The Effect of Income Expansion on Health: Observed by Using the 2009 Expansion of the Earned Income Tax Credit as a Source of Exogenous Variation

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Abstract: The purpose of this study is to use the 2009 expansion of the Earned Income Tax Credit as a source of exogenous variation in income to study the effects of income on childbirth health outcomes. The 2009 expansion increased benefits to families with 3 or more children and therefore allows me to conduct a difference-in-differences model where families with 2 children or less serve as a control group. In theory, the families with 3 or more children would have received a relatively larger increase in disposable income than the families with less than 3 children. This relative increase in income, should allow these families better access to nutrition, healthcare, and exercise. Using data from the 2007 and 2011 Natality Detail File, I will support my hypothesis that the 2009 ARRA expansion will have provided enough disposable income to decrease gestational diabetes and hypertension and normalize infant birth weight as well. In addition to my difference-in-differences models that will be based on binary dependent variables, I will also use quantile regression techniques on birthweight, which is coded as a continuous variable.

Introduction

 From 1960-1973 the payroll tax rate increased from 3 percent to 5.8 percent. This in combination with the economic recession of the mid 1970’s brought attention to the growing tax burden of low-wage workers and allowed the Earned Income Tax Program to be relevant amongst the current political agenda (Hotz 2003, p 144). Politicians on both sides of the aisle pushed for welfare reform in concert with the rhetoric of the War on Poverty and Great Society programs of the era. Despite having similar goals, policy makers in the 1970’s struggled to agree on how these anti-poverty programs should be carried out. Where Republicans and Democrats disagreed about the workforce incentives and cost effectiveness of the guaranteed subsidy programs, the Earned Income Tax Credit (EITC) was one of the few welfare programs that could achieve largely bipartisan support at the time. In the context of negative income tax schemes that were being proposed at the time, the EITC provided resolution for the welfare diatribe by rewarding families that worked to lift themselves out of poverty.

The EITC program has grown faster than any other federal anti-poverty program. In 1975, the first year that the EITC was part of the Federal tax code, $3.9 billion dollars’ worth of credits were given out (Hotz 2003, p 141). 25 years later, the EITC outlays for the year 2000 had reached $31.5 billion dollars. This is just $4 billion dollars short of the combined spending on Temporary Assistance for Needy Families (TANF) and food stamps (Hotz 2003, p 141). While the maximum value of the credit that was initially afforded in 1975 was only $400, the program has been adjusted to mirror cost-of-living increases and inflation changes, allowing for a maximum credit of $6,318 to be claimed in the year 2017 (Tax Policy Center 2017).

As part of the American Recovery and Reinvestment Act passed in 2009 during the Obama administration, the EITC was expanded with provisions targeting 2 groups, married couples and families with 3 or more qualifying children. The ARRA expansion to the EITC provides a “third tier” of the credit for families with 3 or more children where the credit phases in at 45 percent of earned income. Previously families with 3 or more children phased in at 40 percent, which is the same percentage as families with only 2 qualifying children. Appendix A contains a visual explanation of the third child tier and further clarification on how the credit phase-in, flat range, and phase-out periods augment household income.

 The addition of this third tier was estimated to increase the amount of the EITC that large families could claim by a total of $2.2 billion. Americans in all 50 states were eligible for expanded benefits, causing 20% of all EITC eligible tax units to see an increase in their credit value nationwide. In addition, the passage of the 2009 ARRA EITC expansion was estimated to have made over 900,000 families to become eligible for EITC benefits for their first time (Kneebone 2009)( Leibenluft 2015). Cost-benefit analysis conducted by the US treasury from the year 2015 estimates that 3.2 million families were able to benefit from the third child schedule provided by the ARRA in the 2016 tax year (US Dept. of Treasury 2015). Relevant to this paper, families with 3 or more children will be used as a treatment group to study the effects of the 2009 expansion on health indicators.

Appendix B compares the 2016 EITC schedules for married families claiming one, two, or three or more children respectively. Notice, the maximum value of the credit for a married couple claiming one child is $3373, claiming two children qualifies for a maximum credit of $5572, and claiming three or more children earns a maximum credit of $6269. This means in the context of the 2016 schedule, families with 3 or more children qualify for approximately 12.5% more disposable income granted by the EITC as a direct result of the third schedule added by the 2009 ARRA expansions. Furthermore, the phase-in rate for families claiming a third child is 5% higher than the phase-in rate for the two-child schedule, granting faster poverty relief for large families than what would have previously been possible prior to the ARRA expansion.

The purpose of this paper is to use the 2009 expansion of the Earned Income Tax Credit program as a source of exogenous variation in income to understand the link between family income and health indicators. I hypothesize that the increased family income represented by the expansion of the EITC will correspond with lower incidence of low birth weight and lower incidence of gestational hypertension and diabetes. The extra disposable income provided by the expansion in the tax credit should allow for increased access to healthcare and relieve financial burdens that cause stress related health problems among poor households. Evidence has shown that simply being poor can easily cause stress on mothers and thereby foster poorer health decisions and conditions for children. Maternal depression and poor nutrition are leading factors in poor attention spans and impaired development in children (Hamad and Rehkpof 2016). Poor neighborhoods generally have worse access to nutrition and the higher crime rates associated with poor areas often discourage people from exercising. Therefore, increased income may allow families to relocate to safer neighbors that are less affected by crime and drug trafficking (Conway 2016). Even a small increase in disposable income may allow mothers to access better nutrition, healthcare, or allow them to exchange 1 hour of time worked for 1-hour of time spent exercising.

Literature Review

In comparison to wage neutral welfare subsides in the form of guaranteed annual transfers of income, the Earned Income Tax Credit has the advantage of minimizing distortions to work incentives by rewarding households that seek to increase work hours. The Earned Income Tax Credit is a refundable tax credit that reduces a family’s tax burden by a specified amount. If the amount of the tax credit exceeds the family’s tax liability, the family will receive a check from the government for the difference. By reducing the family’s tax burden, their disposable income is increased and therefore the Earned Income Tax Credit behaves as an employee targeting earnings subsidy (Dickert-Conlin and Holtz-Eakin 1999). To qualify for the Earned Income Tax Credit, the family must have at least one worker, so unlike guaranteed transfers, benefits are only received by those who work. The EITC credit also grants additional bonuses for families that claim “qualifying children”. To be a “qualifying child”, the child must be either under 19, under 24 and a full-time student, or disabled. The parent must also be the legal guardian of the child to claim them and the child must live with the claimant at least 6 months of the year (Hotz 2003). According to White House estimates, nearly 8 million qualifying children are claimed each year (Leibenluft 2015).

 The earned income tax credit works by creating three phases that are tailored to different qualifying levels of income and family size with the intent of eventually elevating the family’s income to the point where financial assistance is no longer necessary. Appendix A contains a graphic that explains the three different income ranges of eligibility for the (EITC).

Several adjustments have been made to the federal EITC since it was first enacted in 1975. Legislation in 1978 made the EITC a permanent part of US tax code and added the flat range to the EITC’s phase-in and phase-out ranges, a feature which still exists today. Initially the 1978 legislation did not index the EITC for inflation and as a result the tax credit had diminished in real value substantially by the mid 1980’s. This was remedied by the Tax Reform Act of 1986 (TRA86) which indexed the credit for inflation and increased the value of the credit enough so that the real value of the EITC was equivalent to the initial 1975 values. While the earned income tax credit was originally introduced by Republicans and had bipartisan support, expansion of the EITC has been the hallmark of Democrat politicians since the 1990’s. In 1991, the EITC was amended to include larger benefits for families with 2 or more children for the first time ever. The EITC was again expanded at an unprecedented magnitude with the passage of the Omnibus Budget Reconciliation Act of 1993 (OBRA) under the Clinton administration. This expansion was phased in between 1994-1996 and was largest expansion the credit had ever received (Baughman and Dickert-Conlin 2003) (Hotz 2003). While the credit had previously only been applicable to tax units claiming children, 1994 also marked the first year that an earned income tax credit was available to childless tax units.

As of 2009, 22 states as well as Washington DC, New York City, and Montgomery County Maryland had enacted some form of EITC similar as a supplement to the Federal EITC (Mason 2012). These state tax credits are intended to “piggyback” on the Federal EITC and are usually set up with the same eligibility definitions as the Federal one. State EITC’s are also calculated as percentages of the Federal EITC and allow claimants to apply for the state credit at the same time as applying for the Federal credit (Levitis and Koulish 2008). The Federal EITC is also unique in comparison to other programs in that it operates independently of transfer programs and therefore has little interaction with other Federal anti-poverty programs. Furthermore, applying for the EITC only requires the household to file their taxes, which they should be expected to do even if they weren’t applying for the tax credit. This has the benefit of minimizing non-compliance as well as being a cost-efficient way for the IRS to administer the program (Hotz 2003). Non-compliance issues that do sometimes arise in the filing for the EITC usually pertain to households that inappropriately claim qualifying children or when multiple households accidentally claim the same child.

One of the desired policy goals of the ARRA expansion was to help redress the marriage penalty that existed under current EITC scheduling. The “marriage penalty” refers to the phenomenon under the previous tax code where the EITC would require married couples to report their joint income, resulting in the tax credit being reduced to a value below what they would have been able to acquire had the couple filed separately. The EITC targets low-income families with children; in the event that a working parent that qualifies for the full value of the EITC marries another worker, a marriage penalty would occur in the form of the credit value being reduced as a result of the newly combined household income of the two parents (Ellwood and Sawhill 2009). Using data from the Survey of Income and Program Participation, Dickert-Conlin and Houser (2002) find evidence that married women with children facing large increases in their EITC are more likely to divorce. To reduce the “marriage penalty”, the tax credit phase out threshold was increased for married couples to $5,000 above the amount for unmarried filers in the American Recovery and Reinvestment Act (Kneebone 2009). A marriage incentive that has still yet to be resolved is the marriage reward that occurs when a non-working mother considers marrying a working man. In this scenario the newly wed, non-working mother would expect the value of the household’s credit to increase as a reflection of the wage augmenting feature of the EITC (Dickert-Conlin and Houser 2002).

Whether or not the EITC creates a “natality” incentive has also been researched by scholars. If this natality incentive truly does exist, then EITC-like policies could be viewed as a pro-natalist policy tool with the capability of increasing birthrates in areas where birthrates are otherwise declining. The existence of a natality effect created by the EITC would also threaten the exogeneity of the treatment variables in my model. Baughman and Dickert-Conlin (2003) try to isolate the natality effect by using 1990’s data from the Natality Detail File and find a very small but significant natality effect for both married and unmarried women without children. This means that a woman who is EITC eligible without any children, may be inclined to have a child regardless of her marital status so that she may gain the increased disposable income granted by the EITC. Baughman and Dickert-Conlin (2003) also postulate that there may also be a natality incentive for mothers of higher birth order but are unable to come up with a model that reveals this effect. A critical assumption of the Baughman/Dickert-Conlin model (2003) is that the number of children is exogenous to the value of the credit and that the same value of the credit applies to all EITC eligible tax units. This assumption is not realistic or applicable to my hypothesis that variation in the value of the EITC will have a causal relationship with the health of eligible mothers. In reality the value of the credit is dependent on the number of children claimed and childless tax units have been eligible to receive some EITC benefits since 1994.

In relation to this, researchers have found evidence that expansions of the EITC are associated with declining rates of abortion (Herbst 2011). The increased income provided by the expanded tax credit is believed to reduce unplanned pregnancies via increased access to contraceptives. Therefore, scholars studying the link between the EITC and abortion have argued that the reduction of abortions reflects a reduction in unplanned pregnancies rather than an increase in babies born. Herbst (2011) argues that the expansion influences sexual behavior rather than altering abortion decisions after the pregnancy has occurred. Given the various conclusions about whether the EITC creates a natality incentive, it is acceptable to argue that there is a natality incentive created that may apply to some groups of individuals but not others. However, researchers are unable to agree upon how large this incentive is and who it applies to. For example, in the Baughman & Dickert-Conlin(2007) paper the researchers argue that EITC expansions suggest reductions in fertility for white women while on the other hand, Duchovny(2001) finds in her paper that married white women are the only group who do experience a positive natality incentive resulting from the expanded EITC (Duchovny 2001).

In 2015, the 2009 ARRA expansion to the EITC was made permanent as part of a budget agreement passed by Congress. At the time of the passage of this budget agreement, the 2009 ARRA expansion was estimated to have provided an average of $600-$900 of additional disposable income to approximately 16 million working class families (Kneebone 2009)(Leibenluft 2015). Among these 16 million families it is estimated that approximately 5 million Latino families, 2 million African American, 1 million veterans, 2.6 million rural families and more than 6 million millennial workers benefited from the expanded EITC (Leibenluft 2015).

The EITC is particularly useful to economists who are interested in studying the effects of income on family and household indicators because it represents a change in income that is completely exogenous. Consider the example where a researcher is trying to isolate the effect of increased household income on an indicator for household health. Including panel household income data in a regression is inappropriate because income is endogenously determined. Factors such as parental health, geographic location, and parental education level would be expected to be independent variables in the regression but would also be expected to influence levels of income. Furthermore, the coefficients of the model will likely capture the effects of unobserved variables that will change both income and the dependent variable. The unobserved factors affecting income will create an omitted variable bias, therefore observed income cannot be used in this model. However, expansions of the EITC provide opportunities for economists to conduct natural experiments pertaining to the effects of income and the generosity of EITC programs serve as an instrument that represents exogenous variation in income.

In order to eliminate bias caused by omission of unobserved family and child characteristics, several studies have used EITC expansions as a source of exogenous income variation to illuminate causal effects of enhanced income on several household wellness indicators. Dahl and Lochner (2005) found that a $1,000 dollar increase in the EITC corresponds with an increase of children’s math scores by 2.1% and reading scores by 3.6% of a standard deviation (Dahl and Lochner 2005). In this paper, researchers use a fixed effects instrumental variable approach to control for permanent and time dependent background family characteristics that are provided in the 1979 National Longitudinal Survey of Youth (NLSY) data set. The instrument they use is a complex vector based on features of the tax code and permanent family characteristics such as race and education. For example, Dahl and Lochner (2005) explain that black parents and parents with lower levels of education are more likely to benefit from the EITC. Dahl and Lochner (2005) also note that simply using a fixed effects model is not enough because even though it does help prevent the problems of omitted variable bias, using reported family income does not eliminate the attenuation bias caused by the fact that growth rates in income are noisily measured. The NLSY provides a lot of information on family income, but unfortunately it does not provide information about tax payments or if the family qualifies for the EITC. To overcome this, Dahl and Lochner(2005) were able to impute tax payment and tax burden by using the TAXSIM program provided by the NBER.

Also using the NLSY 1979 cohort, Schmeiser (2009) uses the generosity of state and federal EITC to study the effect of exogenous variation in income on rates of obesity. The increase in income was found to significantly increase the BMI and probability of being obese for women but not for men. According to the results of the model, real family income increases from 1990-2002 can explain between 10 and 21 percent of the increase in sample women’s BMI (Schmeiser 2009).

Using data from the Natality Detail File provided by the National Center for Health Statistics (NCHS), Kevin Baker(2008) exploits the 1993 expansion of the EITC to isolate statistically significant effects on birth weight and prenatal care decisions. Like the 2009 expansion, which disproportionately gave benefits to families with 3 or more children, the 1993 expansion expanded benefits for families with 2 or more children. Using a difference-in-difference approach where families with less than 2 children served as a control group and families with 2 or more children served as a test group, Baker(2008) provides support that the 1993 expansion had a significant reduction in the incidence of low birth weight and reduced the proportion of women that smoked during pregnancy. Conversely, the expansion was found to have little effect on number of prenatal visits by mothers (Baker 2008). In his model regarding low birth weight, a dummy variable is used to indicate when a child is born below 2,500 grams, the cutoff point for when children are considered low birth weight.

Alternatively, rather than viewing incidence of low birth weight as a threshold of above or below 2,500 grams, quantile regression has been used to study how various socioeconomic factors affect birthweight at different ends of the birthweight distribution. Koenker and Hallock (2001) find that the disparity between birthweight of male infants and female infants is significantly smaller at the low end of the birthweight distribution observing that on average “boys are about 45 grams larger at the 0.05 quantile but are about 130 grams larger at the 0.95 quantile” (Koenke and Hallock 2001, p 149). They note that the disparity between infants born to black and white mothers is significantly larger at lower quantiles, meaning that black mothers give birth to underweight babies at a higher rate than white mothers at all levels, but this disparity is at its largest in the lower quantiles of the birthweight distribution. The effect of Mother’s age on birthweight has a quadratic effect, with each year gained from ages 18-30 corresponding to higher birthweight averages but beyond age 30 each year gained corresponds with decreased birth weight (Koenke and Hallock, 2001). Given that my data set allows me to control for mother’s age and race, as well as the child’s gender, I predict that these relationships will be represented in my model. Interestingly, Koenke and Hallock (2011) found that mothers who had delayed their prenatal visits until later in the pregnancy often gave birth to babies with healthier birth weights. The authors attribute this to self-selection bias, where mothers who are feeling healthy are more confident about not going to the doctor.

Data

Data for this project comes from the Natality Birth Data provided by the National Center for Health Statistics (NCHS). The NCHS’ birth data is a part of the National Vital Statistics System (NVSS), which is one of the oldest inter-government data sharing programs in the US. Data is obtained through the NVSS via various contracts between the NCHS and vital registration systems located in jurisdictions around the country that are legally responsible for recording data pertaining to important life events such as births, deaths, marriages and divorces (CDCP 2017). The Natality Birth Data contains information from US women ages 15-44 recorded in all 50 states and the District of Columbia. The file also contains data from the US territories but for the purposes of this study, only the data from the 50 US states and DC will be used. The data is separated by year with data available from every year since 1968 and since 1985 all the data have been based on a 100 percent sample of birth certificates from all states and DC (Roth 2017). The main advantage of using a dataset constructed of birth certificates is that the data will provide a more complete depiction of birth rates in the US. This is because new mothers, particularly those with low income are more likely to drop out of other survey methods such as the Census or Current Population Survey (Baughman and Dickert-Conlin 2007).

The NCHS Natality Birth Data is useful because it contains demographic information such as educational attainment of parents, marital status, and race. More importantly, the Natality Birth Data includes health variables such as birth weight, apgar scores, and a variety of other variables to indicate if the baby is born with any health conditions. Unfortunately, the natality detail file does not contain any information about EITC eligibility or family income, making it impossible to precisely determine which mothers in the dataset qualify for the EITC. As a result of this, I am forced to use education as a proxy for EITC literature. The use of education as a proxy is well supported in the literature; Eissa and Hoynes (2003) find that 60% of married couples with less than a high school degree qualifies for the EITC compared to only 20% of high school graduates that qualify. In addition, Baughman and Dickert-Conlin (2007) find that 45% of the mothers without high school diplomas from the 1997 natality detail file qualify for the EITC. Of those eligible for the EITC, 81% of mothers with a high school degree or more are in the flat range or the phase-out range, compared to 71% of mothers without a high school degree. This means that conditional on qualifying for the EITC, women without high school degrees are more likely to be lower on the EITC schedule. I will therefore restrict my analysis to mothers in the Natality Detail File who have not completed high school.

The Natality Detail File provides data dating back to 1968, but the for the purposes of running a difference-in-differences model examining the effects of the 2009 ARRA expansion, I will only be using data from 2007 and 2011. Using education as a proxy for EITC eligibility, I will drop all observations recorded from mothers with high school diplomas to restrict the sample to mothers who likely qualify for the EITC credit. I will also drop all the observations with missing values recorded for birth weights and number of cigarettes smoked daily, resulting in 61,497 observations being dropped from the 2007 data and 44,455 observations being dropped from the 2011 data. These dropped observations represent 11% of the sample restricted to qualifying mothers in 2007 and 7.2 % of the sample restricted to qualifying mothers in 2011. The descriptive statistics of the dependent variables are detailed in table 1. Four of the dependent variables are dummy variables indicating whether the conditions are present at the time of child birth where 1 represents the presence of the undesirable health condition and 0 represents the absence. The last dependent variable is birthweight measure in grams, a continuous variable that will be used in the quantile regressions. In the Natality Detail File, Gestational Diabetes and Gestational Hypertension the three outcomes are coded as “no”, “yes”, and “unknown”. For ease of interpretation I recoded these as binary variables where “unknown” and “no” are both represented by zero. The number of observations that had ‘unknown’ recorded for any of the variables was so low that this change should be negligible.

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| **TABLE 1- Dependent Variables: Descriptive Statistics and Differences** |
|  | **Treatment (2007)** | **Treatment (2011)** | **Treatment After-Treatment Before** | **Control** **(2007)** | **Control** **(2011)** | **Control After- Control Before**  | **Double Difference (Change in Treatment-Change in Control)**  |
| Incidence of gestational diabetes  | 4.7 % of group | 6.4 % of group | 1.7 % of group | 2.6% of group | 3.5% of group | 0.9% of group | 0.8% of group |
| Incidence of gestational hypertension | 2.2% of group | 3.0 % of group | 0.8% of group | 3.3% of group | 4.0% of group | 0.7% of group | 0.1% of group |
| Average Birth Weight in grams | 3269.68(597.74) | 3251.28(600.42) | -18.4 | 3202.93(570.742) | 3183.88(571.19) | -19.05 | 0.65 |
| Incidence of low birth weight | 8.29% of group | 8.76% of group | 0.47% of group | 8.5% of group | 8.9% of group | 0.4% of group | 0.07% of group |
| Incidence of at risk fetal macrosomia | 1.29% of group | 1.24% of group | -0.5% of group | 0.6% of group | 0.59% of group | -.01% of group | -0.49 % of group |
| Total Observations | 186,539 | 233,786 |  | 292,472 | 331,921 |  |  |

Birthweight is coded as a continuous variable and will be treated as such in my quantile regressions. However, for my difference-In-differences probit models, low birthweight and high birthweight binary variables will be created in correspondence to predetermined thresholds of recorded birthweight. Low birthweight is defined as 1 for all births under 2500 grams and high birth weight is defined as 1 for all births over 4000 grams; which is the cut off point for being at risk for fetal macrosomia. For each respective binary dependent variable, observations that do not fall within the threshold of interest are coded as 0.

By itself, fetal macrosomia is not a condition to cause alarm, but it does have the potential to contribute to complications during delivery and additionally, children affected by fetal macrosomia are more likely to be obese and are more likely to contract metabolic syndrome later in childhood. Birth weight outcomes are important to monitor because the infant mortality rates are significantly higher than average for children with either low or high birth weight (Abrevaya and Dahl 2008)

Tables 2 and 3 contain descriptive statistics for my independent variables. Age of the mother and marital status are variables that have imputed values that were created by the NCHS. Similar to the manipulations performed on the gestational diabetes and hypertension dependent variables, I also lumped “no” and “unknown” responders together in my recoding of the binary independent variables representing the marital status and the preterm risk factors of the mother. The number of variables coded as ‘unknown’ is small enough in all of the variables that this change is negligible and leaving the observations coded as ‘unknown’ would have forced me to pursue a multinomial model. With this in mind, I chose to recode the variables as such in the interest of trying to keep my model similar to the Baker(2008) probit for comparison purposes.

Combined gestation, month prenatal care began, interval between doctors visit and delivery, weight gain, and number of cesarean births are all variables that I imputed missing values at the mean. I believe this to be an appropriate manipulation because I was sure to follow standard conventions of not dropping more than 5% of the data. The largest imputation I conducted was on the variable representing the month prenatal care began, in which 4.3% of the data was imputed at the mean; the other imputed variables initially contained less than 2% missing data. The only exception to this being the variable representing the interval between the most recent prenatal visit and delivery. This variable had significantly more than 5% of the data missing, but for purposes of investigation I still imputed the missing values at the mean and included the variable in my initial regressions. Most of the missing values for interval between prenatal visit and delivery were from the 2011 year, once I realized this I chose to stop including the variable in my models.

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| **TABLE 2- Descriptive Statistics for 2007** |
| **2007** | **Treatment** | **Control** |
| Month Prenatal Care Began | 3.79(2.20) | 3.71(2.06) |
| # of Cigarettes Smoked Daily During 1st trimester | 1.59(5.30) | 1.56(5.09) |
| Previous Cesarean Births | .346(.782) | .086(.283) |
| Combined Gestation | 38.41(2.61) | 38.62(3.67) |
| Born in Hospital | 97.10% | 99.02 % |
| Weight Gained During Pregnancy | 26.63(14.23) | 30.44(15.23) |
| Unintentionally Had Child at Home | 0.12% of group | 0.06% of group |
| Gender of Child (Male=1) | 50.99 % male | 51% male |
| Average age of mother | 28.62(5.61) | 21.75(5.27) |
| Average birth parity | 3.97(1.35) | 1.42(0.49) |
| Average # of prenatal visits | 9.70(4.55) | 10.10(4.26) |
| Percentage of sample that is married | 51.6% | 29.5% |
| Mother’s Race-White | 85.95% | 83.77% |
| Mother’s Race-Black | 11.06% | 12.81% |
| Mother’s Race-American Indian/Alaskan Native | 1.07% | 1.09% |
| Mother’s Race-Asian/Pacific Islander | 1.93% | 2.34% |

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| **Table 3 – Descriptive Statistics for 2011** |
| **2011** | **Treatment** | **Control** |
| Month Prenatal Care Began | 3.63(2.030 | 3.56(1.921) |
| # of Cigarettes Smoked Daily During 1st trimester | 1.54(5.16) | 1.45(4.93) |
| Previous Cesarean Births | .402(.861) | .0952(.2968) |
| Combined Gestation | 38.42(2.634) | 38.63(2.68) |
| Born in Hospital | 96.93% | 98.93 % |
| Weight Gained During Pregnancy | 25.96(14.53) | 29.979(15.29) |
| Unintentionally Had Child at Home | 0.18% of group | 0.10 % of group |
| Gender of Child (Male=1) | 50.74 % male | 51.15% male |
| Average age of mother | 29.18(5.69) | 22.12(5.15) |
| Average birth parity | 4.03(1.37) | 1.42(0.495) |
| Average # of prenatal visits | 9.9(4.45) | 10.31(4.19) |
| Percentage of sample that is married | 46% | 25.2% |
| Mother’s Race-White | 79.67% | 75.97% |
| Mother’s Race-Black | 15.85% | 18.36% |
| Mother’s Race-American Indian/Alaskan Native | 1.60% | 1.66% |
| Mother’s Race-Asian/Pacific Islander | 2.88% | 4.01% |

Methods

To isolate the before and after effects of the expansion on families with 3 or more children, I will be using variations of a difference-in-differences model with the following structure:

Y=β1 + β2THIRDKID+ β3 2011+ β42011 \*THIRDKID+ βjXj +εj

Where Y is one of the previously mentioned dependent variables of interest and β1 is a constant term. β3 2011is a dummy variable representing the control group after the treatment has been applied; families in the year 2011 with less than 3 children. β2THIRDKID is a dummy variable that represents the treatment group prior to the treatment; families with 3 or more children in the year 2007. β42011 \*THIRDKID is the variable of interest which is another dummy variable representing the treatment group after the treatment has been applied; families with 3 or more children in the year 2011. εj is the error term. Lastly, βjXj is a vector representing the partial effects of several control variables including:

-Age and race of mother

-Weight gained by mother during the pregnancy

-Number of previous live births (Birth Parity)

-Number of prenatal visits

-Gender of the Child

-Month prenatal care began

-Indicators for several pregnancy risk factors (diabetes, hypertension, pre-term birth)

-Length of gestation

-Birth month

-Marital status of mother

The key variable of interest in all of my models is a binary variable that represents the interaction between the binary variable representing that the observation being in the year 2011, and the binary variable representing that the observation is mother to 3 or more children. Therefore, if a variable is reported as 1 in the difference-in-differences variable of interest that means that the observation is part of the treatment group (because they have 3 or more children) and they are being observed after the treatment has been applied (because the observation was recorded in 2011 instead of 2007). According to my hypothesis, the β4 coefficient representing the difference-in-differences variable of interest should be indicative of a relationship with the dependent variable and therefore be supportive of my hypothesis that the increased income afforded by the 2009 expansion of the EITC influenced pregnancy outcomes.

I am interested in examining four dependent variables; Incidence of low birthweight, high birth weight, gestational hypertension, and gestational diabetes. Each will be used as a dependent variable in my probit and linear probability models.

Because birthweight is a continuous variable, this allows me to conduct quantile regression to understand how the difference-in-differences variable of interest affects birth weight at different points of the distribution. My quantile regression will control for the same independent variables as my probit models, the only difference being that the dependent variable is continuous rather than categorical. Due to the quantile regression command being quite lengthy to run, I will limit my analysis to the 25th, 50th, and 75th percentiles. I hypothesize that the treatment will normalize birthweights, which will be represented by positive coefficients in the 25th percentile regression and the median regression but will have a negative coefficient in the 75th percentile regression. The advantage of using quantile regression is that it allows me to analyze the distribution of birthweight at thresholds that I decide rather than being forced to rely on conventional definitions of at-risk birthweights.

 When choosing independent variables, I tried to consider known causes of the four health-related dependent variables that I am studying. For example, gestational length is the number one predictor of low birth weight and mothers who smoke as well as teen mothers are at increased risk of giving birth to an underweight baby.

 Maternal obesity, rapid weight gain during the pregnancy and pre-existing diabetes are all important risk indicators for fetal macrosomia, gestational diabetes, and gestational hypertension. Mothers giving birth to boys, overdue pregnancies, and mothers over 35 are more likely to give birth to an overweight baby. Pre-existing high blood pressure is a risk factor for increased likelihood of gestational diabetes and hypertension. Lastly, for reasons unknown, African-American mothers are at higher risk for contracting all 4 of the negative health outcomes measured by my dependent variables.

Results

 The results of my linear probability models do provide some support for my hypotheses. Both the regressions for gestational diabetes and gestational hypertension suggest a statistically significant relationship between the difference variable of interest and the dependent variables. With a negative sign for the coefficient in the low birth weight model and a positive sign for the coefficient in the high birth weight model, this might suggest that application of the treatment has a positive effect on birth weight at the low and high end of the birth weight distribution. However, the coefficients are so small that any omitted variable bias could easily change the sign of the coefficient. The R-squared values of these models are quite low however and the varying levels of significance of the other control variables across the 4 regressions lead me to believe that there was significant omitted variable bias. With R-squared values of 0.0400 and 0.0346 it is difficult to argue that these linear probability models are truly representative of the relationship between the X and Y variables despite having significant coefficients for the variable of interest. Additionally, the results from the gestational diabetes and gestational hypertension models do not provide any useful conclusions as the difference variable of interest is insignificant in both regressions. It is important to note that the variable representing the interval between the last doctors visit and the delivery of the child had to be eliminated from consideration in all future regressions because of collinearity issues caused by too many missing values in the variable.

 In order to prevent bias caused by heteroskedasticity, the *robust* command was used.

|  |
| --- |
| TABLE 4 -Preliminary Linear Probability Model Results |
|  | Dependent: Low Birth Weight | Dependent: High Birth weight  | Dependent: Gestational Diabetes | Dependent: Gestational Hypertension |
| Difference Variable of Interest ( Year 2011 & 3 or More Children) | -0.004(0.008) | 0.008 (0.016) | 0.027\*\*  (0.009) | 0.042\*\*\*(0.010) |
| Treatment (3 or more children) | -0.094\*\*\*(0.006) | 0.300\*\*\*(0.012) | 0.240\*\*\* (0.007)  | -0.149\*\*\* (0.008) |
| After (year 2011) | 0.026\*\*\*(0.005) | -0.019 (0.012) | 0.121\*\*\*(0.006)  | 0.081\*\*\*(0.006)  |
| Month Prenatal Care Began | 0.005\*\*\*(0.001) | -0.007\*\*\* (0.002) |  0.024\*\*\* (0.001) | 0.011\*\*\*(0.001)  |
| # of Cigarettes Smoked Daily During 1st trimester | 0.019\*\*\*(0.000) | -0.025\*\*\* (0.002) | -0.003\*\*\* (0.000) | -0.001  (0.000) |
| Previous Cesarean Births  | -0.018\*\*\*(0.004) | 0.077\*\*\* (0.006) | 0.062\*\*\*(0.003) | 0.005  (0.004) |
| Combined Gestation | -0.261\*\*\*(0.001) | 0.071\*\*\* (0.002) |  -0.024\*\*\* (0.001) | -0.060\*\*\*(0.001)  |
| # of Prenatal Visits | -0.011\*\*\*(0.001) | 0.013\*\*\*(0.001)  | 0.040\*\*\* (0.001)  | 0.010\*\*\*(0.001)  |
| Black | 0.256\*\*\*(0.005 | -0.257\*\*\* (0.015) | -0.184\*\*\*(0.007)  | 0.160\*\*\*(0.006)  |
| Native | -0.050\*\*(0.018 | 0.101\*\* (0.031) | 0.012 (0.019) | 0.069\*\*\*(0.020) |
| Asian | 0.005(0.013) | -0.118\*\*\*(0.027) | 0.226\*\*\*(0.011) | -0.183\*\*\*(0.017)  |
| Interval Between Last Doctors Visit and Delivery | 0.001\*\*\*(0.000) | 0.001\* (0.00)  | -0.000  (0.000) | -0.003\*\*\*(0.000) |
| Weight Gained During Pregnancy | -0.0007\*\*\*(0.000) | 0.010\*\*\*(0.00) | -0.005\*\*\*(0.000) | 0.008\*\*\* (0.000) |
| Born in Hospital  | 0.339\*\*\*(0.023) | -0.417\*\*\*(0.021) | 0.563\*\*\* (0.028) | 0.582\*\*\*(0.037) |
| Unintentionally Had Child at Home | 0.587\*\*\*(0.058) | -0.515\*\* (0.160) | 0.345\*\*\* (0.088) | -0.004  (0.129) |
| Gender of Child (Male=1) | -0.149\*\*\*(0.004) | 0.236\*\*\*(0.008) | 0.025\*\*\* (0.005)  | 0.010\* (0.005) |
| Constant | 8.387\*\*\*(0.044) | -5.399\*\*\*(0.072) | -1.943\*\*\* (0.043)  | -0.525\*\*\* (0.047) |
| Pseudo R-Squared | 0.2884 | 0.0657 | 0.0400 | 0.0346 |

\*\*\* significant at 1% level

\*\* significant at 5% level

\* significant at 10% level

 These models include independent variables representing pre-pregnancy diabetes and hypertension. Y-hat values were determined using the *predict* command in Stata. As indicated by the table, the only difference variable of interest with statistically significant coefficients was the one in the gestational diabetes model. Using the predict command also highlights the flaw of using a linear probability model for binary dependent variables. Summarizing the linear prediction of the Y-hat values shows that many of the linear predictions lie out of bounds. In all four of the linear prediction vectors generated by STATA, at least 10 % of the Y-hat values are less than 0. For this reason, it is necessary to move forward with a probit model.

 In order to be sure that the imputation of missing values at the mean didn’t significantly affect my models I created at dummy variable for each variable that required imputation. It is equal to 1 if an observation was imputed and 0 if it was not, therefore the coefficient of these dummy variables should tell me whether the imputed values might have biased the regression results. Thankfully in most cases these dummy variables were all insignificant with very high P-values, the only exception being the gestational hypertension model where the dummy variables representing the imputed values of month prenatal care began, weight gain, and number of cesarean births all were reported as significant on the 1% level. However, the coefficients of all 3 variables were quite small; -.012, -.004, and -.011 respectively.

|  |
| --- |
| TABLE 5 - Follow up Linear Probability Models |
|  | Dependent: Low birth weight | Dependent: High birth weight | Dependent: Gestational Diabetes | Dependent: Gestational Hypertension |
| Year 2011 | .00290\*\*\*(.00060) | -.00044\*\*(.00019) | .00660\*\*\*(.00043) | .00620\*\*\*(00047) |
| Treatment  | -.01025\*\*\*(.00099) | -.00025(.00040) | -.00590\*\*\*(.00049) | -.00677\*\*\*(.00064) |
| Treatment \*2011 | -.00050(.00099) | -.00020(.00039) | -.00599\*\*\*(.00082) | .00082(.00068) |
| Birth month | .00010\*(.00007) | -.00002(.00002) | .00023\*\*\*(.00005) | -.00007(.00005) |
| Mothers age | -.00011\*\*(.00005) |  .00055\*\*\*(.00002) | .00460\*\*\*(.00047) | .00079\*\*\*(.00003) |
| Mothers marital status | -.00666\*\*\*(.00055) | .00066\*\*\*(.00022) | .00424\*\*\*(.00047) | -.00185\*\*\*(.00038) |
| Live birth order | -.00166\*\*\*(.00020) | .00129\*\*\*(.00012) | -.00296(.00024) | -.00304\*\*\*(.00019) |
| Month prenatal care began | .00111\*\*\*(.00010) | -.00006(.00004) | .00259\*\*\*(.00008) | .00103\*\*\*(.00008) |
| Number of cigs smoked daily | .00288\*\*\*(.00006) | -.00028\*\*\*(.00001) | -.00001(.00003) | -.00006\*(.00003) |
| Number of previous cesarean sections | -.00726\*\*\*(.0004) | .00149\*\*\*(.00019) | .00374\*\*\*(.00041) | -.00536\*(.00030) |
| Combined Gestation | -.0475\*\*\*(.0001) | .0011\*\*\*(.00002) | -.0019\*\*\*(.00007) | -.0050\*\*\*(.00008) |
| Number of prenatal visits | -0.0019\*\*\*(.00006) | .00016\*\*\*(.00000) | .00320\*\*\*(.00005) | .00069\*\*\*(.00004) |
| Black | 0.0341\*\*\*(0.0008) | -0.0033\*\*\*(0.0002) | -0.0052\*\*\*(0.0004) | 0.0149\*\*\*(.00058) |
| Native | -0.0066\*\*\*(0.002) | 0.0034\*\*\*(0.0008) | 0.0102\*\*\*(0.0016) | .00635\*\*\*(.00159) |
| Asian | 0.0003(0.0001) | -.00453\*\*\*(.00047) | 0.0081\*\*\*(.00144) | -0.0132\*\*\*(.00085) |
| Weight gain during pregnancy | -.00085\*\*\*(.00001) | .00027\*\*\*(7.64e-06) | -.00029\*\*\*(.00001) | .00065\*\*\*(.00001) |
| Born in hospital | .01432\*\*\*(0.0013) | -.01499\*\*\*(.00121) | .03700\*\*\*(.00089) | .01490\*\*\*(.00066) |
| Unintentional Birth | .06833\*\*\*(.01022) | -.01534\*\*\*(.00223) | .02795\*\*\*(.00446) | -.00966\*\*\*(.00288) |
| Gender  | -.01744\*\*\* (.00040) | .00511\*\*\*(.00018) | .00214\*\*\*(.00038) | .00051(.00034) |
| Pre-pregnancy diabetes | -.001442(.00322) | .03966\*\*\*(.00248) | -.08333\*\*\*(.00077) | .07599\*\*\*(00.003) |
| Pre-pregnancy hypertension | .07299\*\*\*(.00366) | .00096(.00122) | .07855\*\*\*(.00355) | -.05266\*\*\*(.00058) |
| Preterm birth | .09322\*\*\*(.00244) | -.00274\*\*\*(.00054) | .0179\*\*\*(.00168) | .0185\*\*\*(.00153) |
| constant | 1.9555\*\*\*(.00566) | -.04761(.00164) | -.06811\*\*\*(.0030) | .17044\*\*\*(.00332) |
| R-squared | .2475 | .0928 | .0324 | .0133 |
| Y-hat | .0869 | .0088 | .0417 | .0331 |

\*\*\* significant at 1% level

\*\* significant at 5% level

\* significant at 10% level

 Due to collinearity concerns the pre-pregnancy diabetes variable was not included in the probit model for gestational diabetes and the pre-pregnancy hypertension variable was not included in the probit model for gestational hypertension. Stata would report that including the variables created too many perfectly determined outcomes and Stata would automatically drop thousands of observations to correct for the collinearity. This is because none of the observations with 1 recorded for pre-diabetes or pre-hypertension had been positive for gestational diabetes or hypertension. In order to avoid dropping observations unnecessarily, I chose not to include the two variables in their respective models. The *robust* command was also used in the probit models.

 Only the sign and significance of the coefficients yielded by the probit models can offer useful interpretations. Only the gestational diabetes and gestational hypertension models have significant interaction coefficients, both of which are positive. This would mean that application of the EITC expansion increases the probability of contracting gestational hypertension or diabetes; a conclusion obviously contradictory to the hypothesized outcomes. What could possibly be happening is that the weakness of the models is creating omitted variable bias significant enough to influence the sign of the coefficients. Given that the coefficients for *Treatment\*2011* are so close to zero and the R-squared numbers are so small, I do not believe that any of the probit models can adequately capture the relationship between the treatment and the dependent variables.

 Despite the unexpected signs of the *Treatment\*2011* variable of interest, the signs of the control variables are largely consistent with what would be expected according to theory. For example in the low birth weight probit, the *Black* race variable and the *Number of Cigarettes Smoked Daily* both have a positive relationship with the dependent variable. This is reflective of the previously noted findings that smokers and African-American mothers are more likely to give birth to underweight babies. Also in accordance with theory, my models report that male babies are less likely to be under weight, and more likely to be associated with pregnancies that suffer gestational diabetes and hypertension.

|  |
| --- |
| TABLE 6 - Probit Model Coefficients |
|  | Dependent: Low birth weight | Dependent: High birth weight | Dependent: Gestational Diabetes | Dependent: Gestational Hypertension |
| Year 2011 | .0236\*\*\*(.0053) | -.0285\*\*(.0120) | .1060\*\*\*(.0066) | .0768\*\*\*(.0060) |
| Treatment  | -.0714\*\*\*(.0084) | .0322\*\*(.0158) | -.0128(.0092) | -.1070\*\*\*(.0107) |
| Treatment \*2011 | -.01126(.0084) | .00014(.0158) | .0230\*\*(.0092) | .0390\*\*\*(.0104) |
| Birth month | .0020\*\*\*(.0006) | -.0008(.0011) | .0029\*\*\*(.0006) | -.0011\*(.0007) |
| Mothers age | .00013(.0004) | .0246\*\*\*(.0007) | .0467\*\*\*(.0004) | .0103\*\*\*(.0004) |
| Mothers marital status | -.0470\*\*\*(.0048) | .0413\*\*\*(.0090) | .0654\*\*\*(.0050) | -.0262\*\*\*(.0056) |
| Live birth order | -.0117\*\*\*(.0023) | .0386\*\*\*(.0037) | -.0237\*\*\*(.0024) | -.0459\*\*\*(.0033) |
| Month prenatal care began | .0040\*\*\*(.0010) | -.0061\*\*\*(.0022) | .0330\*\*\*.0012 | .0136\*\*\*(.0012) |
| Number of cigs smoked daily | .0183\*\*\*(.00034) | -.0216\*\*\*(.0015) | .0010\*\*.0004 | -.0009\*\*(.0004) |
| Number of previous cesarean sections | -.0223\*\*\*(.0035) | .0575\*\*\*(.0056) | .0324\*\*\*(.0008) | -.0048(.0044) |
| Combined Gestation | -.2589\*\*\*(.00099) | .0765\*\*\*(.0017) | -.0210\*\*\*(.0008) | -.0579\*\*\*(.0007) |
| Number of prenatal visits | -.0118\*\*\*(.00054) | .0092\*\*\*(.0010) | .0355\*\*\*(.0005) | .0095\*\*\*(.0006) |
| Black | .235\*\*\*(.00549) | -.2193\*\*\*(.0151) | -.0990\*\*\*(.0075) | .1711\*\*\*(.0065) |
| Native | -.0636(.0184) | .1511\*\*\*(.0320) | .1120\*\*\*(.0197) | .0778\*\*\*(.0199) |
| Asian | .0193.0126 | -.2105\*\*\*(.0273) | .0641\*\*\*(.0119) | -.2101\*\*\*(.0170) |
| Weight gain during pregnancy | -.0069\*\*\*(.0001) | .0114\*\*\*(.0002) | -.0031\*\*\*(.0001) | .0081\*\*\*(.0001) |
| Born in hospital | .3122\*\*\*(.0234) | -.3151\*\*\*(.0215) | .6468\*\*\*(.0292) | .5465\*\*\*(.0368) |
| Unintentional Birth | .5616\*\*\*(.0587) | -.4362\*\*\*(.1650) | .4266\*\*\*(.0902) | -.0263(.1296) |
| Gender  | -.1494\*\*\*(.0041) | .2414\*\*\*(.0084) | .0248(.0046) | .0105\*\*(.0048) |
| Pre-pregnancy diabetes | -.0141(.0217) | .2414\*\*\*(.0084) | - | .5397\*\*\*(.0197) |
| Pre-pregnancy hypertension | .3719\*\*\*(.01745) | .0471(.0395) | .4244\*\*\*(.0179) | - |
| Preterm birth | .4320\*\*\*(.0108) | -.1258\*\*\*(.0329) | .1643\*\*\*(.0138) | .2073\*\*\*(.0147) |
| constant | .4320\*\*\*(.0108) | -6.378\*\*\*(.0776) | -.3287(.0459) | -.7429\*\*\*(.0487) |
| R-squared | .2916 | .0882 | .0827 | .0391 |

\*\*\* significant at 1% level

\*\* significant at 5% level

\* significant at 10% level

 The marginal effects of the treatment calculated at the averages are listed in table 7. Notice that they are all very small numbers, close to zero. These marginal effect values were calculated manually in excel so they should not suffer the same problems that marginal effects generated by STATA’s *margins* command.

Marginal Effect Calculated at Averages

|  |
| --- |
| TABLE 7 - Marginal Effect Calculated at Averages |
| Low Birth Weight | High Birth Weight | Gestational Diabetes | Gestational Hypertension |
| -1.530 X 10-24 | 9.754 X 10-7 | 0.000403 | .00592 |

 It is argued by Ai and Norton (2003) that non-linear models cannot have their interaction terms accurately calculated by using the STATA *margins* command. This is because the *margins* command calculates marginal effects using non 0 or 1 values for binary interaction terms. This is illogical though because decimal values for binary terms do not have interpretations. In the context of my model, where *Treatment\*2011* is a binary interaction of *Treatment* and *2011*, the observation is either part of the treatment group in the year 2011 (1) or it is not(0). Since *Treatment* and *2011* are also binary variables, *Treatment\*2011* will only be equal to 1 if both *Treatment* and *2011* are also 1. However, *margins* does not recognize this in a nonlinear model and will choose to represent *Treatment\*2011* as the product of averages from *Treatment* and *2011* when calculating marginal effects. As a result of this incorrect procedure, the margins command could report marginal effects with the wrong sing or magnitude and will likely miscalculate the significance of the coefficient (AI and Norton, 2003).

 Table 8 contains the results obtained from running the *Inteff* command on the probit model for gestational diabetes

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| --- |
| TABLE 8 – *Inteff R*esults |
|  | Mean (Standard. Deviation) | Min | Max  |
| Interaction  | .0017(.0012) | 6.62 x 10-06 | .0100 |
| \_probit\_se | .0007(.0005) | 3.88 x 10-06 | .0037 |
| \_probit\_z | 2.241(.1014) | 1.597 | 2.749 |

 With an average marginal effect of .0017, the interaction variable *Treatment\*2011* has a positive effect on the probability of contracting gestational diabetes according to my model. This is contrary to what I had predicted in my initial hypothesis. Figure 3 is a visual representation of the Z-statistics of the interaction effect



Figure 3: Z-Stat of Interaction Effects

 Quantile regression allows me to examine the effects of the EITC expansion on birthweight when treated as a continuous variable measured in grams. The coefficients yielded by the quantile regression can then be interpreted as representing the number of grams that the average birth can be expected to increase by if the respective independent variable increases by 1 unit. In order to capture the quadratic relationship age has across the weight distribution I chose to add age squared into the regression.

 As described in the literature, the birth weight disparity for babies born to black mothers is largest at the lowest percentile. The partial effect of smoking cigarettes is largest in the low end of the distribution, and the disparity between male births and female births is smallest at the 25th percentile (Koenke and Hallock 2001). None of the *Treatment \*2011* variables returned significant coefficients from any of the 3 quantiles, meaning none of the 3 coefficients are different from zero.

|  |
| --- |
| Table 9 – Birth Weight Quantile Regression |
|  | 25th Percentile | Median Regression | 75th Percentile |
| Year 2011 | -11.95\*\*\*(1.563) | -12.86\*\*\*(1.342) | -15.67\*\*\*(1.498) |
| Treatment  | 30.09\*\*\*(2.533) | 22.76\*\*\*(2.200) | 18.45\*\*\*(2.486) |
| Treatment \*2011 | -.8227(2.505) | .6810(2.178) | .7037(2.428) |
| Birth month | -.0570(.1764) | -.7564\*\*\*(.1526) | -1.123\*\*\*(.1697) |
| Mothers age | 13.31\*\*\*(.7558) | 14.11\*\*\*(.6467) | 15.82\*\*\*(.711) |
| Age Squared  | -.1661\*\*\*(.0138) | -.1486\*\*\*(.0118) | -.1517\*\*\*(.0130) |
| Mothers marital status | 26.88\*\*\*(1.415) | 23.44\*\*\*(1.224) | 22.98\*\*\*(1.373) |
| Live birth order | 11.403\*\*\*(.7186) | 13.204\*\*\*(.6191) | 16.125\*\*\*(.7070 |
| Month prenatal care began | -4.881\*\*\*(.3164) | -2.973\*\*\*(.2747) | -2.410\*\*\*(.3013) |
| Number of cigs smoked daily | -11.23\*\*\*(.1156) | -10.50\*\*\*(.1084) | -9.348\*\*\*(.1231) |
| Number of previous cesarean sections | 8.188\*\*\*(1.137) | 8.409\*\*\*(.9362) | 7.635\*\*\*(1.101) |
| Combined Gestation | 124.1\*\*\*(.2621) | 104.7\*\*\*(.2371) | 81.06\*\*\*(.2632) |
| Number of prenatal visits | 5.908\*\*\*(.1500) | 5.484\*\*\*(.1311) | 5.479\*\*\*(.1467) |
| Black | -128.0\*\*\*(1.759) | -127.2\*\*\*(1.564) | -125.3\*\*\*(1.734) |
| Native | 31.28\*\*\*(5.704) | 51.46\*\*\*(5.192) | 66.34\*\*\*(5.275) |
| Asian | -66.50\*\*\*(3.176) | -90.21\*\*\*(3.106) | -104.1\*\*\*(3.466) |
| Weight gain during pregnancy | 4.501\*\*\*(.0419) | 4.913\*\*\*(.0361) | 5.405\*\*\*(.0400) |
| Born in hospital | -146.2\*\*\*(4.515) | -139.4\*\*\*(3.952) | -132.8\*\*\*(4.507) |
| Unintentional Birth | -291.7\*\*\*(21.10) | -247.8\*\*\*(21.15) | -246.1\*\*\*(20.31) |
| Gender  | 105.7\*\*\*(1.216) | 114.06\*\*\*(1.053) | 121.9\*\*\*(1.172) |
| Pre-pregnancy diabetes | 35.04\*\*\*(9.658) | 120.087\*\*\*(8.554) | 226.4\*\*\*(9.709) |
| Pre-pregnancy hypertension | -175.7\*\*\*(8.146) | -128.6\*\*\*(6.838) | -88.50\*\*\*(7.966) |
| Preterm birth | -192.1\*\*\*(4.608) | -195.622\*\*\*(4.0587) | -193.3\*\*\*(4.542) |
| Constant | -2172\*\*\*(14.69) | -1175.5\*\*\*(13.08) | -27.18\*(14.46) |
| Pseudo R-squared | .1897 | .1311 | .1029 |

 \*\*\* significant at 1% level

\*\* significant at 5% level

\* significant at 10% level

Conclusion

 In review of my linear probability models, probit models, and quantile regression models, there is a lack of strong supporting evidence for my initial hypothesis that increase in disposable from the 2009 expansion of the Earned Income Tax Credit.

 The linear probability models for the low birthweight, gestational diabetes, and gestational hypertension models do report significant negative coefficients for the *Treatment\*2011* variable. However, these coefficients cannot be accurately interpreted due to Y-hat values that would be outside of bounds of possible probability.

 Only the gestational diabetes probit model returned a significant coefficient for the *Treatment\*2011* variable. However, given that this coefficient has a positive sign, this evidence is contradictory to my hypothesis that expansion of the EITC to mothers with 3 or more children should reduce gestational diabetes. Furthermore, marginal effects generated by STATA’s margins command cannot be trusted to be accurate due to the command using average values for interacted terms in a nonlinear model. Rather than treating the interaction term as an interaction of 2 categorical variables, *margins* will incorrectly treat the interaction term as an interaction between two continuous variables by using average values that have no logical interpretation. The *Inteff* command is a more robust way for calculating marginal effects of an interaction term in nonlinear models, but unfortunately for the purposes of my study, STATA SE is not able to handle the *Inteff* command on a data set as large as mine (AI and Norton 2003). Running the command on a 1 percent sample of my data quickly produces results but running the command on my full data set crashes data due to inadequate processing power. I was able to complete the command one time on a computer running Unix. This process took STATA 17 days to complete, finally yielding the theoretically accurate interaction effects for my gestational diabetes model. Due to the time constraints of this process I chose not to pursue applying the *Inteff* command to my other probit models.

 The *Treatment\*2011* variable is insignificant across all 3 percentiles of scrutiny in the quantile regressions. Low R-Squared/Pseudo R-Squared values in all models as well as the varying significance of different variables leads me to believe that all the models suffer from significant omitted variable bias. In fact, I think this is what can explain why Baker(2008) is able to obtain significant results in his models that are in structure very similar to my probit models. The Natality Detail File data from the 2007 and 2011 years do not contain vital information pertaining to geography that was available in the years 1989-1996, which were the years analyzed in the Baker(2008) study. It is possible that geographic location could be among one of the most important indicators on the 4 health dependent variables, and without a variable representing location, my models would suffer from omitted variable bias that Baker(2008) would have been able to avoid. In addition, having access to the locations of the births in the 1989-1996 Natality Detail data also allowed Baker(2008) to utilize other time specific control variables within each state such as unemployment rate, percentage of the population that is black, and per capita disposable income (Baker 2008). Lastly, the success of the Baker(2008) model might be explained by the fact that he used 7 years of data compared to my 2. It is possible that by allowing for more observations in his data set, he also allowed for increased variability in the data that could be captured more easily by his model.

 If I had been able to control for geographic I believe that my results would have provided stronger evidence for my hypothesis. However, based on the limitations of the data it is difficult to support my hypothesis that the increased disposable income granted by the 2009 expansion of the EITC had the effect of normalizing birthweight and reducing incidence of gestational hypertension and diabetes amongst mothers of 3 or more children. Future research on the 2009 expansion could be improved by trying to find a proxy for geographic location or by using another data set with more information. Lastly, accurately calculating interaction effects on a data set of enormous size is not easily done by STATA SE, and possibly for this reason Baker(2008) chose not to describe the marginal effects of his model at all in his 2008 paper.

Appendix A

Figure 1 shows a diagram of the 2017 EITC values for a household with 3 children. Phase 1 or the “phase in” of the EITC is represented by segment AB of the EITC constraint. Households that earn less than 14,040 qualify for a tax credit that is equal to 45 percent of their earnings, therefore a family below point *b* will have net wages 45 percent higher than market wages. Phase 2 represents the flat range of the EITC schedule and is represented by segment DB. Unlike the other 2 segments of the EITC constraint, the slope of segment DB is the same as the slope of the market constraint AC. This means that unlike the other 2 segments of the EITC constraint, the total value of the tax credit does not change corresponding to changes in household income, provided that the family’s income is still between $14,040 and $18,340 (Ehrenberg & Smith 2016, p 203). DB also represents the portion of the EITC where the household qualifies for the maximum tax credit allowed for a household with 3 children, which is $6,318 for households filing in 2017(Tax Policy Center 2016). Although the original EITC only consisted of 2 phases, the 1978 legislation that made the EITC permanent also created the middle flat range to the EITC schedule that is still a part of the policy today (Hotz 2003). Phase 3 is called the “phase-out” segment and is represented by ED on the EITC constraint. This phase is when the value of the earned income tax credit starts to shrink away from its maximum value at a constant rate for each additional dollar earned by the family. In the case of the 2017 tax year, households with three children that earn more than 17,100 dollars will see the value of the tax credit decrease by 21 cents for each additional dollar of income that is earned until the family earns $48,340, at which point the family no longer qualifies for the tax credit (Tax Policy Center 2016).

Dollars earned annually

C

Figure 1: 2017 EITC schedule of a household with 3 children

48,340

(Wn= .79W)

E

18,340

(Wn= W)

(Wn= 1.45W)

*b*

*d*

D

B

14,040

Source: Tax policy Center 2016

A

Hours of work

0

All three segments of the EITC constraint enhances the incomes of the workers who receive the tax credit and therefore creates an income effect to choose less work across all three phases of the tax credit. The substitution effect will be different in each of the three phases because of the differing net wage rates across the three segments. In phase 1, the net wage is greater than the market wage creating a substitution effect that will push the worker to work more. Here the income and substitution effects move in opposite directions. It is impossible to predict which effect will be stronger, but what will likely happen is some workers who would have chosen not to work in the absence of the EITC will decide to seek employment. The second and third phase both represent sections of the EITC where labor supply can be expected to fall. In phase 2, market wage equals net wage so there is no substitution effect; workers in phase 2 experience a pure income effect pushing them to work less. In phase 3, net wage is below market wage, causing the income and substitution effects to move in the same direction, both pushing the worker to choose less work hours. This means that if a new EITC is implanted or an old one is expanded, workers along segments ED and DB will most likely reduce the hours that they work (Ehrenberg & Smith 2016, p 204).

Table 1A provides observations of the fiscal outlays from the EITC and the number of filed returns from the year 2003.

Table 1A

|  |  |  |
| --- | --- | --- |
| **Income Class** | **Number of Returns**(in thousands) | **Value of Returns**(in millions) |
| $0-10,000 | 5,572 | $6,945 |
| $10,000-$20,000 | 5,538 | $13,752 |
| $20,000-$30,000 | 4,534 | $9,766 |
| $30,000-$40,000 | 2,994 | $3,519 |
| $40,000-$50,000 | 608 | $392 |
| $50,000-$75,000 | 38 | $39 |
| $75,000 and over | 0 | $0 |
| Total | 19,284 | $34,412 |

Source: Tax policy Center 2006

Appendix B

Table 1B: comparison of 2016 EITC values for married filers with one, two, and three qualifying children

|  |  |  |  |
| --- | --- | --- | --- |
| Earned Income Range | Credit values for 1 child claimed | Credit values for 2 children claimed | Credit Values for 3 or more children claimed |
| $100-$1000 | $43-$349 | $50-$410 | $56-$461 |
| $1000-$10,000 | $349-$3373 | $410-$4010 | $461-$4511 |
| $10,000-$20,000 | $3373 | $4010-$5572 | $4511-$6269 |
| $20,000-$30,000 | $3373-$2368 | $5572-$4248 | $6269-$4945 |
| $30,000-$40,000 | $2368-$770 | $4248-$2142 | $4945-$2839 |
| $40,000-$50,000 | $770-$0 | $2142-$36 | $2839-$733 |
| $50,000+ | - | $36-$0 | $733-0 |

Source: Center on Budget and Policy Priorities(2017)

Families with one child the phase-in range cuts off at $9,920 of earned income, the flat range lasts from $9,920 dollars of earned income to $23,740, at $44,846 of earned income the credit phases out completely and the family is no longer eligible for the EITC. For the one child schedule the credit phases-in at a rate of 34% and phases-out at a rate of 15.98%

Families with two children, the phase-in range ends at $13,930 of earned income, the flat range lasts from $13,930-$23,740, and $50,198 the credit phases out completely and the family is no longer eligible for the EITC. For the two child schedule the credit phases-in at a rate of 40% and phases-out at a rate of 21.06%

Families with three or more children also have a phase-in range that ends at $13,930 of earned income, as well as a flat range that lasts from $13,930-$23,740. However, unlike the two child schedule the three child schedule phases-out completely at $53,505 rather than $50,198. For the three child schedule the credit phases-in at a rate of 45% and phases-out at a rate of 21.06%

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