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# Fresh Air: The Impact of Reformulated Gasoline on Infant Health

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by

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# 1 Introduction

The invention of the internal combustible engine became one of the greater accomplishments of the early 19$^{th}$ century. It quickly led to the automobile, which continues to be an essential part of everyday life. Unfortunately, the pollution emitted by automobiles has produced a negative externality on society. The transportation sector, particularly motor vehicles, is a main source of emissions in the United States. In 2014, this sector alone was responsible for producing 26% of national greenhouse gas emissions, after an electricity sector that produces 30% of emissions while still using coal[1]. Greenhouse gas emissions have increased by approximately 17% from 1990, from people traveling more along with no major changes in fuel efficiency for cars (Environmental Protection Agency [EPA], 2016d). The estimated total number of miles driven for the 2016 year has gone to 3.17 trillion miles, which is up 110 billion miles from 2015 (Alternative Fuels Data Center [AFDC], 2016). With an increase in traveled miles, the amount of congestion on roads rises and more emissions are released. Emissions rise in this environment because constant braking and accelerating induces more energy than simply moving at a constant speed (Federal Highway Administration [FHWA], 2016). This is especially true in urban areas where congestion is higher and pollution levels reflect this.

The Los Angeles Basin has consistently been in a nonattainment status due to their climate, geography, and vast economic activity [2] (EPA, 2016d). The area is infamous for its traffic, so much so that daily pollution measurements show that the area would consistently go over the permitted threshold making it harmful to be outdoors. The California Air Resource Board (CARB) has come up with stringent policies to help lower the amount of pollutants from vehicle emissions, through gasoline reformulation.

This paper looks to provide estimates of how the California Phase II Reformulated Gasoline program (RFG II) helped to reduce air pollution and consequently improve the health of infants. I observe the effects of the RFG II in 1996, when reformulated gasoline was mandated to produce cleaner emissions from motor vehicles. Pollution levels in this paper will

[1] Coal produces 77% of the carbon dioxide in the sector, but accounts for only 39% of the electricity produced. Coal contains the highest carbon content of any fossil fuel and emits common air pollutants like sulfur dioxide and nitrogen oxides (Center for Climate and Energy Solutions [C2ES], 2016).

[2] Nonattainment status is given to counties that have higher than EPA permitted pollution levels.

be defined as having high levels of ozone, high volatile organic compounds (VOCs), nitrogen oxides ($NO_X$), and to a lesser extent carbon monoxide (CO). These VOCs and $NO_X$ are emitted from factories, power plants, and vehicles. I observe how RFG II affected one of the more vulnerable populations in infants by increasing birth weight and gestational length, and decreasing low birth weight and infant mortality likelihood. Cost benefit analyses provide evidence in favor of having these tough policies.

A study done by Zahran, Weiler, Mielke, and Pena (2012) observed the effect of benzene, one of the more harmful VOCs, on infant health between 1996-1999. They took advantage of a policy implemented in different cities to limit the benzene content in gasoline. They found significant effects for both birth weight and low birth weight in the analysis. Results showed a $1\mu g/m^3$ increase in benzene exposure to the mother led to a reduction in the infant's birth weight by about 16.5 grams. A 25% decline in benzene in cities resulted in an increase in birth weight by approximately 13.7 grams. Similarly, the greater the maternal exposure to benzene the higher the likelihood of the infant having a low birth weight. The infants born to mothers in these areas were found to be on average 33.6 grams lighter compared to less polluted cities. The calculated infant health care costs saved by these counties that conformed to cleaner gasoline reached a maximum of around $350 per infant.

Air quality and its effect on infants is a question of interest because there is evidence that shows that increasing air pollution for pregnant mothers decreases the infant's birth weight (Currie, Neidell, & Schmieder, 2009). Poor health at the beginning of a person's life could lead to future health complications (Currie & Walker, 2011). Infants are considered the most vulnerable population due to their inability to advocate for themselves. Prenatal and postpartum periods are extremely sensitive for infants because of the rapid development that occurs (Currie, Zivin, Mullins, & Neidell, 2014). An infant will eat a larger portion of their body weight than a regular person would, making them susceptible to illnesses from something they have ingested. If pollution is inhaled, the infant will feel the effect of the toxin more than a normal adult.

Despite the growing amount of literature and interest surrounding environmental protection and health, I have not encountered literature that considers the effect of the 1996 California Air Resource Board (CARB) policies on infant health. The regulations limit the pollutants that are integral in forming ozone and remove loopholes for refiners by adding in content regulation. California itself has been a constant in the literature regarding its environmental situation and the policies that it has created to improve air quality. The CARB has created a cleaner environment by reducing the amount of toxic emissions released, providing results not seen by other states (Auffhammer & Kellogg, 2011). I believe that an analysis of RFG II with respect to infant's health indicators can portray a new residual benefit from the policy.

I will compare the infant health indicators for the state of California against the rest of the United States, excluding Arizona. This is done by comparing mothers in urban counties of California and urban counties of the other states before and after the adoption of RFG II. The analysis provides significant results consistent with previous literature. The difference-in-differences models provided estimates of an increase in birth weight for infants of a little less than 5 grams after RFG II was enacted. The largest effect was seen for Black mothers with a 20.9 gram increase in birth weight. The incidence of having a low birth weight was strongest for Black mothers with a -0.108-percentage point decrease. Gestational length was also increased because of the policy, by approximately less than a day. The infant mortality rate decreased for the models by 0.06-0.125 percentage points, and low birth weight from 0.01-0.11 percentage points.

The remaining paper is laid out as follows: Section I provides the background information for the surrounding topics. Section II describes the data used, with Section III including the methods used in the analysis and Section IV provides the results. Then Section V includes both the discussion of the magnitude of these effects and the conclusion.

## 2 Background

The policy being studied in the paper is the California Phase II Reformulated Gasoline (RFG II) program, implemented March 1, 1996, and includes limitations on sulfur, oxygen, olefin, benzene, Reid vapor pressure (RVP) and other pollutants. The reformulated gasoline was inspected by government officials to check if content regulations were followed by suppliers. The policy dictated that if the gasoline was found to be non-compliant then suppliers would be required to produce cleaner gasoline to offset the emissions from the gasoline already sold. A supplier may even come up with a different formula if it becomes certified by proving that it can reduce emissions at least as much as the policy mandates. RFG II looked to reduce certain toxins in the air and was weighted based off how hazardous the pollutant type was. The CARB had refiners and importers adhere to the new policy and worked with them so they could transition to a reformulation (CARB). CARB gasoline was required for all parts of California including rural sections, which were already in compliance with the EPA's ozone standard. This included being compliant of the benzene content, which constitutes as having 1 percent of benzene by volume. Usually, refiners chose to remove butane from gasoline to make it compliant with environmental standards; however, VOCs are three to ten times more reactive and thus worse than butane. Reid vapor pressure is used to measure the intensity of VOCs being released from gasoline either by emissions or evaporation (Auffhammer & Kellogg, 2011).

VOCs are created through burning a fuel source like coal, natural gas, and gasoline and these VOCs are air pollutants that can combine with $NO_X$ to produce ground-level ozone. Ground-level ozone is formed right above the surface of the earth, mainly produced through human activity (Environment and Climate Change Canada [ECCC], 2016). Concentrations of VOCs are found outdoors as well as indoors, because they are released from a plethora of products, such as solvents and paints (National Institutes of Health [NIH], 2016). These products can produce ozone and when combined with oxides or VOC's can damage the mother's lungs and tissues, which indirectly affects the fetus. The smallest particles such as $PM_{10}$ and $PM_{2.5}$ cause the most harm because they can be easily inhaled deep into the lungs to the bloodstream (EPA, 2016c; Currie, Neidell, & Schiemeider, 2009). Benzene, a colorless liquid with a sweet odor, is a type of VOC found in crude oil, gasoline, and cigarette smoke. People living in high traffic areas are exposed to high levels of benzene and have higher leukemia rates. Benzene has been seen to affect the hematological, neurological, and immunological systems of the body (Agency for Toxic Substances and Disease Registry [ATSDR], 2016; Cancer, 2016). Symptoms from ozone can arise quickly over a short period, thus going indoors, can help to reduce the symptoms (Chang, Koutrakis, Catalano, & Suh, 2000; Moretti & Neidell, 2010).

In recent years, the United States has acted in favor of reducing pollution. From the

Organization for Economic Cooperation and Development (OECD) outlook (2011) 1.5 million people are expected to die from exposure to particulates each year in OECD countries, greater than the number of people who die due to malaria or unclean water. This number is expected to increase to 3.5 million people by 2050. Furthermore, developing countries are seen to have even larger effects on infant mortality due to pollution compared to developed countries (Arceo, Hanna, & Oliva, 2016). Recently, the Paris Climate agreement was negotiated to limit greenhouse gasses worldwide. In the United States, the most stringent reductions in greenhouse gasses have come from California where the CARB has enacted a plethora of policies to curb the amount of pollution emitted. These policies include the 1996 RFG II created by the CARB which place restrictions on gasoline suppliers requiring them produce cleaner fuel with lower amounts of toxic emissions being released. By having content regulations, some suppliers were unable to distribute gasoline because of the rising costs. RFG II increased refining costs by 6.2 to 8.0 cents per gallon and consequently gasoline by 7.1 to 9.6 cents per gallon, compared to the Clean Air Act which only raised prices by 7 cents (Sweeney, 2014). However, one of the main reasons to advocate for environmental regulations is to help protect human health. These policies would be able to reduce ground-level ozone (tropospheric ozone) which may lead to health complications such as asthma and bronchitis. High levels of ozone deter the body from being able to fight respiratory diseases because ozone can react with organic material inside the human body creating a dangerous effect (EPA, 2016a).

During the 1990s California experienced environmental policy changes that include the 1996 reformulated gasoline policy this paper is considering. Currie and Neidell (2005) study California's experience with air pollution and its effect on infant health. The study looks at different pollutants, CO, $O_3$, and $PM_{10}$ and finds the largest effect to be from CO's impact on infant mortality. They found that with the reductions in CO, 1,000 infants lives were saved during the sample period. Even at low levels of air pollution, they found a significant effect on infant mortality. At a $1.6 million valuation per life this would result in $1.6 billion saved.

The Clean Air Act Amendments (CAA) of 1970 regulated nonattainment counties that had higher than allotted total suspended particles (TSPs), a measurement of particulate matter. Before the passage of the CAA no federal regulations were set and so it became the responsibility of the state to pass regulations. Nonattainment counties had pollution levels drop drastically after the law was enacted compared to attainment counties as a consequence of the tougher regulations. A one percent decrease was seen to cause a 0.5% decrease in the infant mortality rate. Many of the infants saved during the first month of their lives, showing the causal effect of TSPs on fetuses and the importance of having clean air during pregnancy. TSPs of $75\mu g/m^3$ and lower was seen to help reduce infant mortality. In 1972 alone, approximately 1,300 infant lives were saved from the CAA. With other studies observing the adverse effects on health from fine particulate matter, the EPA has begun to regulate even finer particles of $PM_{10}$ which are under $10\mu m$ in diameter compared to TSPs which includes particulate matter under $100\mu m$ in diameter (Chay & Greenstone, 2003a).

Studying the health effect for adults becomes much more challenging due to the wide range of years that need to be covered. In infants, the effects of pollution arise immediately and therefore provide for an ideal study population. Currie and Walker (2011) also found that mothers usually do not move often, and if they do decide to move, they do not move out of the same county. Furthermore, the studies of infants show the effects of early exposure to ambient air quality on their lives. Currie, Neidell, and Schmieder (2009) have shown that infants are negatively affected by adverse air quality from a study done on the effects of using E-ZPass's throughout New Jersey[3]. The results concluded that CO has a negative significant effect on infants even at low concentration levels[4]. In adult populations, they have found that pollution has a negative relationship regarding worker productivity. Ozone decreases lung functionality and in agricultural work, where many hours of manual labor is required, productivity decreases. California has suggested that a reduction of only 10 ppb (parts per billion) in ozone would be able to save about $700 million in labor expenditure (Zivin & Neidell, 2012).

There have been other papers that have tested the effect of air pollution on health by using different indicators. They have found an inverse relationship between carbon monoxide and birth weight. In the classic Currie and Walker (2011) paper, they showed that with the

[3]E-Z pass is an electronic toll collection service.

[4]In December of 1952 London was covered in coal smoke, often called the 'Killer Fog', it caused significant increases in mortality among infants as well as others.

introduction of E-ZPass in New Jersey there was a reduction in the number of premature and low birth weight infants within 2km of the booths. E-ZPass was implemented to decrease the amount of traffic caused by manual toll booths[5]. However, it also had an inconsequential positive effect on health outcomes for infants in the surrounding area. There were no drastic changes in the characteristics of the mothers nor the housing prices within the radius, during the early days of its enactment. E-ZPass reduced prematurity by 10.8% and low birth weight by 11.8% within the 2km. This would ultimately effect around 8,600 births nationwide if traffic congestion could be reduced, which would be approximately a $444 million per year. They suggest a $9.8-$13.2 million value (based off $51,600 per infant) of prematurity costs saved after the first 3 years (Currie & Walker, 2011). Currie, Neidell, and Schiemeder (2009) also find that in New Jersey a decrease in carbon monoxide from 4 ppm (parts per million) to 1 ppm is like having a 10 cigarette per day smoker quit, which exemplifies the drastic changes from reducing pollution levels. A study done in Connecticut and Massachusetts looked at birth weight and low birth weight and found that $NO_2$, CO, and $PM_{2.5}$ lowered birth weights by approximately 8-9 grams. The first trimester was mostly effected by CO, $NO_X$, and $SO_X$ and the third trimester was mostly affected by CO. They found that $PM_{2.5}$ had a larger impact on Black mothers, while White mothers were effected by CO (Bell, Ebisu, & Belanger, 2007).

A paper by Salam, Millstein, Li, Lurmann, Margolis and Gilliland (2005) studied the effects of air pollutants in California on birth weight during 1975-1987. The study found that a 12 ppb increase in 24-hour ozone over pregnancy led to a 47.2-gram lower birth weight, and was robust for the second and third trimesters. Exposure to ozone in the second and third trimester and carbon monoxide in the first trimester reduced birth weight. Another study done in California by Ritz, Yu, Chapa, and Fruin (2000) looked at the effects of air pollution amongst children that were preterm and born in during 1989-1993. A preterm birth is classified as a birth before the $37^{th}$ week of gestation, where the normal length is 40 weeks. The pollutants studied were CO, $NO_2$, $O_3$, and $PM_{10}$, and found through risk-ratios that a $50\mu g$ increase in $PM_{10}$ results in a 20% increase in preterm births. The bulk of preterm

[5] E-ZPass allows for vehicles to travel at a slower speed through the toll booth, instead of having to stop and manually pay the toll operator.

births came to mothers who had previous low birth weight infants, were very old or young, had no prenatal care, were African-American, and/or used tobacco.

Increases in incomes along with growing cities have led to more suburban areas being settled into, causing more commutes to cities. With more commutes one would automatically believe that this would result in higher pollution levels. However, California's major urban areas have experienced drastic decreases in the amount of pollution even when more people are driving with evidence from 1997. The explanation of this improvement in air quality comes from technological advancement that has taken place in vehicles. They found ambient 1-hour $O_3$, $NO_2$, and CO decline by 1.7, 2.6, and 3.9%, respectively, per year as vehicles improved. They also find that Green Party registered areas, which are much more environmentally conscious, emit less even when maintenance of these vehicles is costlier (Kahn & Schwartz, 2006).

Other forms of transportation have caused ambient air quality, ports such as docks and airports are also areas of study. In a study by Moretti and Neidell (2010), daily boat traffic from Los Angeles and Long Beach, California was used as a telltale sign for pollution in the area. Weather forecasts were also used to determine ozone levels[6]. Boats would come in from different countries that do not possess the technology or strict policies of regulating emissions. Thus, ships produced approximately 20% of the total $NO_X$ in the Los Angeles area (Air Quality Management District [AQMD], 2002). In the ordinary least squares (OLS) model they found that a 5-day increase of 0.01 ppm in ozone levels led to a 1.2% increase in hospitalization and in the two-stage least squares (2SLS) model it led to a 4.7% increase. With respect to the costs the OLS model estimated around $462,000 while the 2SLS model estimated around $1,852,000. A similar study done by Schlenker and Walker (2015) focusing on airports looked at the effect of airport congestion and its effect on air quality and consequently health outcomes. They look at the effect in California's airports and their surrounding areas. They find similar effects where an increased carbon dioxide exposure lead to more hospitalizations for respiratory and cardiac related health complications. Finding that a one standard deviation increase in daily pollution levels would add about $1 million in hospital costs for cardiac and respiratory problems within a 10km

[6]Ozone levels increase with warm weather.

radius of the 12 major airports in California. Thus, the findings from other types of transport is also important to note because the gasoline produced elsewhere may not have as strict content regulations and can mitigate results.

A recent study done by Herrnstadt and Muehlegger (2015) showed the effects of emissions on mental health. The authors used a twelve-year period in Chicago to show violent crime rates increasing because of an increase in pollution levels. They observed that when facing downwind from a major interstate the violent crime rate was 2.2% higher. This supports psychological evidence that pollution tends to raise aggression, caused by CO joining with hemoglobin instead of oxygen, hypoxia. Crime costs are estimated at several hundred billion dollars annually and from the area tested would cost approximately $100-$200 million annually. Estimates have shown that there was a 0.111 increase in the log of daily crime when CO increased by 1 ppm. In Currie, Hanushek, Kahn, Neidell, and Rivkin (2009) CO was linked to a greater number of absences, which harm parents, children, and schools. Parents because they may need to miss work to care for the child, children because they are less engaged in the class due to their absence, and schools because funding ultimately depends on attendance of the children.

Another study also looks at the effect of air pollution on infant mortality after the 1981-82 recession. By looking at geographic variations that cause sharp changes in air quality, the study found that between 1980-82 there was a lot of particulate matter variation between counties and concluded $1 mg/m^3$ decrease in particulates resulted in about 4-8 fewer infant deaths for every 100,000 births within the first month. In total 2,500 infants were saved between this time because of the reductions in pollution levels from the recession that hurt some counties more than others. Due to the recession in Pittsburgh TSP levels decreased by $25\text{-}30\ mg/m^3$ resulting in a reduction of 1 death per 1,000 births. Thus, the paper provides evidence of the adverse effects of particulates on fetuses and the importance of air quality during the prenatal stage (Chay & Greenstone, 2003b).

A study conducted by Clay, Lewis, and Severnini (2016) on the impact of coal-fired power plants on the effect of local infant mortality and property values. The rise in air pollution in the immediate areas caused 3,500 more infant deaths per year. At low electricity levels a thermal power plant was an amenity and people had a positive marginal willingness to pay, but with greater access to electricity the plants became the opposite. The study also pushes the idea that most people have no direct willingness to pay for better air quality, but can be shown in property prices. However, with data limitations they found no significant effect for their theory. The Chay and Greenstone (2005) study proved that during the 1970's and 1980's where pollution regulations were put into effect, those counties saw an increase in housing prices greater than non-regulated counties. Reducing TSPs by one-unit resulted in a 0.7-1.5 percent increase in the value of the home, and an overall aggregate economic gain of $80 to $50 billion for the property owners in the 1970's and 1980's respectively.

Chay and Greenstone's (2005) analysis of housing prices and air quality found individuals with higher incomes chose to stay in areas with better air quality, reflecting property prices. This may lead to an overestimation of pollution caused by poorer individuals living in these areas. However, highly educated high income individuals live in congested urban areas and have better health care access. Therefore, these two points counter each other's biased effects on the ultimate result (Currie & Walker, 2011).

# 3 Data

In this paper, I use a combination of two data sets that includes county level pollution data and infant vital statistics. The pollution data used in this analysis comes from Auffhammer and Kellogg's (2011) paper. They calculated the EPA's 8-hour mean ozone and maximum ozone pollution level for that day for all counties in the United States. Not all counties have an EPA monitor within them, so they created an algorithm that would take several of the closest monitors readings for the county and weight them to then find an approximate reading for the county. This provided each county with a reading for pollution for each day from 1989-2003. The data set also included the type of policy implemented in the county. Weather data, such as the maximum-minimum temperature and precipitation was included as well. From here, I aggregated values to the monthly level creating a mean value for the ozone levels, temperature, and precipitation for each month. Leading and lagging month-trimester values were also created for each county.

The infant vital statistics from 1989-2001 used in the analysis came from the National Bureau of Economic Research (NBER), where they formatted the Center for Disease Control's (CDC's) Birth Cohort Linked Birth and Infant Death Data (Roth). The CDC did not report infant health statistics from 1992-1994. The linked data included information about the parent's characteristics, vital statistics about the mother, social characteristics, and most importantly infant health indicators. Observations that had missing values for the variables of interest were removed from the sample. This included unreported counties, infant health indicators, mother's characteristics, and mother's health indicators. The data is self-reported meaning that for some variables the person filling in the answers may falsely write information or choose not to answer questions and create missing values. The data reports on only urban counties, which are defined as having greater than 250,000 people. This is done for anonymity purposes and helps protect the identity of the families in small counties. I created additional variables from the data set that were used in the regression such as low birth weight and infant mortality.

The two data sets were merged together and each infant observation was linked to the specific county and month they were born in. This provided the aggregated pollution levels for the month, along with the weather data for a total of 186 different counties out of more than 3,000. Each state had at least one county that was used within the sample, except for Arizona. The data now included each infant and their characteristics alongside the data for the county. A 30 percent sample was taken from the original data set, leaving more than 6 million observations remaining for the sample. The sample was stratified by county, year, and month.

The main infant health indicators that served as the dependent variables in the study are birth weight, mortality rate, low birth weight, and gestational length in weeks. Table 1 provides details of the variables such as the average birth weight of the sample being 3,311 grams and low birth weight infants consisting of 7.9% of the sample. The infant mortality rate in total was approximately 0.7% with the average gestational length being 39.8 weeks in the sample. The independent variables used were the mother's education, age, prenatal care, race, marital status, and infant's gender. The pre-policy period was from 1989-1996 (until February) and the post-policy is from (March) 1996-2001. The treatment group includes all the urban counties in California and the non-treatment group included all the other urban counties in the United States, except Arizona. Arizona was excluded from the analysis because the same RFG II program was used in the winter months, while federal RFG standards were used in the summer months (Auffhammer & Kellogg, 2011). A few of the main indicators used include the mother's education which was broken into five educational attainment categories, with the highest level being graduated college and higher and the lowest level being having 0-8 years of education. The mother's race was used as a separation tool in the regressions and the categories there were White, Black, and Other. The population of each race group is unequal. White's represent 75% of the sample, Black's 16%, and Other only around 8%. Prenatal care was also added in the regressions showing in which trimester prenatal care began if at all. Other variables such as smoking were looked into, but were not used in the analysis due to under reporting.

# 4 Methods

A difference-in-differences estimation model used in this study shows the effect of gasoline reformulation on infant health indicators. In this paper the treatment is the RFG II program. A difference-in-differences estimation is used when there are two groups with two different time periods for both groups. The control group goes through both periods and is not exposed to any treatment. The treatment group is given a treatment in one of the periods and in the other period is not exposed to the treatment. The average gain of the treatment group is subtracted by the average gain of the control group and this removes the biases within and between periods and groups The difference-in-differences model is able to mitigate problems that are associated with having permanent differences seen between the control and treatment group as well as differences caused over time within the same group (Imbens & Wooldridge). A key assumption in a difference-in-differences analysis is that both treatment and control groups would follow the same time trend when a treatment is not present (Waldinger).

The model used shows a basic setup of the difference-in-differences estimation with variables:

$$Outcome_{it} = \beta_0 + \beta_1 Post_{it} + \beta_2 Treat_{it} + \beta_3 Post_{it} * Treat_{it} + \beta_4 Char_{it} + \epsilon_{it} \tag{1}$$

The $Outcome_{it}$ variable used in the first model is the infant's birth weight in grams, all infants born even if pronounced dead had their birth weight recorded. The $Post_{it}$ variable is binary and identifies the infants after the policy was introduced, which is 1996 and onward. The $Treat_{it}$ variable is also binary and identifies the infants born in California, the counties effected by the policy. The interaction term, $Post_{it}*Treat_{it}$, shows the effects of being born in California after the policy was introduced. $Char_{it}$ represents the mother's characteristics that include the mother's education, age, race, prenatal care, marital status, and the infant's gender.

The second variation of model (1) is to add county and year level dummies to create a fixed-effect to control for any biases that are time-invariant. Standard errors are also clustered for all regressions by county, to allow for infants to be correlated within county and not between different counties. The regressions were separated by race into three different categories. Along with adding characteristics about the infant and mother which include marital status, infant's gender, prenatal care, mother's age and education.

A similar model to (1) consisted of gestation length of the infant in weeks as the dependent variable. This dependent variable was used to observe if the mother would have a shorter gestation period with or without the policy. The same difference-in-differences OLS estimation was used in this model and included the same set of independent variables that were used in (1). Standard errors were clustered for each regression and fixed effects for the county and year were also included.

A logistic model was used in the analysis of infant mortality, a binary variable with outcomes of either the infant being alive or dead. A logistic model is used when the dependent variable is binary, and removes the problem of heteroskedasticity when a linear model is used for estimation. The regressions include the same independent variables placed in (1), with county and year fixed effects, and clustered standard errors. The regressions are also stratified by race to observe the effects the policy on different groups.

Low birth weight was also used as a dependent variable in the logistic model where the options were if the infant had a low birth weight (less than 2,500 grams) or a normal birth weight (greater than 2,500 grams). The regressions included the same mother and infant characteristics as independent variables, with the standard errors clustered by county, and county and year fixed effects.

## 5 Results

An initial check was done to gauge if there was an effect of the policy on the ozone levels. I ran a difference-in-differences regression and utilize the two variables that measured ozone (EPA 8-hour and mean ozone) to check if they decreased after the policy was implemented in California. There was a significant negative effect of the interaction term, supporting the fundamental claim of the paper; RFG II reduces ground-level pollution. With a simple difference-in-differences model excluding covariates the infant's birth weight for OLS and fixed effects was significant, however when clustered the interaction term became insignificant.

Table 3 shows the results from estimating (1) with the outcome variable, the effects of RFG II on infant's birth weight. The coefficients are listed with column (1) representing the full sample and shows a 3.9 gram increase in the birth weight, but is insignificant. Columns (2), (3), and (4) show the effect of the policy based off the race of the mother. Column (2) and (3) were found to be significant showing that White and Black mothers have infants with 8.8 and 20.9 gram increases, respectively, from the policy being in place. Column (4) shows that the other race had a negative interaction value, but was insignificant. White compared to other races had the highest birth weight, with infants being more than 100 grams compared to Other and 250 grams greater compared to Blacks.

Table 4 includes all the covariates in the regression and we find that the policy has a positive coefficient increasing the birth weight. However, columns (1), (2), and (4) show insignificant results with 2.2, 5.2, and 0.2 gram increases in birth weight from the policy, respectively. Column (3) had the largest significant effect with Black having a 23.7 gram increase in birth weight. This table also showed the effect of the child's gender, where having a male translates to a higher birth weight compared to female infants. The mother's education also plays a role and is shown in the table that when the mother has at least gone to college the infant has a higher birth weight, compared to not having gone to college. The mother's age provides the biggest increase in birth weight as they come to an optimal age to have an infant. Again, the White mothers have the highest birth weight among the three race groups.

In table 5 low birth weight was then imputed as the dependent variable in the logistic regression, with "1" meaning the infant had a low birth weight. Initial results show the interaction term is negative for all columns, which provides evidence towards the policy helping to reduce the chance of an infant being born with a low birth weight. However, most of the marginal effects shown have an insignificant value. Column (3) represents the White mother's and shows that with the policy there is a significant 0.04-percentage point decrease in giving birth to a low birth weight infant. Low birth weight decreases at a larger percentage for infants with a Black mother, by having a decrease of 0.11 percentage points in column (4). Resulting in a change of 0.073%. Being male for all columns showed to reduce the chance of the infant having a low birth weight.

A logistic regression is used again for the binary variable infant mortality. Table 6 presents the effects of the policy on infant mortality. From column (1), which includes the basic difference-in-differences estimation's marginal fixed effects we find a 0.08-percentage point decrease when the policy was in effect. Each column in the table has a significant interaction term which shows the policy had a negative effect on the infant mortality rate, except for column (5) which is the Other race category. The remaining variables were included in column (2) and the interaction coefficient had a 0.082-percentage point decrease in the infant mortality rate when the policy was put into effect. The White and Black category have a decrease in infant mortality by 0.07 and 0.13 percentage points, respectively. Resulting in a change of 9.6 and 7.7% for White and Black mothers, respectively. The Other category had an increase, however as stated previously is insignificant. Male infants had a positive coefficient and thus are seen to have a higher likelihood of dying in the first year than females. The model finds a mother with a low education level will have a higher likelihood of having an infant die within the first calendar year. As the education level increases the likelihood decreases and becomes negative, representing the importance of education for mother's as well. Marital status is important, when the mother is married the infant has a higher likelihood of being alive.

Finally, table 6 represents the policy's effect on gestational length in weeks using the standard OLS model with all the previous maternal and infant characteristics used. The interaction term is positive in the difference-in-differences estimator for the fixed effects models. Column (1) shows a significant interaction term, but results in a .042 weeks increase in gestation length translating to less than a day. When separating regressions by race, White mothers had an effect of 0.08 weeks compared with Other and Black mothers who had 0.04 and 0.03 weeks respectively. However, the interaction coefficient for both Black and Other mothers was insignificant in the analysis. Prenatal care beginning in the third trimester seemed to cause a higher gestational length compared to mother's who began in their first or second trimester.

# 6 Conclusion

The results suggest that the implementation of the policy led to improvements in infant health. A few different approaches were used with different health indicators and the conclusion remained consistent. The magnitude of the effects reported are subject to criticism due to other policies used within California possibly diminishing the effect of RFG II. An example of this comes from Neidell (2009) where people responded to air quality alerts by decreasing visits to outdoor facilities. Other states used different regulatory standards to help improve air quality, and even though only Arizona was found to be the same, other policies may have helped to diminish the effect of RFG II along with other forms of transportation. However, these negative relationships on infant health indicators are still able to show that with less pollution infants have a higher birth weight, longer gestational length, less likelihood of dying early, and less likelihood of having a low birth weight. The policy impacted infants with Black mothers the greatest because they had a large increase in birth weight, along with a decrease in the likelihood of having a low birth weight and mortality rate. This group had the largest effects for three of the four indicators tested. The White mother's category also had significant outcomes, while the Other mothers category may have been too bunched with minorities to have a true effect. The Other category may have also driven the insignificance when all race groups were grouped together. However, we may still conclude that the policy was significant in improving air quality and the health of infants.

A simple approach was used to help calculate the effect of a policy on infant health indicators. A difference-in-differences OLS and logit model were used, which included county and year fixed effects along with county level clusters. The policy reduced the amount of ozone in the air and from this we can conclude air quality improved, because other toxins are needed to produce ozone. The estimated cost of a human life regardless of the demographic is $7.4 million (2006 dollars) (EPA, 2016b). The infant mortality rate with respect to the data set was 0.78% and by implementing the policy led to a 0.083 percentage point decrease. This would result in a 10.6% decrease in the infant mortality rate and save approximately 5,034 infants in the sample data set. Translating to $37 billion (2006 dollars) being saved. This would save upwards of $37 billion (2006 dollars) with respect to lives. Gasoline prices will rise from the reformulation, however a cost-benefit analysis can be used to gauge the policies effectiveness. Vehicles have become a necessity for everyday life and so we find ourselves dependent on them, however, it is important to help diminish the negative externality caused on the environment by creating policies that reduce pollution levels.

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# 8 Tables

Table 1: Summary Statistics by Treatment

| | Non-California | California | Total |
|---|---|---|---|
| Birth Weight | 3295.3 | 3360.6 | 3316.4 |
| (grams) | (618.4) | (580.2) | (607.1) |
| Low Birth Weight | 0.0827 | 0.0609 | 0.0757 |
| (grams) | (0.275) | (0.239) | (0.264) |
| Mortality Rate | 0.00734 | 0.00551 | 0.00675 |
| | (0.0854) | (0.0740) | (0.0819) |
| Gestational Age | 38.79 | 39.00 | 38.86 |
| (weeks) | (2.701) | (2.487) | (2.636) |
| Treatment Group | 0 | 1 | 0.323 |
| | (0) | (0) | (0.468) |
| Post Period | 0.644 | 0.620 | 0.636 |
| | (0.479) | (0.485) | (0.481) |
| Treatment*Post | 0 | 0.620 | 0.200 |
| | (0) | (0.485) | (0.400) |
| Mother's Prenatal Care | 1.191 | 1.205 | 1.195 |
| | (0.503) | (0.494) | (0.500) |
| Mother's Race | 1.434 | 1.267 | 1.380 |
| | (0.795) | (0.587) | (0.738) |
| Mother's Age | 27.44 | 27.41 | 27.43 |
| | (6.134) | (6.195) | (6.154) |
| Mother's Age Squared | 790.5 | 789.8 | 790.3 |
| | (343.0) | (349.1) | (345.0) |
| Married | 0.688 | 0.680 | 0.686 |
| | (0.463) | (0.467) | (0.464) |
| Male | 0.512 | 0.512 | 0.512 |
| | (0.500) | (0.500) | (0.500) |
| Mother's Education | 3.448 | 3.115 | 3.340 |
| | (1.197) | (1.298) | (1.240) |

| | | | |
|---|---|---|---|
| EPA 8-hour Reading | 0.0372 | 0.0415 | 0.0386 |
| | (0.0131) | (0.0162) | (0.0143) |
| Max Ozone | 0.0429 | 0.0514 | 0.0456 |
| | (0.0153) | (0.0203) | (0.0175) |
| Rain | 11.53 | 4.401 | 9.232 |
| (mean) | (9.094) | (7.825) | (9.322) |
| Snow | 0.497 | 0.0326 | 0.347 |
| (mean) | (1.869) | (0.479) | (1.577) |
| Min. Temp. | 50.32 | 51.92 | 50.84 |
| (mean) | (16.54) | (7.651) | (14.31) |
| Max. Temp. | 70.06 | 74.85 | 71.61 |
| (mean) | (17.21) | (9.800) | (15.38) |
| First Trimester | 0.0367 | 0.0415 | 0.0382 |
| EPA 8-hour Reading | (0.0114) | (0.0153) | (0.0130) |
| Second Trimester | 0.0372 | 0.0421 | 0.0388 |
| EPA 8-hour Reading | (0.0116) | (0.0153) | (0.0131) |
| Third Trimester | 0.0375 | 0.0422 | 0.0390 |
| EPA 8-hour Reading | (0.0115) | (0.0150) | (0.0129) |

mean coefficients; sd in parentheses

Table 2: Summary Statistics by Period

| | Before Policy | After Policy | Total |
|---|---|---|---|
| Birth Weight | 3326.4 | 3310.6 | 3316.4 |
| (grams) | (606.0) | (607.6) | (607.1) |
| Low Birth Weight | 0.0736 | 0.0768 | 0.0757 |
| (grams) | (0.261) | (0.266) | (0.264) |
| Mortality Rate | 0.00764 | 0.00624 | 0.00675 |
| | (0.0871) | (0.0788) | (0.0819) |
| Gestational Age | 38.99 | 38.78 | 38.86 |
| (weeks) | (2.678) | (2.609) | (2.636) |
| Treatment Group | 0.338 | 0.314 | 0.323 |
| | (0.473) | (0.464) | (0.468) |
| Post Period | 0 | 1 | 0.636 |
| | (0) | (0) | (0.481) |
| Treatment*Post | 0 | 0.314 | 0.200 |
| | (0) | (0.464) | (0.400) |
| Mother's Prenatal Care | 1.228 | 1.177 | 1.195 |
| | (0.542) | (0.474) | (0.500) |
| Mother's Race | 1.388 | 1.375 | 1.380 |
| | (0.751) | (0.731) | (0.738) |
| Mother's Age | 27.05 | 27.64 | 27.43 |
| | (5.951) | (6.256) | (6.154) |
| Mother's Age Squared | 767.3 | 803.4 | 790.3 |
| | (329.4) | (352.9) | (345.0) |
| Married | 0.699 | 0.678 | 0.686 |
| | (0.459) | (0.467) | (0.464) |
| Male | 0.512 | 0.512 | 0.512 |
| | (0.500) | (0.500) | (0.500) |
| Mother's Education | 3.271 | 3.380 | 3.340 |
| | (1.220) | (1.249) | (1.240) |
| EPA 8-hour Reading | 0.0387 | 0.0385 | 0.0386 |

| | | | |
|---|---|---|---|
| | (0.0155) | (0.0136) | (0.0143) |
| Max Ozone | 0.0468 | 0.0450 | 0.0456 |
| | (0.0197) | (0.0161) | (0.0175) |
| Rain | 8.950 | 9.394 | 9.232 |
| (mean) | (8.996) | (9.499) | (9.322) |
| Snow | 0.276 | 0.387 | 0.347 |
| (mean) | (1.017) | (1.820) | (1.577) |
| TempMin | 50.13 | 51.24 | 50.84 |
| (mean) | (14.30) | (14.29) | (14.31) |
| TempMax | 71.21 | 71.83 | 71.61 |
| (mean) | (15.29) | (15.43) | (15.38) |
| First Trimester | 0.0384 | 0.0381 | 0.0382 |
| EPA 8-hour Reading | (0.0139) | (0.0124) | (0.0130) |
| Second Trimester | 0.0396 | 0.0383 | 0.0388 |
| EPA 8-hour Reading | (0.0142) | (0.0124) | (0.0131) |
| Third Trimester | 0.0398 | 0.0385 | 0.0390 |
| EPA 8-hour Reading | (0.0141) | (0.0122) | (0.0129) |

mean coefficients; sd in parentheses

Table 3: Simple OLS Difference-in-Difference Regression with Birth Weight

| | All | White | Black | Other |
|---|---|---|---|---|
| | b/se | b/se | b/se | b/se |
| Treatment*Post | 3.870 | 8.803$^{*}$ | 20.920$^{***}$ | -1.493 |
| | (3.24) | (3.53) | (5.19) | (4.41) |
| White Mother | 0.000 | | | |
| | (.) | | | |
| Other Mother | -139.025$^{***}$ | | | |
| | (5.81) | | | |
| Black Mother | -253.706$^{***}$ | | | |
| | (6.18) | | | |
| constant | 3340.786$^{***}$ | 3358.890$^{***}$ | 3039.365$^{***}$ | 3257.709$^{***}$ |
| | (3.12) | (1.41) | (3.87) | (3.64) |
| N | 6038114 | 4627274 | 1037937 | 372903 |

All regressions include county and year level fixed effects

Standard errors are clustered with 186 counties

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Table 4: OLS Difference-in-Difference Regression with Birth Weight

| | All Vars. b/se | White b/se | Black b/se | Other b/se |
|---|---|---|---|---|
| Treatment*Post | 2.163 | 5.242 | 23.694*** | 0.157 |
| | (3.44) | (3.97) | (4.26) | (4.48) |
| Male | 113.504*** | 116.211*** | 110.555*** | 87.626*** |
| | (0.84) | (1.06) | (1.36) | (1.60) |
| Mother's Age | 27.396*** | 33.166*** | 15.050*** | 36.642*** |
| | (2.06) | (2.19) | (1.89) | (1.83) |
| Mother's Age Squared | -0.458*** | -0.543*** | -0.331*** | -0.545*** |
| | (0.03) | (0.03) | (0.03) | (0.03) |
| Married | 73.382*** | 69.066*** | 93.679*** | 13.569*** |
| | (4.11) | (4.26) | (3.49) | (3.60) |
| 0-8 years Education | 0.000 | 0.000 | 0.000 | 0.000 |
| | (.) | (.) | (.) | (.) |
| 9-11 years Education | -36.138*** | -33.892*** | -29.231*** | 11.433 |
| | (2.72) | (3.11) | (8.07) | (8.64) |
| 12 years Education | -5.826 | -4.730 | 10.377 | 24.702** |
| | (4.35) | (4.74) | (8.87) | (8.67) |
| 13-15 years Education | 19.714** | 22.325** | 41.912*** | 12.524 |
| | (6.08) | (6.73) | (9.67) | (8.68) |
| $\geq$ 16 years Education | 36.896*** | 40.420*** | 79.611*** | 1.158 |
| | (7.70) | (8.02) | (12.02) | (9.52) |
| No Prenatal Care | 0.000 | 0.000 | 0.000 | 0.000 |
| | (.) | (.) | (.) | (.) |
| $1^{st}$ Trimester Prenatal Care | 293.601*** | 242.143*** | 369.415*** | 208.590*** |
| | (14.10) | (15.04) | (12.02) | (16.50) |
| $2^{st}$ Trimester Prenatal Care | 287.078*** | 235.559*** | 364.755*** | 208.934*** |
| | (14.03) | (15.07) | (11.12) | (16.32) |
| $3^{st}$ Trimester Prenatal Care | 294.985*** | 233.656*** | 393.134*** | 227.105*** |
| | (14.23) | (14.55) | (10.67) | (17.11) |
| White Mother | 0.000 | | | |
| | (.) | | | |
| Other Mother | -159.572*** | | | |
| | (5.66) | | | |
| Black Mother | -193.107*** | | | |
| | (5.26) | | | |
| constant | 2526.915*** | 2501.806*** | 2415.204*** | 2397.941*** |
| | (25.28) | (28.20) | (26.13) | (32.54) |
| N | 5703776 | 4388922 | 964971 | 349883 |

All regressions include county and year level fixed effects

Standard errors are clustered with 186 counties

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Logit Difference-in-Difference Regression with Low Birth Weight

| | All Vars. | White | Black | Other |
|---|---|---|---|---|
| | b/se | b/se | b/se | b/se |
| Treatment*Post | -0.027 | -0.043* | -0.108*** | -0.011 |
| | (0.02) | (0.02) | (0.02) | (0.03) |
| Male | -0.147*** | -0.128*** | -0.198*** | -0.116*** |
| | (0.00) | (0.01) | (0.01) | (0.01) |
| Mother's Age | -0.076*** | -0.109*** | -0.013 | -0.162*** |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| Mother's Age Squared | 0.002*** | 0.002*** | 0.001*** | 0.003*** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Married | -0.290*** | -0.275*** | -0.309*** | -0.201*** |
| | (0.01) | (0.01) | (0.01) | (0.02) |
| 0-8 years Education | 0.000 | 0.000 | 0.000 | 0.000 |
| | (.) | (.) | (.) | (.) |
| 9-11 years Education | 0.191*** | 0.185*** | 0.034 | 0.149*** |
| | (0.01) | (0.02) | (0.03) | (0.04) |
| 12 years Education | 0.094*** | 0.096*** | -0.108** | 0.066* |
| | (0.02) | (0.02) | (0.04) | (0.03) |
| 13-15 years Education | 0.001 | -0.008 | -0.214*** | 0.115*** |
| | (0.03) | (0.03) | (0.04) | (0.03) |
| $\geq$ 16 years Education | -0.140*** | -0.159*** | -0.359*** | 0.060 |
| | (0.03) | (0.03) | (0.05) | (0.04) |
| No Prenatal Care | 0.000 | 0.000 | 0.000 | 0.000 |
| | (.) | (.) | (.) | (.) |
| 1st Trimester Prenatal Care | -0.968*** | -0.930*** | -0.984*** | -0.897*** |
| | (0.03) | (0.04) | (0.03) | (0.06) |
| 2nd Trimester Prenatal Care | -0.963*** | -0.934*** | -0.972*** | -0.890*** |
| | (0.03) | (0.04) | (0.03) | (0.06) |
| 3rd Trimester Prenatal Care | -1.114*** | -1.068*** | -1.155*** | -0.969*** |
| | (0.03) | (0.04) | (0.03) | (0.07) |
| White Mother | 0.000 | | | |
| | (.) | | | |
| Other Mother | 0.183*** | | | |
| | (0.02) | | | |
| Black Mother | 0.565*** | | | |
| | (0.03) | | | |
| constant | -0.394*** | 0.035 | -0.504*** | 0.867*** |
| | (0.10) | (0.08) | (0.11) | (0.20) |
| N | 5703776 | 4388922 | 964912 | 349833 |

All regressions report marginal effects

All regressions include county and year level fixed effects

Standard errors are clustered with 186 counties

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Logit Difference-in-Difference Regression with Infant Mortality

| | All Vars. b/se | White b/se | Black b/se | Other b/se |
|---|---|---|---|---|
| Treatment*Post | -0.082** | -0.065* | -0.125* | 0.007 |
| | (0.03) | (0.03) | (0.06) | (0.09) |
| Male | 0.205*** | 0.214*** | 0.185*** | 0.224*** |
| | (0.01) | (0.01) | (0.02) | (0.04) |
| Mother's Age | -0.072*** | -0.112*** | -0.003 | -0.112** |
| | (0.01) | (0.01) | (0.01) | (0.04) |
| Mother's Age Squared | 0.001*** | 0.002*** | 0.000 | 0.002*** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Married | -0.315*** | -0.328*** | -0.225*** | -0.456*** |
| | (0.02) | (0.02) | (0.02) | (0.07) |
| 0-8 years Education | 0.000 | 0.000 | 0.000 | 0.000 |
| | (.) | (.) | (.) | (.) |
| 9-11 years Education | 0.069*** | 0.112*** | -0.093 | 0.042 |
| | (0.02) | (0.03) | (0.06) | (0.09) |
| 12 years Education | 0.005 | 0.009 | -0.134* | -0.006 |
| | (0.02) | (0.03) | (0.05) | (0.09) |
| 13-15 years Education | -0.130*** | -0.137*** | -0.256*** | -0.207* |
| | (0.04) | (0.04) | (0.06) | (0.09) |
| $\geq$ 16 years Education | -0.360*** | -0.386*** | -0.356*** | -0.303** |
| | (0.04) | (0.04) | (0.06) | (0.10) |
| No Prenatal Care | 0.000 | 0.000 | 0.000 | 0.000 |
| | (.) | (.) | (.) | (.) |
| 1$^{st}$ Trimester Prenatal Care | -1.182*** | -1.242*** | -1.127*** | -1.228*** |
| | (0.03) | (0.04) | (0.03) | (0.15) |
| 2$^{nd}$ Trimester Prenatal Care | -1.237*** | -1.252*** | -1.269*** | -1.119*** |
| | (0.03) | (0.04) | (0.04) | (0.14) |
| 3$^{rd}$ Trimester Prenatal Care | -1.379*** | -1.365*** | -1.468*** | -1.162*** |
| | (0.05) | (0.06) | (0.06) | (0.16) |
| White Mother | 0.000 | | | |
| | (.) | | | |
| Other Mother | -0.026 | | | |
| | (0.03) | | | |
| Black Mother | 0.516*** | | | |
| | (0.03) | | | |
| constant | -2.118*** | -1.460*** | -2.499*** | -1.432** |
| | (0.10) | (0.12) | (0.17) | (0.48) |
| N | 5703776 | 4388922 | 963841 | 342480 |

All regressions report marginal effects

All regressions include county and year level fixed effects

Standard errors are clustered with 186 counties

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: OLS Difference-in-Difference Regression with Gestational Length

| | All Vars. b/se | White b/se | Black b/se | Other b/se |
|---|---|---|---|---|
| Treatment*Post | 0.042** | 0.077*** | 0.032 | 0.026 |
| | (0.02) | (0.01) | (0.04) | (0.03) |
| Male | -0.125*** | -0.132*** | -0.075*** | -0.172*** |
| | (0.00) | (0.00) | (0.01) | (0.01) |
| Mother's Age | 0.069*** | 0.071*** | 0.056*** | 0.134*** |
| | (0.00) | (0.00) | (0.01) | (0.01) |
| Mother's Age Squared | -0.002*** | -0.002*** | -0.002*** | -0.003*** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Married | 0.150*** | 0.119*** | 0.242*** | 0.157*** |
| | (0.01) | (0.01) | (0.01) | (0.02) |
| 0-8 years Education | 0.000 | 0.000 | 0.000 | 0.000 |
| | (.) | (.) | (.) | (.) |
| 9-11 years Education | -0.058*** | -0.049*** | 0.012 | 0.012 |
| | (0.01) | (0.01) | (0.04) | (0.03) |
| 12 years Education | 0.007 | 0.007 | 0.101** | 0.048 |
| | (0.01) | (0.01) | (0.04) | (0.04) |
| 13-15 years Education | 0.047** | 0.043** | 0.171*** | 0.051 |
| | (0.01) | (0.02) | (0.04) | (0.04) |
| $\geq$ 16 years Education | 0.144*** | 0.147*** | 0.272*** | 0.112** |
| | (0.02) | (0.02) | (0.04) | (0.04) |
| No Prenatal Care | 0.000 | 0.000 | 0.000 | 0.000 |
| | (.) | (.) | (.) | (.) |
| $1^{st}$ Trimester Prenatal Care | 1.344*** | 1.011*** | 1.843*** | 1.039*** |
| | (0.08) | (0.08) | (0.06) | (0.11) |
| $2^{nd}$ Trimester Prenatal Care | 1.407*** | 1.100*** | 1.843*** | 1.106*** |
| | (0.08) | (0.08) | (0.07) | (0.10) |
| $3^{rd}$ Trimester Prenatal Care | 1.566*** | 1.208*** | 2.132*** | 1.261*** |
| | (0.09) | (0.08) | (0.07) | (0.10) |
| White Mother | 0.000 | | | |
| | (.) | | | |
| Other Mother | -0.164*** | | | |
| | (0.02) | | | |
| Black Mother | -0.572*** | | | |
| | (0.01) | | | |
| constant | 36.915*** | 37.311*** | 35.749*** | 35.880*** |
| | (0.08) | (0.10) | (0.11) | (0.18) |
| N | 5633167 | 4333815 | 956148 | 343204 |

All regressions include county and year level fixed effects

Standard errors are clustered with 186 counties

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$