this policy reduces the incidence of low birth weight, premature and cesarean born infants for women over the age of 35. Reduction in maternal age at first birth is one main channel to the improved birth outcomes for these women.

This paper also studies the impact of the PFL policy on the labor market outcomes of women after child birth. The literature shows that women especially with higher maternal age at first birth reveal more absenteeism from work and reduction in hours worked (Herr, 2008). Results show that this policy improved labor market attachment by increasing the likelihood of employment after childbirth. However, this policy reduces weeks of work after child birth in the year following childbirth which is because of an increase in leave taking that has been well documented in the related literature (e.g. Berger and Waldfogel, 2003; Baum and Ruhm, 2013; Rossin et al, 2013; Espinola-Arredondo and Mondel, 2010). Results are robust to a wide range of controls and robustness checks including different samples and data sets of Integrated Public Use Microdata Series (IPUMS – USA), synthetic control method and falsification tests.

5.2 Pollution and Infant Health: Evidence from the Oil Spill of the Gulf of Mexico

Chapter 3 investigates the impact of the largest oil spill in the U.S history in the Gulf of Mexico in 2010 on air quality and newborns' health outcomes. Oil spill of 2010 is considered as an exogenous shock that affected coastal counties and parishes of Alabama, Florida, Mississippi, Louisiana, and Texas. Using daily averages of main air pollutants including N02, PM10, SO2, and CO form Environmental Protection Agency (EPA) and a Difference in Difference methodology, we find that oil spill of 2010 reduces air quality. Next, using Vital Statistics data from National

Center for Health Statistics (NCHS) and a Difference in Difference methodology, we find that oil spill increases the incidence of low birth weight (<2500 gr) and premature births (<37 weeks of gestation). It also decreases the gestation in weeks and birth weight in grams of babies born in coastal counties after oil spill of 2010. Heterogeneity effects reveal more pronounced adverse health impacts for back mothers, less educated mothers, unmarried, and mothers less than 20 years old. The paper has important policy implications as certain mothers are more affected by the oil spill. Our results point to avoidance measures that certain mothers can successfully apply against negative impacts of pollution. Results are robust to a wide range of controls and robustness checks.

5.3 Party affiliation and Public Spending: Evidence from U.S. Governors

It is commonly believed that Democrats support social policies, favor higher government involvement and are more likely to spend higher share of their budget on education and health. However, literature is ambiguous whether party affiliation of governors matters in budgetary decisions. Exploiting gubernatorial election results from 1960 to 2012 and a Regression Discontinuity Design (RDD), this paper investigates the partisan impact of governors on total spending and allocative budgetary decisions over five key sectors of education, health/hospitals, public safety, social welfare, and we combine the other sectors (other sectors are combined as follow: highway, natural resources, parks and recreation, interest on general debt, and governmental administration). We find no significant impact of political party of governors on total spending, only on allocation of funds. Results show that Democratic governors spend respectively 2.4 and 4.9 percentage points higher on education and health/hospitals sectors and 2.3 percentage points less on other sectors compare to Republican governors. This is important because the literature documents benefits to higher funding to education and health (e.g., Barro

1991; Cellini, Ferreira, and Rothstein 2010; Gupta, Verhoeven, and Tiongson 2002; Martin et al. 2012). Our results support political difference between political parties and reject the median voter theorem for allocation of spending. Results are robust to a wide range of controls and numerous RDD robustness checks including non-parametric and parametric estimates using different orders of polynomials (linear, quarter, cubic, and quartic), and falsification tests.

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APPENDIX A: SUPPLEMENTARY TABLES FOR CHAPTER 2

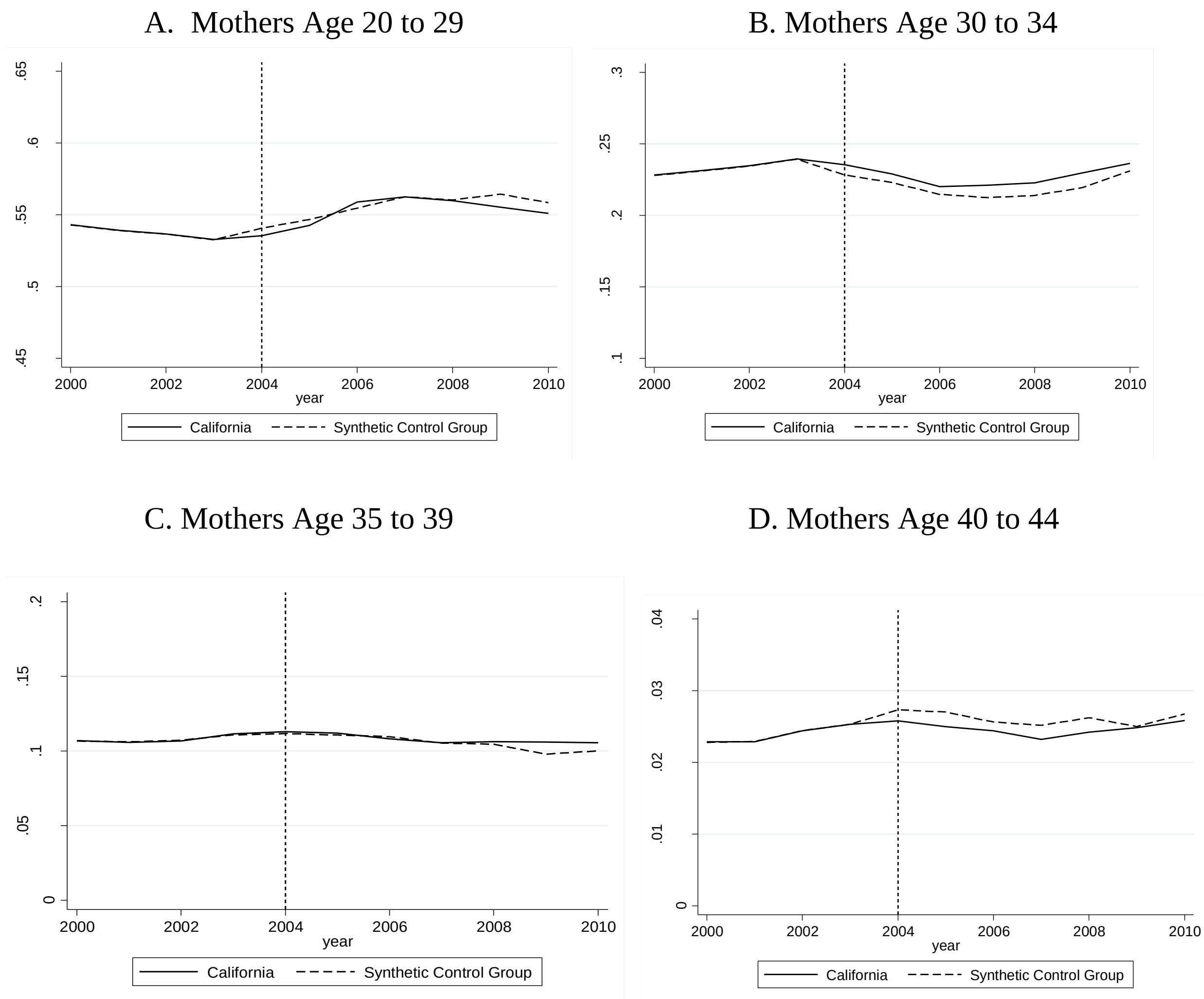

Figure A.1: Trends of California vs. Synthetic California in Proportion of Mothers at Different Age Groups Including age 20 to 29 (A-top left), age 30 to 34 (B-top right), age 35 to 39 (C-bottom left), age 40 to 44 (D-bottom right)

Table A.1: DID Estimates for Proportion of Women at Different Age Ranges

	(1) Age 20-24	(2) Age 25-29	(3) Age 30-34	(4) Age 35-39	(5) Age 40-44
CA*Post 2004	-0.00392	-0.00562	0.0695***	-0.0548***	-0.123***
	(0.00639)	(0.0122)	(0.0140)	(0.0172)	(0.0260)
Pre-Treatment Mean	0.4504	0.2673	0.1816	0.0828	0.0172

Note: Outcome variable is proportion of women at 5 years interval age groups at county level. Year 2004 and TDI states are dropped. Also, sample is limited to mothers with first live births. There are 20854 counties in the sample. All estimates include control variables. All regressions include time and state fixed effects and State time trends. Standard errors are clustered at the state level and are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$.
Sources: Sources: National Center for Health Statistics (NCHS).

Table A.2: DID Estimates for Heterogeneity of Infant Health Outcomes for Women Over 35 Years Old

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	Education>12	Education<=12	white	black	Hispanic	married	unmarried
Premature	-0.0155***	-0.0116***	-0.0117***	-0.0144***	-0.0146***	-0.0103***	-0.0107***	-0.0222***
	(0.0017)	(0.0015)	(0.0024)	(0.0022)	(0.0036)	(0.0018)	(0.0017)	(0.0025)
Pre-Treatment Mean	0.1183	0.1162	0.1293	0.1130	0.1714	0.1309	0.11618	0.13038
Gestation in weeks	0.0005***	0.0004***	0.0003***	0.0003***	0.0020***	0.0003***	0.00046***	0.00044***
	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.00008)	(0.00012)
Pre-Treatment Mean	38.7030	38.7319	38.5871	38.8237	38.0516	38.5506	38.7265	38.5715
LBW (<2500 g)	-0.0114***	-.0071***	-.0101***	-.0107***	-.0109***	-.0031**	-.0062	-.0200
	(0.0013)	(0.0010)	(0.0018)	(0.0013)	(0.0027)	(0.0012)	(0.00117)	(0.0019)
Pre-Treatment Mean	0.0999	0.0972	0.1090	0.0912	0.1691	0.1037	0.0972	0.1150
LBW (<1500 g)	-0.0047***	-0.0046***	-0.0011***	-0.0057***	-0.0026**	0.0004	-0.0043***	-0.00302***
	(0.0005)	(0.0004)	(0.00075)	(0.0005)	(0.0011)	(0.0005)	(0.00045)	(0.0008)
Pre-Treatment Mean	0.0192	0.0182	0.0219	0.0168	0.0503	0.0229	0.01804	0.0258
BW (g)	0.0145***	.0022	.0169***	.0075**	.0341***	.0044	.00438*	.03812***
	(0.0028)	(0.0017)	(0.0036)	(0.0036)	(0.0053)	(0.0027)	(0.0026)	(0.0044)
Pre-Treatment Mean	3253.171	3261.982	3219.233	3299.514	3044.799	3245.45	3259.828	3216.772
C-section	-0.0314***	-.0321***	-.0173***	-.0487***	-.0019	-.0064	-.0290***	-.02658***
	(0.0032)	(0.0025)	(0.0029)	(0.0028)	(0.0035)	(0.0049)	(0.00269)	(0.0025)
Pre-Treatment Mean	0.4420	0.4342	0.4773	0.4221	0.5210	0.4901	0.4391	0.4579

Note: Outcome variables are infant health outcomes for mothers over 35 years old with different socioeconomic characteristics. Year 2004 and TDI states are dropped. Also, sample is limited to mothers with first live births. There are 11,574,452 mothers with first live births in the sample. All regressions include time and state fixed effects and State time trends. Standard errors are clustered at the state level and are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$. Sources: Integrated Public Use Microdata Series (IPUMS – USA) and U.S. Census Bureau.

Table A.3: DID Estimates for Robustness check with IPUMS-USA Sample of Eldest Child Less than One Year Old

	(1)	(2)	(3)	(4)	(5)	(6)
	All	<35 yrs	>35 yrs	>35 yrs & College	>35 yrs & Some College	>35 yrs & High School & less
CA*Post 2004	-0.3806***	-0.1461***	-1.5852***	-1.8845***	-0.7842***	-0.6541***
(w working cond.)	(0.0374)	(0.0376)	(0.1223)	(0.1032)	(0.0698)	(0.0985)
Pre-Treatment Mean	29.7597	28.4995	38.4955	38.4701	38.6412	38.3703
CA*Post 2004	-0.3819***	-0.1618***	-1.5581***	-1.9899***	-0.8278***	-0.3818***
(w/o working cond.)	(0.0349)	(0.0355)	(0.1299)	(0.1090)	(0.0632)	(0.0907)
Pre-Treatment Mean	29.4579	28.0608	38.5524	38.4777	38.7616	38.6108

Note: Outcome variable is age of mother at first birth. Year 2004 and TDI states are dropped. Also, sample is limited to mothers with the eldest child less than one year old. First row shows the estimates for mothers with first live births who have worked any usual hours during previous year or during their pregnancy. There are 75,321 mothers with first live births in this sample. Second row shows estimates without limiting sample to mothers who have worked any usual hours and includes 92,566 mothers with first live birth. Column one, two and three show estimates for all mother, mothers over 35, and mothers less than 35 years old. Column four, five, and six show results for new mothers over 35 years old with college degree, some college and high school or less respectively. All estimates include individual control variables. All regressions include time and state fixed effects and State time trends. Standard errors are clustered at the state level and are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$.
Sources: Integrated Public Use Microdata Series (IPUMS – USA).

Table A.4: DID Estimates for Robustness Check with USA-CPS Sample of Youngest Child

	(1)	(2)	(3)	(4)	(5)	(6)
	All	<35 yrs	>35 yrs	>35 yrs & College	>35 yrs & Some College	>35 yrs & High School & less
CA*Post 2004	-0.1950***	0.0094	-1.0718***	-1.4188***	-0.6194***	-0.2208***
	(0.0285)	(0.0295)	(0.1013)	(0.0894)	(0.0545)	(0.0685)
Pre-Treatment Mean	30.7758	29.0823	38.5822	38.4909	38.6260	38.8023

Note: Outcome variable is age of mother at first birth. Year 2004 and TDI states are dropped. Also, sample is limited to mothers with the youngest child less than one year old who have worked any usual hours during previous year or during their pregnancy. This sample includes 165,222 observations. I investigate the impact of the PFL of California on age of mother at first birth. Column one shows estimate for all women aged 20 to 45 years old. Column two and three show results for women over 35 and less than 35 years old. Column four, five, and six present results for mothers over 35 years old with college degree, some college and high school or less respectively. All estimates include individual control variables. All regressions include time and state fixed effects and State time trends. Standard errors are clustered at the state level and are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$.
Sources: Integrated Public Use Microdata Series (IPUMS – USA).

Table A.5: DID Estimates for Falsification Test for Women Over 35 Years Old

	(1)	(2)	(3)	(4)	(5)
	Age of mom at first birth	premature	LBW (<2500 g)	C-section	Employmen t
2001	-0.0069	-.0038*	0.0003	0.0026	0.0396
	(0.0088)	(0.0022)	(0.0024)	(0.0037)	(0.1811)
2002	-0.0169**	-0.0031	-0.0013	-0.0035	-0.0198
	(0.0082)	(0.0020)	(0.0014)	(0.0037)	(0.0904)
2006	0.0122	.0027	0.0008	-0.0086	-0.0533
	(0.0102)	(0.0016)	(0.0018)	(0.0142)	(0.0491)
2007	0.0126	-0.0023	-0.0024*	-0.0086	-0.0295
	(0.0152)	(0.0022)	(0.0013)	(0.0142)	(0.0360)

Note: Outcome variable is age of mother at first birth, premature (<37 weeks of gestation), low birth weight (<2500 g), C-section method of delivery, and employment for mothers over 35 years old. Year 2004 and TDI states are dropped. Also, sample is limited to mothers with first live births. I test for placebo year of enactment of PFL for different years. This table shows falsification test when I limit time frame to either pre 2004 or post 2004 for investigating placebo interactions of 2001, 2002, and 2006, and 2007 respectively. All estimates include individual control variables. All regressions include time and state fixed effects and State time trends. Standard errors are clustered at the state level and are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$.
Sources: National Center for Health Statistics (NCHS).

Table A.6: DID Estimates using Synthetic Control Method

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Age of mom at first birth	premature	Gestation in weeks	LBW (<2500 g)	LBW (<1500 g)	BW	C-section	Employmen t
All	-0.0644**	-0.0009	0.0001**	-0.0017	-0.0003	0.0032	0.0008	0.0107
	(0.0240)	(0.0011)	(0.0001)	(0.0019)	(0.0003)	(0.0042)	(0.0023)	(0.0172)
Less 35	0.1571***	0.0002	0.0000	-0.0007	0.0001	0.0019	0.0044*	0.0247
	(0.0375)	(0.0011)	(0.0001)	(0.0019)	(0.0003)	(0.0042)	(0.0024)	(0.0233)
Over 35	-1.9915***	-0.0084***	0.0004***	-0.0107***	-0.0040***	0.0145**	-0.0314***	0.0467**
	(0.2371)	(0.0019)	(0.0001)	(0.0015)	(0.0005)	(0.0049)	(0.0032)	(0.0194)

Note: Outcome variable is age of mother at first birth, premature (<37 weeks of gestation), gestation in weeks, low birth weight (<2500 gr and <1500gr), Birth weight, C-section method of delivery, and employment for mothers over 35 years old. TDI states are dropped. Also, sample is limited to mothers with first live births. This table shows the results for main outcome variables using synthetic control method. All estimates include individual control variables. All regressions include time and state fixed effects and State time trends. Standard errors are clustered at the state level and are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$.
Sources: National Center for Health Statistics (NCHS), and Integrated Public Use Microdata Series (IPUMS – USA).

APPENDIX B: SUPPLEMENTARY TABLES FOR CHAPTER 3

Table B.1: Impact of oil spill on air pollutants – different time frame treatment

	(1) PM10	(2) NO2	(3) SO2	(6) CO
Oil spill	3.2291***	8.4799**	1.2983	0.0400**
(2006 to July 2010)	(0.7993)	(4.2257)	(1.3613)	(0.0157)
N	618632	545067	676892	507206
Oil spill	1.9088***	8.8645***	1.8385	0.0271*
(2006 to October 2010)	(0.6392)	(2.1358)	(1.4867)	(0.0138)
N	653217	574732	711361	531688
Oil spill	2.3316***	7.7164***	2.0403	0.0112
(2006 to 2010)	(0.4366)	(1.8603)	(1.3787)	(0.0139)
N	676283	594041	735028	548877
Oil spill	2.3903**	5.3163**	2.5891**	0.0154
(2006 to 2011)	(0.9840)	(2.1909)	(1.2399)	(0.0174)
N	817471	708705	872581	649020
Oil spill	2.8945**	5.3285**	2.5391**	0.0162
(2006 to 2012)	(1.1203)	(2.2072)	(1.2415)	(0.0178)
N	966687	827971	1013119	747828

Note: This table shows the impact of oil spill shock in April 20 2010 on air pollutants using different time periods. All the regressions include month, year and state fixed effects and state linear and quadratic time trends. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$
Source: US EPA AirData.

Table B.2: The effect of the oil spill on infant health outcomes – different time frame treatment

	(1) Premature	(2) lbw2500	(3) Gestation (weeks)	(4) BW (gr)
Oil spill	0.0071***	0.0035**	-0.0645**	-8.3600***
2006 to July 2010	(0.0022)	(0.0013)	(0.0276)	(2.6985)
N	16420787	16420787	16420787	16420787
Oil spill	0.0059***	0.0033***	-0.0587***	-9.3763***
2006 to Aug 2010	(0.0019)	(0.0012)	(0.0205)	(2.4690)
N	16724095	16724095	16724095	16709052
Oil spill	0.0050**	0.0017	-0.0593**	-6.2200***
2006 to Oct 2010	(0.0021)	(0.0015)	(0.0251)	(2.2077)
N	17319922	17319922	17319922	17319922
Oil spill	0.0054*	0.0011	-0.0658**	-3.1530
2006 to Dec 2010	(0.0029)	(0.0029)	(0.0278)	(2.4025)
N	17894355	17894355	17894355	17878268
Oil spill	0.0038*	0.0001	-0.0549***	-3.0701
2006 to July 2011	(0.0020)	(0.0012)	(0.0177)	(2.2040)
N	19869828	19869828	19869828	19852164
Oil spill	0.0041**	0.0016*	-0.0590***	-3.7539*
2006 to Dec 2011	(0.0021)	(0.0009)	(0.0178)	(2.0823)
N	21325543	21325543	21325543	21325543
Oil spill	0.0075***	0.0032***	-0.0752***	-9.5735***
2006 to Dec 2012	(0.0025)	(0.0012)	(0.0206)	(2.3829)
N	24755728	24755728	24755728	24733717

Note: This table shows the results for the impact of oil spill on infant health outcomes using different duration of the treatment. Control variables consist of mother characteristics including mother's age, mother's education, mother's race, whether mother is married, and risk factors of the pregnancy including birth order, an indicator for whether it is a multiple birth, and whether the child is male as well as father's age group and father's race. All the regressions include month, year and state fixed effects and state linear and quadratic time trends. Time period is 2006 to 2012. Standard errors are clustered at the county level. * p < 0.10, ** p < 0.05, *** p < .01

Source: National Center for Health Statistics (NCHS).

Table B.3: The effect of the oil spill on infant health outcomes at different time frames and trimesters

	(1) Premature	(2) lbw2500	(3) Gestation (weeks)	(4) BW (gr)
Oil spill	0.0071***	0.0035**	-0.0645**	-8.3600***
2006 to July 2010 (trimester 3)	(0.0022)	(0.0013)	(0.0276)	(2.6985)
N	16420787	16420787	16420787	16420787
Oil spill	0.0050**	0.0017	-0.0593**	-6.2200***
2006 to Oct 2010 (Trimester 3 & 2)	(0.0021)	(0.0015)	(0.0251)	(2.2077)
N	17319922	17319922	17319922	17319922
Oil spill	0.0050**	0.0006	-0.0632***	-4.1701*
2006 to Jan 2011 (Trimester 1, 2, &3)	(0.0021)	(0.0011)	(0.0186)	(2.4537)
N	18171420	18171420	18171420	18171420

Note: This table shows the results for the impact of the oil spill on infant health outcomes at different time periods. Time spans have been limited to include women who have been exposed to the oil spill shock at different trimesters of pregnancy. Control variables consist of mother characteristics including mother's age, mother's education, mother's race, whether mother is married, and risk factors of the pregnancy including birth order, an indicator for whether it is a multiple birth, and whether the child is male as well as father's age group and father's race. All the regressions include month, year and state fixed effects and state linear and quadratic time trends. Time period varies by trimesters being considered. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Source: National Center for Health Statistics (NCHS).

Table B.4: Impact of oil spill on infant health outcomes for women using different treatment groups

	(1) Premature	(2) lbw2500	(3) Gestation (weeks)	(4) BW (gr)
gulf states	0.0042**	0.0026***	-0.0390**	-7.2311***
	(0.0017)	(0.0009)	(0.0154)	(2.1837)
N	18718974	18718974	18718974	18718974
Coastal counties	0.0071***	0.0035**	-0.0645**	-8.3600***
	(0.0022)	(0.0013)	(0.0276)	(2.6985)
N	16420787	16420787	16420787	16420787
Narrow coastal counties	0.0067*	0.0042**	-0.0817*	-4.7851*
	(0.0031)	(0.0021)	(0.0494)	(2.2865)
N	15596495	15596495	15596495	15596495
Coastal counties + close counties	0.0070***	0.0029***	-0.0516***	-9.1293***
	(0.0018)	(0.0011)	(0.0195)	(2.5464)
N	17193064	17193064	17193064	17193064

Note: This table shows the results for the impact of oil spill on infant health outcomes using different samples. Control variables consist of mother characteristics including mother's age, mother's education, mother's race, whether mother is married, and risk factors of the pregnancy including birth order, an indicator for whether it is a multiple birth, and whether the child is male as well as father's age group and father's race. All the regressions include month, year and state fixed effects and state linear and quadratic time trends. Time period is 2006 to 2012. Standard errors are clustered at the county level. * p < 0.10, ** p < 0.05, *** p < .01
Source: National Center for Health Statistics (NCHS).

Table B.5: The effect of the oil spill on infant health outcomes for different coastal counties (CC)

	(1) Premature	(2) lbw2500	(3) Gestation (weeks)	(4) BW (gr)
Oil spill * CC of Alabama	0.0048	0.0153***	-0.0871*	-23.5916**
	(0.0102)	(0.0035)	(0.0514)	(9.4652)
Oil spill *CC of Florida	0.0007	0.0042*	0.0448	-8.7253
	(0.0030)	(0.0024)	(0.0427)	(5.6868)
Oil spill *CC of Louisiana	0.0184***	0.0056*	-0.1074***	-11.4115**
	(0.0040)	(0.0026)	(0.0304)	(5.0019)
Oil spill *CC of Mississippi	-0.0040	0.0036	-0.1242*	-11.7629
	(0.0094)	(0.0044)	(0.0750)	(10.7582)
Oil spill * CC of Texas	0.0080***	0.0013	-0.1055***	-6.1848
	(0.0029)	(0.0013)	(0.0351)	(4.5982)
N	16420787	16420787	16420787	16420787

Note: This table investigates potential heterogeneity of the effect by states, using interaction terms. Control variables consist of mother characteristics including mother's age, mother's education, mother's race, whether mother is married, and risk factors of the pregnancy including birth order, an indicator for whether it is a multiple birth, and whether the child is male as well as father's age group and father's race. All the regressions include month, year and state fixed effects and state linear and quadratic time trends. Time period is 2006 to 2012. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$
Source: National Center for Health Statistics (NCHS).

Table B.6: Heterogeneity effect of oil spill for women at their 3rd trimester

	(1) all	(2) College	(3) Some college	(4) High School Or less	(5) Age over 35	(6) Age 26-35
Panel A						
premature	0.0071***	-0.0011	0.0011	0.0134***	-0.0095*	0.0106***
	(0.0022)	(0.0034)	(0.0044)	(0.0038)	(0.0053)	(0.0031)
LBW	0.0035**	-0.0004	-0.0015	0.0063**	-0.0023	0.0035
	(0.0013)	(0.0028)	(0.0037)	(0.0025)	(0.0048)	(0.0022)
gestation	-0.0645**	-0.0163	-0.0037	-0.0986***	-0.0306	-0.0934***
	(0.0276)	(0.0329)	(0.0303)	(0.0342)	(0.0460)	(0.0286)
BW	-8.3600***	-6.7041	-8.0763	-11.8239**	-1.0350	-9.2551***
	(2.6985)	(4.7911)	(5.6089)	(5.0351)	(7.4017)	(3.5462)
N	16420787	3151016	1996274	4761411	1831656	8067642
Panel B						
	(7) Age below 25	(8) White	(9) Black	(10) Hispanic	(11) Married	(12) Unmarried
premature	0.0077**	0.0014	0.0131***	0.0079**	0.0048**	0.0083***
	(0.0032)	(0.0025)	(0.0043)	(0.0035)	(0.0023)	(0.0028)
LBW	0.0053***	0.0029*	0.0082	0.0017	-0.0002	0.0067**
	(0.0019)	(0.0017)	(0.0057)	(0.0020)	(0.0015)	(0.0026)
gestation	-0.0494	-0.0171	-0.0452	-0.1104***	-0.0650**	-0.0456*
	(0.0314)	(0.0215)	(0.0422)	(0.0423)	(0.0303)	(0.0274)
BW	-10.3457***	-5.6060	-7.0915	-11.5330*	-3.3513	-12.0685***
	(3.8645)	(4.0750)	(7.4627)	(6.0260)	(4.1090)	(3.5675)
N	6521489	9111655	2259938	3810858	9924189	6496598

Note: This table shows the results for the impact of the oil spill on infant health outcomes for mothers who have been exposed to the oil spill shock in their third trimester of pregnancy. Control variables consist of mother characteristics including mother's age, mother's education, mother's race, whether mother is married, and risk factors of the pregnancy including birth order, an indicator for whether it is a multiple birth, and whether the child is male as well as father's age group and father's race. All the regressions include month, year and state fixed effects and state linear and quadratic time trends. Time period is 2006 to 2012. Standard errors are clustered at the county level. * p < 0.10, ** p < 0.05, *** p < .01
Source: National Center for Health Statistics (NCHS).

Table B.7: The effect of the oil spill on age of mother at different birth orders

	(1) All	(2) Parity-1	(3) Parity-2	(4) Parity-3	(5) Parity-4 more
Age of mom at birth	-0.0120	-0.0495	-0.0306	-0.0020	-0.0031
	(0.0154)	(0.0320)	(0.0242)	(0.0429)	(0.0378)
	22433230	8016125	7418661	4033840	2826865

Note: This table shows the results for the effect of the oil spill on age of mother. Control variables consist of mother characteristics including mother's age, mother's education, mother's race, whether mother is married, and risk factors of the pregnancy including birth order, an indicator for whether it is a multiple birth, and whether the child is male as well as father's age group and father's race. All the regressions include month, year and state fixed effects and state linear and quadratic time trends. Time period is 2006 to 2012. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$
Source: National Center for Health Statistics (NCHS).

APPENDIX C: SUPPLEMENTARY TABLES FOR CHAPTER 4

Table C.1: Summary Statistics

Variables	Mean	S.d.
Total spending	10.819	1.134
Share of spending on Education	0.331	0.068
Share of spending on Health/Hospital	0.060	0.019
Share of spending on Public Safety	0.030	0.011
Share of spending on Social Welfare	0.160	0.065
Share of spending on Other	0.419	0.090

Note: Summary statistics of outcome variables including share of spending on education, health/hospitals, public safety, social welfare, and other sectors as well as log of total spending. The number of observations is 2343.
Source: ICPSR 7757 (1995), Atlas of U.S. Presidential Elections (2011), and U.S. Census Bureau.

Table C.2: Summary Statistics for party switch

	$D_{t+1}\|R_t$		$R_{t+1}\|D_t$		$D_{t+1}\|D_t$		$R_{t+1}\|R_t$	
Variables	Mean	S.d.	Mean	S.d.	Mean	S.d.	Mean	S.d.
Total spending	10.711	1.149	10.98	1.079	10.655	1.182	10.848	1.239
Share of spending on Education	0.339	0.064	0.319	0.077	0.345	0.061	0.306	0.066
Share of spending on Health/Hospital	0.068	0.018	0.054	0.015	0.064	0.016	0.055	0.013
Share of spending on Public Safety	0.031	0.009	0.029	0.008	0.033	0.012	0.028	0.008
Share of spending on Social Welfare	0.164	0.069	0.169	0.065	0.158	0.062	0.160	0.071
Share of spending on Other	0.398	0.079	0.429	0.070	0.400	0.075	0.451	0.094

Note: Summary statistics of outcome variables including share of spending on education, health/hospitals, public safety, social welfare, and other sectors as well as log of total spending when party switches.
Source: ICPSR 7757 (1995), Atlas of U.S. Presidential Elections (2011), and U.S. Census Bureau.

Table C.3: Robustness check: Regression Discontinuity Estimates for Predetermined Characteristics of the States and Governors

Outcome Variables	(1) Linear polynomials	(2) Quadratic polynomials	(3) Cubic polynomials	(4) Quartic polynomials
Log Personal income	0.0283	0.0143	0.0183	0.0205
(million $)	(0.0199)	(0.0141)	(0.0223)	(0.0222)
Log of Population	0.00296	0.00695	-0.00186	-0.00330
	(0.0125)	(0.0126)	(0.0179)	(0.0163)
Upper house majority	0.0423	0.0241	0.0426	0.0139
	(0.0292)	(0.0301)	(0.0310)	(0.0399)
Lower house majority	0.0071	-0.0082	-0.0006	-0.0197
	(0.0359)	(0.0369)	(0.0400)	(0.0416)
Both houses majority	0.0028	-0.0080	0.0051	-0.0152
	(0.0349)	(0.0349)	(0.0357)	(0.0427)
Female governor	0.0397	0.0422	0.0410	0.0410
	(0.0246)	(0.0256)	(0.0278)	(0.0292)

Note: In this table, control variables regarding state characteristics (i.e. demographic and political characteristics of the states) are used as outcome variables. The explanatory variable is gubernatorial party of the governor. The number of observations is 2343. Standard errors are in parentheses and are clustered at the state level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$
Sources: ICPSR 7757 (1995), Atlas of U.S. Presidential Elections (2011) and U.S. Census Bureau.

Table C.4: Summary Statistics – Democratic vs Republican Governors at Margin of victory of 5%

	Democratic Governor		Republican Governor		Difference	
Variables	M	SD	M	SD	Diff	SD
Log Personal income (million $)	5.853	1.183	6.037	1.22364	-0.184	.104
Log of Population	7.937	1.098	8.112	1.073	-0.176	.093
House majority democrat	0.610	0.407	0.629	0.382	-0.019	.034
Senate majority democrat	0.603	0.425	0.586	0.381	0.0169	.034
Majority democrat both houses	0.660	0.413	0.672	0.366	-0.012	.033
Female governor	0.074	0.174	0.052	0.145	0.022	.014

Note: Summary statistics of control variables including log of population and personal income of the states, dummy variable whether majority of the state legislators in the Senate or House or both houses are Democrats or Republicans, and a dummy variable whether the governor is female.
Source: ICPSR 7757 (1995), Atlas of U.S. Presidential Elections (2011), and U.S. Census Bureau.

Table C.5: Summary Statistics - Whole sample vs Margin of victory of 5%

	Whole sample		Margin of victory (5%)		Difference	
Variables	M	SD	M	SD	Diff	SD
Log Personal income (million $)	6.001	1.130	5.925	1.221	0.076	.055
Log of Population	8.065	1.027	8.015	1.080	0.050	.05
House majority Democrat	0.633	0.346	0.613	0.323	0.021	.016
Senate majority Democrat	0.602	0.353	0.597	0.328	0.006	.017
Majority Democrat both houses	0.693	0.331	0.674	0.313	0.019	.016
Female governor	0.052	0.145	0.067	0.125	-0.016	.007

Note: Summary statistics of control variables including log of population and personal income of the states, dummy variable whether majority of the state legislators in the Senate or House or both houses are Democrats or Republicans, and a dummy variable whether the governor is female.
Source: ICPSR 7757 (1995), Atlas of U.S. Presidential Elections (2011), and U.S. Census Bureau.

Table C.6: RD estimates for total spending and share of spending Using Different Order of Polynomials and optimal bandwidth procedures

	(1) Total Spending	(2) Education	(3) Health/ Hospital	(4) Public Safety	(5) Social Welfare	(6) Other
Panel A						
Democratic Governor	0.0007	0.0230**	0.0498**	0.0329	-0.0148	-0.0244***
Linear polynomials	(0.0026)	(0.0086)	(0.0218)	(0.0197)	(0.0236)	(0.0081)
Democratic Governor	-0.0009	0.0295***	0.0490*	0.0276	-0.00919	-0.0303**
Cubic polynomials	(0.0036)	(0.0107)	(0.0284)	(0.0199)	(0.0258)	(0.0116)
Democratic Governor	-0.0006	0.0276**	0.0549*	0.0381*	-0.00956	-0.0309**
Quartic polynomials	(0.0037)	(0.0105)	(0.0274)	(0.0223)	(0.0260)	(0.0115)
Panel B						
Democratic Governor	-0.0015	0.0251**	0.0693**	0.0451**	0.0169	-0.0311**
IK bandwidth	(0.0047)	(0.0110)	(0.0330)	(0.0200)	(0.0379)	(0.0137)
	BW= 12.033	BW= 13.032	BW= 12.076	BW= 15.201	BW= 7.520	BW= 9.437
Democratic Governor	-0.0016	0.0250**	0.0876**	0.0403**	0.0229	-0.0295**
CCT bandwidth	(0.0046)	(0.0103)	(0.0411)	(0.0203)	(0.0295)	(0.0110)
	BW= 14.28	BW= 14.260	BW= 9.414	BW= 14.776	BW= 11.914	BW= 17.728

Note: Outcome variables are the share of spending on education, health/hospitals, public safety, social welfare, and other sectors as well as log of total spending. The number of observations is 2343 for Panel A. The controls are the same as Table 4.3. Panel B use optimal bandwidth procedures of Calonico, Cattaneo and Titiunik (CCT) (2014), and Imbens and Kalyanaraman (IK) (2012). There are 1222 and 1367 observations for IK and CCT optimal bandwidth for RD estimates for Education. Number of observations for RD estimated for health/hospitals using bandwidth of IK and CCT are 1181 and 943 respectively. Number of observations for Public Spending using bandwidth of IK and CCT are 1433 and 1396 respectively and 815 and 1222 for Social Welfare and 976 and 1597 for Other. Standard errors are in parentheses and are clustered at the state level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Sources: ICPSR 7757 (1995), Atlas of U.S. Presidential Elections (2011) and U.S. Census Bureau.

Table C.7: Regression Discontinuity Estimations for Shares of Spending & Total Spending Using Small bandwidth

	(1) Total Spending	(2) Education	(3) Health/ Hospital	(4) Public Safety	(5) Social Welfare	(6) Other
Democratic Governor	0.0017	0.0361*	0.0889*	0.0393	-0.0788*	-0.025
BW=3	(0.0130)	(0.0263)	(0.0500)	(0.0334)	(0.052)	(0.019)
Democratic Governor	-0.0027	0.0272*	0.0701**	0.0223	-0.0469	-0.0207*
BW=5	(0.0080)	(0.0164)	(0.0339)	(0.0237)	(0.0293)	(0.0124)
Democratic Governor	0.0032	0.0237*	0.0671**	0.0214	0.0280	-0.0324**
BW=10	(0.0052)	(0.0133)	(0.0267)	(0.0185)	(0.0217)	(0.0140)
Democratic Governor	0.0015	0.0236**	0.0640***	0.0325**	0.0229	-0.0338**
BW=12	(0.0046)	(0.0117)	(0.0228)	(0.0159)	(0.0208)	(0.013)
Democratic Governor	0.0010	0.0267**	0.0734***	0.0444*	0.0003	-0.0275**
BW=15	(0.0043)	(0.0110)	(0.0207)	(0.0240)	(0.0192)	(0.013)

Note: Outcome variables are the share of spending on education, health/hospitals, public safety, social welfare, and other sectors as well as log of total spending. Number of observations for RD estimated using bandwidths of 3, 5, 8, 12, and 15 are 338, 540, 843, 1222, and 1425 respectively. Standard errors are in parentheses and are clustered at the state level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$
Sources: ICPSR 7757 (1995), Atlas of U.S. Presidential Elections (2011) and U.S. Census Bureau.

Table C.8: Placebo RD Test: Regression Discontinuity Estimates on Outcome variables at Previous Term

	(1) Total Spending	(2) Education	(3) Health/ Hospital	(4) Public Safety	(5) Social Welfare	(6) Other
Democratic Governor	-0.0208	-0.0029	-0.0047	0.0215	-0.0152	0.00152
Linear polynomials	(0.0231)	(0.0121)	(0.0266)	(0.0230)	(0.0251)	(0.0092)
Democratic Governor	-0.0401	-0.0093	-0.0036	0.0153	0.0067	0.0011
Quadratic polynomials	(0.0316)	(0.0139)	(0.0297)	(0.0236)	(0.0242)	(0.0107)
Democratic Governor	-0.0275	-0.0131	0.00210	0.0180	-0.0007	0.0034
Cubic polynomials	(0.0327)	(0.0156)	(0.0357)	(0.0250)	(0.0250)	(0.0126)
Democratic Governor	-0.0337	-0.0230	0.0098	0.0224	0.0152	0.0043
Quartic polynomials	(0.0401)	(0.0162)	(0.0345)	(0.0287)	(0.0285)	(0.0129)

Note: Outcome variables are the share of spending on education, health/hospitals, public safety, social welfare, and other sectors as well as log of total spending. The number of observations is 2343. The controls are the same as table 4.3. In all specifications, state and year fixed effects are included. Standard errors are in parentheses and are clustered at the state level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$
Sources: ICPSR 7757 (1995), Atlas of U.S. Presidential Elections (2011) and U.S. Census Bureau.

Table C.9: Regression Discontinuity Estimates for Total spending & Share of Spending by sectors: heterogeneity of the effect, if Democrats are in power in other office.

	(1) Total Spending	(2) Education	(3) Health/ Hospital	(4) Public Safety	(5) Social Welfare	(6) Other
Panel A						
Democratic Governor	-0.0051	0.0204**	0.0513***	0.0365***	0.00345	-0.0256***
	(0.0039)	(0.0086)	(0.0162)	(0.0130)	(0.0173)	(0.0072)
Democratic Governor×	0.0137***	0.0148	-0.0396	-0.0011	-0.0476	0.0097
Democratic President	(0.0043)	(0.0141)	(0.0280)	(0.0267)	(0.0345)	(0.0125)
Panel B						
Democratic Governor	-0.0010	0.0293***	0.0384*	0.0398***	-0.0234	-0.0272***
	(0.0041)	(0.0090)	(0.0182)	(0.0140)	(0.0191)	(0.0072)
Democratic Governor×	0.0026	-0.00453	0.0121	-0.0092	0.0159	0.0098
Majority Democrat both houses	(0.0041)	(0.0169)	(0.0418)	(0.0229)	(0.0315)	(0.0136)
Panel C						
Democratic Governor	-0.0071	0.0232**	0.0451**	0.0403***	-0.00301	-0.0319***
	(0.0047)	(0.0098)	(0.0196)	(0.0151)	(0.0201)	(0.0080)
Democratic Governor×	0.0140***	0.0142	-0.0384	-0.0012	-0.0470	0.0108
Democratic President	(0.0044)	(0.0142)	(0.0274)	(0.0260)	(0.0346)	(0.0127)
Democratic Governor×	0.0035	-0.00362	0.00966	-0.0093	0.0129	0.0106
Majority Democrat both houses	(0.0041)	(0.0167)	(0.0424)	(0.0230)	(0.0314)	(0.0136)

Note: Outcome variables are the share of spending on education, health and hospitals, public safety, social welfare, and other sectors as well as log of total spending. The number of observations is 2343. This table investigate heterogeneity of the effect of Democratic governors if Democrats are in power in other office. In all specifications, state and year fixed effects are included. Control variables are the same as Table 4.3.
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$
Sources: ICPSR 7757 (1995), Atlas of U.S. Presidential Elections (2011) and U.S. Census Bureau.

VITA

Sara Oloomi was born and grew up in Esfahan, Iran. In 2011 she finished his Bachelor and Master of Economics from University of Isfahan. Afterward she moved to the United States, Louisiana where she started his Ph.D.in Economics. Her primary research interests are Health Economics, Labor Economics, Public Policy, and Political Economy.