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Maternal Education and Infant Health Gradient: New Answers to Old Questions

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Maternal Education and Infant Health Gradient: New Answers to Old Questions

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Abstract

By using data from the National Vital Statistics System, this study provides an in-depth investigation of the well-documented mother's education–infant health gradient. The study allows for differential relationship between mother's education and infant health outcomes across localities based on income status by using birthweight and low birthweight as health measures. The results show that mother's education–infant birthweight relationship is more concentrated at relatively poor geographic areas. This can partially be explained by increases in utilization of health services among educated mothers residing in poorer areas compared to mothers with lower levels of education. Although the magnitude of education–health gradient has decreased in recent years, the gradient is still more pronounced in poorer localities. Access to health care during pregnancy, measured by adequacy of care, has improved particularly among less educated mothers living in poorer areas. However, smoking participation during pregnancy has declined substantially among less educated mothers across all geographic localities in recent years. Additionally, mother's education–infant health gradient is similar across black and white race groups.

JEL: I10, I26, I30

Keywords: Education-Health Gradient, Infant Health, Birthweight, Poverty

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1 Introduction

A positive relationship between education and health outcomes has been widely documented in health economics, with formal years of schooling completed being the most important correlate of better health (Grossman and Kaestner (1997)). Grossman (1972) provides a theoretical framework to understand the effects of schooling on the demand for health. Following his study, a substantial amount of empirical evidence points to the consensus that educated individuals are more likely to have better health outcomes, including improved birth outcomes given by reductions in infant mortality rate and increased birthweight (Currie et al. (2003); Abrevaya and Dahl (2008); Chou et al. (2010); Breierova and Duflo (2004)), higher life expectancy (Richards and Barry (1998); Lleras-Muney (2005); Elo and Preston (1996); Mustard et al. (1997); Kunst and Mackenbach (1994)), and better health behaviors often measured by a reduction in smoking and heavy drinking (Kenkel (1991); Jensen and Lleras-Muney (2012); Cutler and Lleras-Muney (2010)).

Similarly, it is well established at the national level that parents' lower socioeconomic status is associated with poor health outcomes among children, with income being one of the main drivers, giving rise to income-health gradient (Case et al. (2002); Currie et al. (2003)). Figure 1 shows the cross-sectional disparity on infants' birthweight across geographic areas based on poverty ranking.[1] The figure indicates that relatively affluent areas (the first group) has a reduced probability of low birthweight by more than 2 percentage points compared to poor areas — a huge improvement given the base probability of 0.07. Although education-health and income-health gradients are well-established in isolation, it is unclear as to how education-health gradient varies based on income status of localities.

Education allows individuals to self-select into better neighborhoods. But locality itself can induce positive effects on health (Chetty and Hendren, 2018; Chetty et al., 2018). Currie and Schwandt (2016) suggest that the locality of residence can pose significant differences in health outcomes, mainly due to specific "features of particular areas (for example, air pollution)" and spillover effects. In fact, Chetty et al. (2016) show that low income individuals live longer if they reside in rich areas with high proportion of educated people.

Theoretically, education can interact with environmental factors to produce varying extent of education-health relationship across localities. At one instance, higher education can reinforce the availability of external inputs such as better healthcare providers in relatively rich neighborhoods — educated individuals can be more efficient producers of health, given the same health inputs. On the other hand, a certain threshold of education may contribute to an equal level of "productive efficiency"[2] across neighborhoods, regardless of income status.

[1] Here, counties are grouped into four groups with each representing about 25 percent of the total number of births in the sample.

[2] This efficiency refers to whether given resources are being used the fullest of possibility in producing

For example, a college graduate living in a relatively poor neighborhood can be equally as efficient in processing information from a single doctor visit compared to a college graduate from a richer neighborhood. For households in low-income areas with poor resources, education may induce a protective shield as knowledge may compensate for lack of adequate health inputs to an extent.

Can mother's education–infant health gradient vary across localities based on income? Answers to such a question can shed light regarding the interactive relationship between education and other inputs that enter the health production function. I use birth data from the National Vital Statistics System to evaluate the effects of mother's education on infant health, which is proxied by birthweight and low birthweight—arguably the most widely used measures to attest infant health.[3] It is important to highlight that the health production function that are linear in years of education are commonly used in the literature when exploring the education-health gradient.[4] In such studies, the marginal effect of one more year of schooling on health outcome is assumed to be similar throughout the entire education distribution and ignores the possibility of non-linear effects at certain levels of education. "Sheepskin effect" — additional benefits attached to completion of a degree (e.g. high school, college) due to positive signaling, is widely documented in labor economics. This effect can potentially trickle down to health measures through access to better insurance provision (employer sponsored insurance), job-related stress and positive peer effects,[5] which further validates specifying a health production function with distinctive educational landmarks.[6]

To evaluate health returns associated with maternal education across geographic areas, I rank mother's county of residence based on poverty rates by using county-level poverty measures from the Census. The counties are grouped into ten (twenty) county-groups with each county-group comprising a share of almost ten (twenty) percent of the total number of births in the sample. Then I evaluate the relationship between mother's education and infant's birthweight for each county-group. Rather than specifying education linearly in the health production function, I allow for the marginal effects of an additional year of schooling

health.

[3]Birthweight serves as a leading indicator of infant health and cases of low birthweight (LBW) (classified as less than 2,500 grams) are associated with increased risk of infant-mortality and high medical expenses (McCormick (1985); Barker et al. (1993)). Several studies have also illustrated the long-term effects of low birthweights on cognitive development, educational and labor market outcomes (See Hack et al. (1995); Corman and Chaikind (1998); Behrman and Rosenzweig (2004); Case et al. (2005); Currie et al. (2003); Almond and Mazumder (2008)).

[4]Abrevaya and Dahl (2008); Lindeboom et al. (2009); McCrary and Royer (2011);Chou et al. (2010); Carneiro et al. (2013); Güneş (2015)

[5]See conceptual framework for more details.

[6]As such, some studies make distinctions between the landmarks of educational achievement, a common one being: 1) Less than high school; 2) High school or more (Grossman and Joyce (1990)); and 3) College graduates (Heckman et al. (2015)).

to vary at different levels of education by using a more flexible model specification. One main challenge that I incur is that natality files do not report labor market information. It is important to control for income in model specifications as income tend to increase sharply following the completion of educational landmarks. By using individual level data from CPS Merged Outgoing Rotation Groups (MORG 1990 and 2000) and CPER Uniform Extracts (2015) combined with several publicly available county-level data sets, I compute per-capita income for sub-groups in a county adjusted by education, race and age.[7] I carefully include income indicators based on this per-capita income measure in model specifications to adequately control for income.

Four distinct findings arise from the analysis. First, I show that mother's education and infant's health relationship is stronger in relatively poorer geographic areas compared to affluent areas. This finding can be supported by dramatic increases in utilization of prenatal care (measured by both initiation of visit in the first two months of pregnancy and adequacy index) associated with educated mothers residing in poor geographic areas compared to mothers with low levels of education, whereas less educated mothers residing in richer areas still benefit from better prenatal care. The former finding is consistent with higher levels of allocative efficiency among educated individuals regardless of locality based on income and the later finding is not surprising as individuals with relatively low levels of education but residing in rich neighborhoods are still exposed to better health infrastructure and medical services. Second, the gradient has decreased in recent years, although it is still statistically significant and stronger in poorer localities. Third, such decreases in gradient can be explained by: 1) a substantial reduction in smoking during pregnancy among less educated mothers across all localities, and 2) disproportionate improvements in prenatal care among less educated mothers living in poorer localities in recent years. Among mothers with less than high school attainment, the share who did not smoke while pregnant increased from 60 percent in 1990 to 90 percent in 2015. Fourth, the magnitude of the gradient is similar among non-Hispanic black and white mothers.

The main limitation of this study is that years of schooling may be associated with other third factors not accounted in the model, which can simultaneously affect birth weight of an infant. This disallows me from making causal interpretations. However, rather than focusing to establish a causal relationship between mother's education and infant's health outcome, the main objective of the paper is to evaluate the possibility of differential relationship between mother's education and infant health across geographic areas based on poverty levels by allowing for a more flexible model specification to capture potential non-linearity. Such analyses provide guidance to several queries that arise when evaluating mother's education-

[7] A detailed computation is discussed in section 3 and Appendix A10.1.

infant health relationship, and can benefit future work in this area. Particularly, the findings of the study shed light on the matter of whether maternal education acts as a substitute for external inputs or reinforces the benefits through better health-inputs available in relatively richer neighborhoods (e.g. access to better quality service providers).

The study is structured as follows. Section 2 discusses the conceptual framework of the study. This is followed by the discussion of data (Section 3), model specification (Section 4), results (Section 5), and possible mechanisms (Section 6). Section 7 provides discussion by comparing the findings of this study with the existing literature and concludes the study.

2 Conceptual Framework

In this section, I highlight the role of three inputs that enter the health production function – i) education, ii) income, and iii) neighborhood or environment.[8] To access the effect of mother's education on infant health outcomes, I reflect on mother's health during pregnancy, which determines an infant's health and creates variation in birthweights. Borrowing from Grossman (1972), education can directly affect health in two main ways. First, education increases the marginal product of medical care. As such, a fewer number of prenatal visits are required to produce a given amount of gross investment in mother's health during pregnancy. Second, education increases the marginal product of time spent on health. Hence, increases in education leads to a reduction in marginal cost if education increases marginal product of direct inputs (medical care and time spent on health). Holding wages and marginal product of stock of health before pregnancy constant, increases in education will increase marginal efficiency of health capital (MEC) and shift the marginal efficiency capital curve to the right as shown in Figure 2. This will lead to differences in the amount of mother's health demanded during pregnancy across different education levels, with educated mothers demanding higher stock of health.

The infant health production function also involves other inputs beside education, such as proper medical care and nutrition, which highly depends on income. The Case et al. (2002)'s study highlights the origins of income-gradient and several other studies have directly analyzed the effects of income on health outcomes, including child health. It is well-established that higher income improves health outcomes (Horn et al., 2017; Lenhart, 2017). While the past studies evaluate the effects of education and income on health outcomes in isolation, these two inputs perhaps should not be depicted as isolated inputs in the health production function. Both of these inputs can have interactive effects — to an extent, one input can either reinforce or compensate the other input. More importantly, given the growing impor-

[8]It has to be noted that some of these inputs may affect the health production function itself.

tance of "neighborhood effects" in health and human capital formation (Currie and Schwandt, 2016; Chetty et al., 2016; Chetty and Hendren, 2018; Chetty et al., 2018), it is important to understand how the health-returns to education vary across neighborhoods based on income status. Although empirical evidence regarding health-returns to education has been well-presented in the literature, the possibility of varying returns to education by geographic area has surprisingly been ignored.

Mother's education can interact with available resources of neighborhoods (say, counties),[9] categorized by income in two main ways. First, education can have a reinforcement effect — educated mothers living in a rich county with better resources will not only get to enjoy better quality of health inputs (such as better health providers)[10] but can use their knowledge to get the most out of those health inputs, leading to gains in "productive efficiency" compared to less educated mothers living in the same county. At the same time, better neighborhood resources along with positive spillover effects can also benefit less educated mothers, as exposure to better resources and commonly used resources (e.g. clean air and better environment) may compensate for lack of education.[11] Second, under certain conditions, education can act as a substitute for other inputs in the health production function. Specifically, for mothers in relatively poor counties, education can provide protection against certain health behaviors that are absolutely detrimental for infant health, for example, smoking when pregnant. In fact, tobacco marketing and advertisement is particularly more focused in neighborhoods with lower income (See Lee et al. (2015)). Hence, a certain level of education may be required to appreciate the negative implications of such behaviors. This represents improved allocative efficiency among higher educated mothers. In contrast, these behaviors can be curtailed even among less educated mothers living in richer counties through channels of peer effects, spillover effects, and increased awareness.

The other channel that can contribute to differential mother's education-infant health gradient across localities is through social networks. A strand of literature in health economics focuses on the effects of social network on health outcomes.[12] For relatively less educated mothers residing in richer neighborhoods with more educated individuals, awareness realized through education can be transferred indirectly from educated to less educated mothers. One example that can be highlighted is participation in risky activities during the

[9] This is to be consistent with the depiction of neighborhood used in the paper as county similar to Chetty and Hendren (2018). I realize the presence of heterogeneity in income across local areas within a county, but such categorization is constrained due to the availability of data. In future work, varying effects of education on health based on local income status should be evaluated at narrower geographical areas.

[10] This point is illustrated in Figure A1 by using data from Area Health Resource File merged with National Vital Statistics System (year 2015).

[11] In fact, Chetty et al. (2016) provides evidence that poorer individuals live longer in richer neighborhoods.

[12] See Christakis and Fowler (2007, 2008); Fowler and Christakis (2008); Card and Giuliano (2013); Gwozdz et al. (2015); Fletcher (2010); Trogdon et al. (2008); Lundborg (2006); Fletcher (2012); Ali and Dwyer (2010)

time of pregnancy. Studies suggest that an increase in schooling lowers substance use such as smoking and heavy drinking (Kenkel (1991); Cutler and Lleras-Muney (2010)). Consequently, Christakis and Fowler (2008) find substantial peer-effects in smoking cessation and such effects are concentrated among more educated individuals. But the mechanism as to how improvements in education and peer-effects affect smoking decision is different. Better education can guide a mother to pick healthier inputs during pregnancy, and hence reduce smoking participation across all localities, whereas the channel of peer-effect may decrease smoking rate among less educated mothers living in rich neighborhoods compared to mothers with similar education level but residing in poorer areas. Thus, emulation of proper health habits within in a network can decrease risk during the time of pregnancy and this may disproportionately benefit less educated mothers living in better neighborhoods.

Figure 3 shows the proportion of mothers residing across various county-groups arranged by poverty ranking. The figure shows quite an uniform spread of mothers with high school education or more across county groupings. In contrast, residence of mothers with less than high school education is sharply correlated with poverty rate, with more than 60 percent of mothers with less than high school degree living in relatively poorer geographic areas. Additionally, the bottom panel in Figure 3 replicates the top panel but by using the Census data for respective years and focusing among all non-elderly individuals of 25 years of age and over, regardless of gender. The results across two panels are comparable.

One important point to note is that the marginal product of direct inputs can decrease with an increase in levels of schooling after a certain point due to diminishing returns. The effect of an additional level of schooling on health stock can be concentrated at certain levels of education, with landmarks of schooling (high school completion, college completion) being the valid contenders. This notion is consistent with the screening theory of education pertaining to labor market, which states that employers use education as a screening device to access the innate productivity of an employees (Arrow (1973); Spence (1973)). The completion of a degree gives an additional boost to employees during the process of screening, which is referred to as "sheepskin effects" in context of labor economics.

Similar to the context of sheepskin effect in labor market outcomes, the effects of mother's completion of a degree may play a salient role in determining an infant's health. An additional year of schooling leading up to the completion of a degree, say from 11^{th} grade to high school completion, can create sizable improvements in access to medical care. Hall et al. (1999) show that 48 percent of individuals with less than high school have access to employer sponsored insurance, whereas the magnitude increases to 68 percent when focusing on high school graduates. A significant improvement in the likelihood of obtaining health insurance coverage after completing a degree opens access to relatively better quality medical services. This increases the marginal product of medical inputs, which according to Figure 1 increases the optimal stock of health demanded (from H_1^* to H_2^*) .

3 Data

3.1 National Vital Statistics System (NVSS)

The primary data I use is from the National Vital Statistics System of the National Center for Health Statistics (NCHS), which provides demographic and health information for births occurring in respective calendar years. The data is based on information from birth certificates filed in vital statistics offices of each state and the District of Columbia. I use data for calendar years 1990, 2000 and 2015 not only to analyze mother's education-infant health relationship but also to evaluate whether the relationship changed over time. The infant health measure of interest is birthweight (in grams). Demographic variables used include date of an infant's birth, mother's age, mother's education, marital status, infant's gender, birth order and metropolitan statistical area (MSA), county and state identifiers. The geographic variables are publicly available before 2004, however geographic details pertaining to identification of counties, cities and metropolitan areas are limited to population size of 100,000 or more. I use the restricted geographic codes for year 2015 obtained from NCHS.

The mother's education variable reported in the National Vital Statistics System can potentially create measurement error when constructing education variables of interest in this study. The education variable is reported as years of schooling and not whether certain level was actually completed for years 1990 and 2000, whereas for year 2015 education is divided into categorical levels, e.g. include: 1) lower than high school, 2) high school completion, 3) some college, and 4) college or higher. Hence, in years 1990 and 2000, reporting of four years of college is unclear as to whether an individual finished college or is still enrolled in the fourth year of college. Similarly, reporting of four years in high school is unclear whether an individual finished high school or dropped out while in the fourth year of school. To access the severity of such measurement error, I refer to the June supplement of the Current Population Survey in 1990, which reports the level of highest schooling attended along with the highest level completed. Focusing among individuals over 25 years of age, the survey suggests that 94 percent of individuals reporting education level of four years in high school (12^{th} grade) actually completed high school and 90 percent of individuals reporting four years in college completed college level education. As per this check, the measurement issue regarding education is unlikely to be severe. Hence, for years 1990 and 2000 of NVSS data file, schooling level of four years in high school is treated as completion of high school degree and four years in college represents college graduates. Formal years of reported schooling of five or more years in college refers to both college level education or higher. For purposes of empirical specification and to be consistent with reporting of education variable over the years, I group schooling into four categories: 1) less than high school, 2) high school graduates, 3) some college, and 4) college completion or more. Less than 1 percent of observations with missing education are dropped.

Participation in risky activities such as consumption of cigarettes during the time of mother's pregnancy affect infant health outcomes and increases the likelihood of preterm birth, sudden infant death syndrome (SIDS), and certain birth defects (fetal alcohol syndrome in case of alcohol). The decision of a mother to participate in risky behaviors during pregnancy can be determined by education as better education can help select proper inputs into the health production function. At the same time, participation in risky activities can be driven by a latent factor of riskiness, which might jointly determine the level of schooling. For instance, a risk averse individual with higher discount factor might be more willing to invest in human capital (schooling) as well as in health (Shaw (1996); Belzil and Leonardi (2013)). I present results from both specifications excluding and including variables that accounts for a mother's pattern of smoking during the time of pregnancy. Precisely, I generate seven categorical variables depending on mother's smoking behavior during pregnancy: 1) non-smoker; 2) 1-5 cigarettes per day; 3) 6-10 cigarettes per day; 4) 11-20 cigarettes per day; 5) 21-40 cigarettes per day; 6) 41 or more cigarettes per day; and 7) the number of cigarettes not stated. Next, to illustrate another important mechanism, I present results that explore differences in prenatal care utilization among various education categories across neighborhoods defined by poverty. It has to be noted that after a certain number of visits, an increase in prenatal visit may suffer from selection since high-risk mothers during pregnancy are likely to have increased prenatal visits. As a different measure, I construct a binary measure of whether prenatal care was started within the second month of pregnancy to track initiation of care. Additionally, I create prenatal care adequacy index that accounts for gestation by following Kotelchuck (1994). First, I determine the expected number of prenatal care visits given the initiation of prenatal care and the date of delivery based on the number of recommended visits by the American Congress of Obstetricians and Gynecologists (ACOG). Next, I calculate the ratio between the observed and expected number of visits and I construct an adequacy indicator based on the ratio if it takes a value of 1.1 or more.

To avoid concerns regarding reverse causality in the model specification, which can arise if pregnancy affects education outcomes of mothers, I restrict the sample to mothers of 25 years or over. Typically mothers beyond this age should have finished college level education. To account for the possibility of differences in infant health by birth order, the sample is limited to singleton birth from the first time mothers. The first born restriction further limit the sample to 25 percent of total births among mothers of age 25 years and over.

3.2 Other Data

Although natality files provide information regarding mother's education (and father's education, but only in certain years) and several other demographic characteristics, these files do not include variables pertaining to labor market outcomes, making me unable to directly control for personal income at the individual level. Controls for income is highly pertinent in specifications of the study as income is correlated with both education and health outcomes, and more importantly income tend to rise quite sharply after completion of educational landmarks such as high school and college degree. To properly account for income, I use individual level data from the CPS Merged Outgoing Rotation Groups (MORG) for years 1990 and 2000 and CPER Uniform Extracts 2015 file, along with aggregate data at the county level from various sources including the U.S. Bureau of Labor Statistics for county level per capita personal income, age-race specific population files from the NBER website, and education attainment by race for years 1990, 2000, and 2015 are extracted from the U.S. Census Bureau for two former years and American Community Survey for the latter. Following the steps highlighted in Appendix A10.1, I compute per capita personal income for sub-groups in a county adjusted by education, race and age for individuals of 25 years and above. The distribution of county-level computed income by race, education category, and age groups are presented in Figure A2. The figure shows that computation of income captures the fundamental income dynamics — per capita income is higher for whites compared to other race groups, income increases with education levels, and it follows the life-cycle income hypothesis such that income increases with age and falls after a certain age (see Figure A3). The computed income is merged with NVSS file by county, year, education attainment, race, and age group.

To rank mother's county of residence based on poverty rates I use the county level poverty measures from the 1990, 2000 and 2015 Census and form county-groups based on the rankings. This approach has been used in the Currie and Schwandt (2016) and Singh and Siahpush (2006) studies. Figure 4 maps the U.S. counties based on poverty rates for years 1990 and 2000. In both maps, poverty is concentrated in the Appalachian region in the South, whereas north eastern states, western states and some states in the mid-west have fairly low levels of poverty. Additionally, I rely on data from the Agency for Healthcare Research and Quality (AHRQ) to measure access to care across localities defined by poverty rates. Unfortunately, this is only viable for year 2015 as AHRQ's data is only available starting from 2010. Data from Behavioral Risk Factor Surveillance System (BRFSS) is used to compute the availability of health insurance across localities in year 2000 by education categories. Unfortunately, BRFSS excludes questionnaire regarding the type of medical insurance in year 2015, which disallows me from consistently analyzing the trend in access to different types of health insurance over the years.

Several potential concerns arise when combining the dataset for years 1990, 2000 and 2015 while using the county-rank approach. First, the share of population by education status has changed quite significantly between these years. For instance, 18 percent of women who were over 25 years of age had completed bachelors degree in 1990 but the share increased to 24 percent in 2000.[13] If such improvements in college completion are concentrated among women in relatively better socio-economic status who are also likely to have children with better health, then the findings will be partially driven by selection from particular group of women joining the pool of college graduates in 2000. Second, selective migration across counties over time can also raise concerns if educated individuals who have higher preference of better health leave poor counties in favor of richer counties. Selection of such a kind may lead to results that suppress the association between education and health in poorer counties. To ensure that the main results are not being driven by demographic changes, I conduct analyses separately for each survey year 1990, 2000 and 2015 as a robustness exercise.

Although counties include more heterogeneous group of population compared to narrower areas used to represent the neighborhood (i.e. Census tracts), county level approach is beneficial in several context. First, counties are consistently reported in both the natality and Census files, making it possible to link crucial variables such as income and earnings, and poverty rates. As previously mentioned, one challenge is that counties may expand or shrink over time. If such changes in population is systematically related to socio-economic status and health preference — for example, if healthy group moves away from a county, say A — then county-to-county comparison will not result in appropriate comparison as child health in county A will seemed to have declined even if nothing changed except selective migration. As suggested by Currie and Schwandt (2016), such an issue can be corrected by grouping counties into groups that represent approximately equal share of births (in our case). We adapt the county-group approach as undertaken by Currie and Schwandt (2016) and conceptualize it in a regression framework as discussed in the following section.

4 Model Specification

I estimate the following model specification.

$$BirthWeight_{itc} = \alpha + \sum_{j=2}^{j=4} \beta_j Education_{itcj} + \sum_{k=2}^{k=5} \delta_k Earnings_{itck} + \lambda_1 X_{itc} + \lambda_2 Z_{tc} + \delta_c + \rho_t + e_{itc} \tag{1}$$

[13] https://www.census.gov/content/dam/Census/library/publications/2016/demo/p20-578.pdf

Here, $Birth\,Weight_{itc}$ represents birthweight (in grams) extracted from medical records for an infant i born in year t and in county c; α is the intercept term. $Education_{itcj}$ is an indicator variable that takes a value "1" if the mother's years of schooling is equivalent to j, otherwise the value given is "0." Here, $j \in \{2,3,4\}$ represents high school graduates, some college, and college completion, respectively, and less than high school is used as the comparison category. Rather than maintaining a parametric structure for education, years of schooling is allowed to enter the model in a non-parametric setting in equation 1. $Earnings_{itck}$ represents income indicators in relation to poverty bins ($j \in \{2,3,4,5\}$ represents $>$200 to 300,$>$300 to 400,$>$400 to 500, and $>$500 percent of poverty level, respectively) constructed by using poverty thresholds of specific years and county specific per capital personal income adjusted by education, race, and age group computed as discussed in the data section. The vector X_{itc} includes personal characteristics such as mother's age, age squared, race indicators (white, black and other race), marital status, and child's gender in the baseline specification. Z_{ts} includes county level unemployment rate, real cigarette taxes per pack and beer taxes per gallon expressed in 2015 dollars. δ_c and ρ_t represents county fixed effects and year fixed effects, respectively. To account for correlation within states, standard errors are clustered at the state level.[14]

Next, to evaluate the relationship between mother's education and incidence of low birth weight (LBW), I estimate the following specification using a linear probability model.

$$LBW_{itc} = \alpha + \sum_{j=2}^{j=4} \beta_j School\,Year_{itcj} + \sum_{k=2}^{k=5} \delta_k Earnings_{itck} + \lambda_1 X_{itc} + \lambda_2 Z_{tc} + \delta_c + \rho_t + e_{itc} \tag{2}$$

where, LBW indicates whether an infant is of a low birth weight ($< 2,500$ grams) and the model is specified similar to equation (1). The reason for using the linear probability model in favor of non-linear models is because non-linear estimation do not favor inclusion of county fixed effects due to incidental parameter problem.[15]

Area specific inherent effects can influence years of schooling and also affect infant's health even in models with state fixed effects due to wide variation in socio-economic characteristics across different localities within a respective state. To lessen such a concern of residential

[14] Additionally, I also estimate the specification of the form: $Birth\,Weight_{itc} = \alpha + \sum_{j=9}^{j=17} \beta School\,Year_{itcj} + \delta Earnings_{itc} + \lambda_1 X_{itc} + \lambda_2 Z_{tc} + \delta_c + \rho_t + e_{itc}$, where $School\,Year$ represents the number of formal years in school, capped at 17 year, using NVSS data for years 1990 and 2000. I am unable to estimate this form of specification for year 2015 as reporting of education variable changed as discussed in section 3.

[15] The results are similar when estimating the models by using probit when state fixed effects are included instead of county fixed effects. The results are not presented but are available upon request.

effects driving both education and infant health outcomes, the preferred specification includes county fixed effects, which limits variation in socio-economic status compared to using state fixed effects. Moreover, the use of county level fixed effects is consistent to the county-ranking approach described in the upcoming paragraph.

The next part of the analysis directly evaluates the potential of differential mother's schooling-infant health gradient across geographic areas given by counties. Using the 1990, 2000 and 2015 census data, I first rank the counties by their poverty rates in 1990, 2000 and 2015. Next, I divide counties into 10 groups with each group representing about 10 percent of the share of infants born in the respective year and estimate specification 1 for each county-group.[16] Also, to examine the robustness and for visual interpretation, I repeat similar empirical exercise but by grouping counties into 20 county-groups with each group representing about 5 percent of the share of infants born. This is followed by fitting lowess lines over the obtained coefficients for each education category (high school, some college, college) across the county-groups aligned with an increasing poverty ranking. This approach provides estimates of differential relationship between maternal education (at various levels) and infants' birth outcomes across geographic areas based on income.[17] One concern is that education can allow for selective ranking of the counties in the first place as poor counties are likely to have higher percentage of high school dropouts, thus, the findings are conditional on area of residence. Nevertheless, this approach provides several attractive features. First, this approach reduces wide variation in socio-economic status across geographic regions that can simultaneously affect mothers' schooling and infants' health. Second, and more importantly, it allows for investigating the effects of mother's education across different geographic regions based on poverty levels. As previously discussed, most studies that have investigated the relationship between maternal education and child health are at the national level or state levels, but to what extent do the relationship vary at the local levels based on poverty? Answers to this question will allow us to better understand the trifecta of relationship between education, income, and infant health outcomes.

5 Results

I begin the analysis by observing some local level trends that describes the relationship between mother's levels of education and infant health outcomes based on poverty ranking of

[16] This procedure is similar to that used by Currie and Schwandt (2016), except that county groups here is based on the share of infants born rather than the share of the total population.

[17] Although the county-ranking approach allows for variation in health returns to education across geographic areas based on poverty, it ignores within county heterogeneity in health returns based on a measure of income inequality. This can be an important aspect when defining association between mother's income and infant's health outcomes and future work can address this concern.

county groups. Next, I conduct regression based analysis to identify the patterns in mother's education-infant health gradients. This is followed by an investigation of some mechanisms that can potentially describe the existing relationship between mother's education and infant health outcomes across localities. Throughout the study, I present results for both birthweight and low birth weight, however, the results pertaining to low birthweight category (described as $< 2,500$ grams) are presented in the Appendix section.

5.1 Persistent Trends in Mother's Education-Infant Health Gradient

Table 1 shows the summary statistics of the main variables used in this study. The mean birthweight increases with education but at a decreasing rate. For example, mothers with a high school degree on average have infants weighing 107.19 grams more than infants from mothers with less than high school, but the difference is only 60 grams between infants from mothers with high school degree and mothers with four or more years of college. Also, mothers with high school degree on average have a reduced probability of infant's low birthweight by 3.9 percentage points compared to high school dropouts. There exists a stark difference in personal per capital income across education levels. Having a high school degree on average is associated with an increase in annual earnings by over $11,000 compared to individuals without a high school diploma, however, having a college degree more than doubles the annual earnings compared to people with only a high school degree. Consistent with the existing studies, substance use such as cigarette consumption during pregnancy decreases with levels of education.

Figure 5 provides a visual depiction of mother's education-infant health gradient defined by birthweight, not just at the mean, but throughout the entire distribution of infants' birthweight. It is observed that having a high school level of education or more shifts the empirical cdf of birthweight towards the right to the group without high school level education, suggesting that infant health outcome of mothers with high school level of education or more is better at all points of the distribution compared to births from mothers with less than high school.

Figure 6 shows the relationship between mother's education and infant health outcomes across the county-groups defined by poverty ranking approach for years 1990, 2000 and 2015. The horizontal axis denotes the poverty ranking of counties that increases in poverty, and each county-group comprises about 5 percent share of the total births in the sample. Each point on the figure represents an average outcome at the specific bin, where circle, triangle, square, and diamond markers are used to distinguish outcomes between mothers with no high school degree, high school degree, some levels of college, and college or more, respectively.

The lines show the best fit obtained from the OLS regression. When individually taken, each best fit line reflects the income-gradient conditional upon mothers' education level. These lines typically have negative slopes for the top panel (birthweight) and positive slopes for the bottom panel (low birthweight), indicating that infant health stock falls with residence in poorer localities even for mothers with higher levels of education. A comparison of best fit lines across education categories portrays mother's education-infant health gradient across localities based on income.

The fact that the y-intercept of the best fit lines presented in Figure 6 increases with education category in the top panel and decreases in the bottom panel shows that birth outcomes are better among educated mothers within each county-group. However, the magnitude of gap between the intercepts across education categories have changed over time. For example, the gap between the line intercepts decreases with increases in education in years 1990 and 2000 — the difference in intercepts between no high school group and high school is more than twice as large compared to the difference between high school and some college in these years. The magnitude of this gap has reduced quite substantially in 2015 for both birthweight and low birthweight outcomes.

A comparison of best fit lines across education categories and county-groups shows that infant health outcomes of mothers with high school degree and belonging to county-group of the highest poverty ranking are essentially similar to the outcomes pertaining to mothers with no high school diploma but residing in county-group representing the lowest poverty level in 1990 and 2000. More importantly, the magnitude of income-gradient pertaining to the group with less than high school is steeper than the rest and the gradient flattens with improvements in education. This indicates that discrepancies in infant health outcomes between education categories increases with locality ranking (based on poverty rate). When comparing across years, both income-health and education-health gradients were similar in 1990 and 2000 but the gradient in 2015 flattened. Although just descriptive, these findings highlight the possibility of differential relationship between mother's education and infant health across localities based on income status. Moreover, a comparison across years points to evolution of mother's education-infant health gradient over time, with infant health among less educated mothers living in relatively poor localities improving in the recent years.

One important question is how do these findings relate to the recent influential studies evaluating trends in health outcomes (Currie and Schwandt, 2016; Chetty et al., 2016). Although there are several differences at a smaller level (choice of outcomes, time frame), the salient one is that this study stresses the relationship between locality, income and health outcomes by accounting for differences due to education, whereas the previous study focuses on changes in health inequality over time or geographical variation in the relationship between income and mortality, without considering potential differences by education levels.

5.2 Regression Based Relationship

Table 2 provides a basic understanding of the relationship between mother's education and infant's birthweight by estimating five different specifications. Columns (1) to (5) show findings after estimating specification (1). All specifications include county and year fixed effects. Additionally, Column (1) includes education variables and Column (2) includes per capital income indicators based on the reported poverty categories separately. Column (3) includes both education variables from Column (1) and income variables used in Column (2). Column (4) adds other personal characteristics such as mother's age, age squared, race dummies, marital status and child's gender as well as aggregate variables such as county unemployment rate and state-level cigarette and beer taxes (converted to 2015 dollars). Column (5) excludes beer and cigarettes taxes from Column (4) and directly adds variables accessing mother's risk factor by including mother's smoking status during pregnancy and the number of prenatal visits. The results from models with mother's smoking status during pregnancy should be interpreted with caution as education can influence one's smoking behavior.[18]

Column (1) in Table 2 indicates that having a high school level education is associated with significant improvements in an infant's birthweight, on average by 70.5 grams, compared to mothers with less than high school and this relationship increases with higher levels of education. For instance, mothers with college degree or more give birth to infants who on average weigh 155.7 grams more than infants from mothers with less than high school.[19] Column (2) shows that per capita personal income is positively associated with an infant's birthweight — moving away from the poverty level is associated with higher infant birthweight, which highlights the income gradient. In specification that includes both education and income, as shown in Column (3), the coefficients on both education and income indicators shrink but are still statistically significant at the 1 percent level. The coefficients on income indicators are precisely estimated with relatively low standard errors even in specifications with education indicators. This instill confidence on the income computation method as defined in section A10.1. The addition of important controls such as mother's age (age squared), race indicators, mother's marital status, and child's gender increases education coefficients, whereas coefficients on income indicators are reduced. It has be noted that additional controls implemented in Column (4) reduces the standard errors of all the reported coefficients compared to Column (3). The specification used to estimate results in Column (4) is regarded as the

[18] At the same time, one can think of smoking status acting as proxy for health knowledge and innate level of riskiness, which can directly affect infant health outcomes. In upcoming analysis, I show results from both including and excluding these risk factors as control variables.

[19] The difference in coefficients across education categories are tested by using a bootstrap method from 499 replications, as shown in Figure A4, under the null hypothesis that the coefficients are not different from one another. The blue dotted lines represent the 2.5^{th} and 97.5^{th}percentiles of the distribution, whereas the red dashed line pertain to the actual difference between the coefficients.

preferred specification. Findings reported in Column (4) suggests that mothers with high school completion give birth to infants who on average weigh 47 grams more than infants from mothers without high school degree. The mother's education-infant birthweight relationship strengthens with higher educational attainment and the associated benefit to infants' birthweight increases up to 115 grams for mothers with college completion compared to less than high school education. Column (5) adds additional covariates including mother's smoking habits during pregnancy. Although the magnitude of coefficients shrink compared to Column (4), the pattern of the relationship between both education-infant health and income-infant health are well defined in Column (5).[20]

Table A1 in the Appendix shows the results from a linear probability model when the dependent variable used is an indicator for low birthweight instead of birthweight.[21] The findings presented in Table A1 is consistent with the results shown in Table 2. The results show a reduction in probability of low birthweight infants associated with completion of high school education, some college, and college completion compared to less than high school. Moreover, the coefficients on income indicators are negative, indicating a negative relationship between income and infant health.

In additional specifications, I consider alternative ways of accounting for access to medical care. I control for 1) Month when prenatal care began; 2) Attendant at birth (doctor of medicine, doctor of osteopathy, and others); and 3) Place of facility of birth (hospital, clinic, home, others). The results are similar to those shown in Table 2.[22] In summary, these findings suggest that on average mothers' education, categorized as high school completion, some college attainment, and college completion or higher is associated with a sharp increment in infants' birthweight and reduced probability of low birthweight infants even in models that precisely control for per capita income, mother's health behaviors (smoking pattern), and access to medical care (the number of prenatal visits). These findings demonstrate the conventional mother's education-infant health gradient by highlighting the need to include education as flexibly as possible in model specifications rather than imposing the assumption that the marginal return to an additional year of schooling is similar across all levels.

[20] To access mother's education-infant health relationship when education is entered linearly, as an auxiliary exercise, I re-run specifications with years of schooling representing the education regressor instead of classification by education categories. The coefficient on years of schooling indicate that an additional year of schooling on average is associated with an increase in birthweight by 12.35 grams (in analogous specification to Column (4) in Table 2). A comparison between the coefficient on years of schooling (when entered linearly) and findings in Column (4) provides very misleading information regarding the relationship between education and infant health.

[21] Using probit estimation leads to similar results as of linear probability model when including state fixed effects instead of county fixed effects. The reason for using linear probability model in favor of probit is because probit estimation does not favor inclusion of county fixed effects due to incidental parameter problem.

[22] Results are not presented but are available upon request.

5.3 Health Returns to Education Across Geographic Areas

The more important question is does the education-health gradient vary across geographic areas defined by income status. For instance, marginal benefits associated with completion of high school and higher levels of education may be higher for mothers living in poor geographic areas with scarce resources (doctors, hospitals) compared to rich areas with better quality hospitals and sufficient resources. In this case, education may substitute for lack of relevant health inputs in poorer neighborhoods. In fact, Figure 6 provides a descriptive evidence that although education is valuable, the mother's education-infant health relationship is stronger in poorer localities. In this section, I conduct a regression based analysis by holding other observable factors fixed to generate a more robust pattern that describes the relationship between mother's education and infant health across localities defined by poverty ranking.

Table 3 shows the relationship between mother's education and infant's birthweight across county groups based on poverty ranking.[23] The county groups, represented by columns in the table, are ranked from the lowest poverty rate to the highest and each county group consists approximately 10 percent of the total births in the sample. For example, Column (1) is conditional on counties with the lowest poverty rates that makes up about 10 percent share of the total births in the sample; Column (2) pertains to the group that consists of counties with the next higher ranking in terms of poverty rate, with this county group also comprising about 10 percent share of the total number of births in the sample. Similarly, Columns 3-10 involve counties with increasing poverty with each column to the right and each county-group consisting about 10 percent of the total births. The results are presented by using controls similar to Column (4) in Table 2.

Table 3 provides some fruitful insights. The findings presented in Table 3 indicate that the relationship between mother's education and infant health outcomes is higher in relatively poor areas compared to rich areas for all categories of education. The magnitude of associations between mother's education and infant's birthweight typically increases as we move to the next column to the right, suggestive of a stronger education-health relationship in relatively poor county-groups. These patterns are similar when using prevalence of low birthweight or very low birthweight as the dependent variable (See Appendix A2 and A3). To test whether coefficients reported in Table 3 within each education category but across county-groups are statistically different, I implement a bootstrap method from 499 rounds of estimation to test for the difference in coefficients under the null hypothesis that the coefficients on respective education category across county-groups are not different from one another. The results from bootstrap estimates of difference in coefficients from 499 replications and under the null are shown by using histograms for each education category between

[23] Here, separate models are estimated for geographic areas in each group based on poverty ranking.

Group (1) ($0-10^{th}$ percentile) and Group (6) ($50-60^{th}$ percentile) in Figure A5. The blue dotted lines represent the 2.5^{th} and 97.5^{th} percentiles of difference in coefficients under the null, whereas the red line represents the actual difference in coefficients between the two county-groups. It is seen that in most cases the actual difference is of the expected sign (positive for birthweight and negative for low birthweight) and above the critical lines, which allows rejecting of the null hypothesis that the coefficients across the two groups are not statistically different in favor of the alternative hypothesis.[24]

Next, as a robustness exercise and for visual interpretation, I form a tighter grouping of counties after ranking them by poverty levels with each county-group comprising about 5 percent of the total births in the sample. For each county group, I re-estimate infant health specification similar to Table 3, which gives 20 coefficients for every education category. The comparison sub-group is still less than high school group. The magnitude of these coefficients are plotted along the county group ranking in Figure 7 when using birthweight (left), prevalence of low birthweight (middle), and very low birthweight (right) as the dependent variables. The dotted lines presented over these coefficients are fitted using a local linear regression on coefficients of each education category and the smoothing parameter is selected by using the leave one out cross-validation method to minimize the root mean squared error.[25] For the figure pertaining to birthweight, mother's education-infant health gradient increases for the first half of the county groupings after which the curves flatten. This pattern is highly prominent for mother's who completed college. The results are even more striking when using prevalence of low birthweight as the dependent variable — the gradient decreases quite significantly for the first half of county groupings before flattening out for mother's with less than college completion, whereas the gradient is much steeper for mother's with college level education or more. The fact that the gap between the curves increases across education categories when moving towards poorer localities highlights the strengthening of mother's education and infant health relationship in poorer neighborhoods.

To incorporate mother's behavior during pregnancy that determines the risk factor, I re-estimate the coefficients presented in Table 3 by including mother's habit of smoking during pregnancy and usage of prenatal care. The results from this exercise are presented in Table

[24] Additionally Figure A6 plots the histogram for each education category between Groups (2) ($10-20^{th}$) percentile and Group 10 ($90-100^{th}$) percentile. The actual difference is outside the critical region for coefficients pertaining to college level for both birthweight and prevalence of low birthweight.

[25] For coefficients of each education category, I estimate a local linear regression leaving one coefficient out by using a starting smoothing parameter. Using the estimates of the model, I generate predicted values and store the predicted value of the left out coefficient. I repeat this exercise using the same smoothing parameter but excluding each of the other coefficient until every coefficient is excluded once. Then I calculate the root mean squared error (RMSE) using the actual and predicted values. I repeat this process for varying values of smoothing parameter. Finally, I choose the value of smoothing parameter that minimizes the RMSE for each education criteria.

4. Although the coefficients that describe the relationship between mother's education and birthweight are now lower compared to those presented in Table 3, the pattern of coefficients across the county groups are consistent — the magnitude of the relationship is stronger in poorer localities. On average, a high graduate mother living in the poorest of the county grouping (Column 10) has an infant that weighs 50 grams more compared to an infant from a mother with less than high school education, whereas the high school graduate living in the richest county grouping (Column 1) has an infant that weighs 32 grams more than the comparison group. Such differences increases with education levels. For instance, the magnitude on the coefficient pertaining to mothers with college level education and living in the poorest county-group is more than double compared to mothers living in the richest group but of the same education category.

Next, we turn to the question of whether mother's education-infant health relationship has evolved over time. Various need-based policies targeted towards improving access to health care (expansion of Medicaid, Supplemental Feeding Program for Women, Infants, and Children (WIC), Earned Income Tax Credits, and several provisions of the Affordable Care Act), state and federal policies against smoking (smoke free air laws and cigarette taxes), and public health awareness has improved in recent decades. If such provisions disproportionately benefit individuals in poorer localities, specifically mothers from low education sub-groups, then we can expect the education-infant health gradient to flatten in recent years. In fact, Aizer and Currie (2014) show that health of infants from mothers in disadvantaged socio-economic backgrounds are converging to infant health from advantaged mothers. Similarly, Currie and Schwandt (2016) argue that improvements in life expectancy among younger populace in recent years has been concentrated in poor localities rather than rich areas. These recent evidence warrants further investigation as to how mother's education-infant health gradient has evolved over time.

The results presented in Table 5 pertain to estimation of specification that allows the relationship between education and birthweight across different county-groups to vary in more recent year (2015) compared to previous years (1990 and 2000). The specification estimated is similar to equation 1, with addition of education categories interacted with an indicator representing year 2015.[26] In Table 5, the coefficients on the education categories (High School Graduate, Some College, College or More) are positive and show similar pattern as to Table 3, although the magnitude on the coefficients are typically larger. These coefficients represent mother's education-infant health relationship in 1990 and 2000. The coefficients on the interaction terms between education categories and the year indicator for 2015 show whether

[26]This specification is given by: $Birth\,Weight_{itc} = \alpha + \sum_{j=2}^{j=4} \beta_j Education_{itcj} + \sum_{j=2}^{j=4} \gamma_j Education_{itcj} * I(t = 2015) + \sum_{k=2}^{k=5} \delta_k Earnings_{itck} + \lambda_1 X_{itc} + \lambda_2 Z_{tc} + \delta_c + \rho_t + e_{itc}$, where $I(t = 2015)$ is an indicator variable for year 2015.

the relationship for each education category changed in 2015 compared to the prior years. In most cases except for Group 1, the coefficients on the interaction terms are negative and statistically significant at conventional levels, indicating weakening of mother's education and infant health relationship over time.[27] However, it can be observed that mother's education-infant health relationship is still positive and more concentrated in relatively poorer localities in 2015. Next, we analyze some potential drivers contributing to varying education-infant health gradient across localities and changes in gradient in recent years.

5.4 Potential Mechanisms

To shed light on some potential mechanisms driving the main findings of the study, I further explore why education-health relationship is stronger for mothers residing in relatively poor county-groups compared to mothers in richer county-groups. There are two main potential drivers. First, it may be that low educated mothers residing in richer neighborhood are self-selected such that they hold higher preference for better health stock and are less likely to participate in health depreciating behaviors such as consumption of cigarettes and alcohol during pregnancy compared to low educated mothers in poorer areas. Due to this, allocative efficiency to select appropriate inputs (prenatal care, smoking behavior, diet) into the health production function may be relatively higher for educated mother in poor localities compared to educated mothers residing in rich areas. Second, suppressed availability of access to adequate health infrastructure and services can hinder infants' health among mothers in poorer areas and education may improve such barriers to access through provision of health insurance.

Table 6 shows the relationship between mother's education and utilization of prenatal care within the first two months of pregnancy across county-groups. The findings suggest that the probability of prenatal care initiation within the first two months of pregnancy increases with education across all county-groups and for the most part income is positively associated with initiation. Figure 8 shows trends in prenatal care using two different measures: 1) whether prenatal care was initiated in the first two months of pregnancy, and 2) adequacy of care throughout pregnancy by education categories across localities in years 1990, 2000 and 2015. The slope of the best fit line pertaining to sub-group of mothers with no high school is negative and steep in 1990 for both initiation and adequacy of prenatal care. This indicates below par utilization of prenatal care among less educated mothers living in poor neighborhoods

[27] The magnitude of relationship particularly for 2015 can be obtained by adding the coefficient on the interaction term and that on respective education criteria together. As an additional robustness exercise, we directly estimate specifications used to obtain Table 2 for each year separately. The results are presented in Table A4. The results show a reduction in the magnitude of coefficients on education indicators over the years.

compared to mothers with the same level of education but living in richer areas. In recent years, the slope of the line for mothers with less than high school has flattened. Noticeably, the intercepts of the best fit lines pertaining to initiation have decreased in 2015 across all education categories. Caution should be provided in conducting a direct comparison in prenatal care initiation period across the years due to changes in recording of information regarding prenatal care starting from 2003.[28] However, the slope for less educated sub-group of mothers pertaining to initiation of PNC has reversed in 2015, with mothers living in poorer localities being more likely to initiate PNC within the first two months of pregnancy. A comparison across best fit lines representing the adequacy of care (bottom panel) indicates that about 65 percent of mothers with less than high school and living in the poorest county-group met the prenatal care adequacy threshold in 1990, whereas this share improved to 75 percent in 2015. These findings provide evidence that utilization of prenatal care, particularly among less educated mothers living in poor localities, has improved quite dramatically in recent years.

Table 7 shows the relationship between education and smoking status during pregnancy using a regression-based framework. The findings are consistent with the well-established relationship that improvements in education is associated with a reduction in smoking participation. Some interesting patterns can be noted — the education-health behavior relationship during pregnancy is concentrated towards relatively poor localities. For instance, completion of college is associated with an increased probability of being a non-smoker by 20 percentage points for mothers in the poorest county-group (Group 10), compared to mothers with less than high school education. To understand the evolution of smoking behavior over the years, Figure 9 shows trends in cigarette consumption among pregnant mothers. It is apparent that cigarette consumption decreases with education. For example, 40 percent of mothers with less than high school education reported smoking while pregnant in 1990, and the share reduced to 20, 10, and 5 percent for mothers with high school completion, some college, and college or more, respectively. However, there has been dramatic improvements in smoking behavior over time among low educated mothers, which is shown by the upward shift in the intercept of the best fit line in 2015, compared to prior years. The share of less educated mothers who participated in cigarette consumption reduced to 10 percent in 2015, a massive improvement compared to the share of 40 percent in 1990.

Next, I directly investigate the role of access to health insurance in potentially explaining the main findings of the paper. I use data from the Behavioral Risk Factor Surveillance System (BRFSS) years 1996-2000 and categorize health insurance into two groups: 1) employer

[28] The natality files only reported the initiation month of prenatal care prior to 2003. In 2003, NVSS collected the date of the first prenatal care visit, including month, day, and year. This change in structure in questionnaire disallows one to directly compare initiation of prenatal care across the years.

sponsored insurance (ESI) or self-purchased (private insurance), and 2) Medicaid. Then I group the counties according to the county-rank approach used in this paper such that each group represents about 5 percent of the total people in the sample and plot the fraction of individuals with ESI or self purchased insurance and Medicaid by education category across county groupings. The descriptive analysis is presented in Figure 10 (top panel). The figure provides some striking patterns – the prevalence of ESI or self insurance is quite high for individuals residing in relatively richer county groupings, even among individuals with less than high school education. The share of private insurance reduces as we move to the right towards the poorer county-groups, as shown by the negative gradients of the best fit lines, but the gradient is steeper for the line pertaining to less than high school sub-group. There is approximately 25 percentage points of reduction in this share when looking at the difference between the richest and poorest county groups. A reduction in private insurance is compensated by Medicaid as shown in the right-top panel, however such compensation is not one-to-one — the prevalence of Medicaid only increases by about 10 percentage points when moving from the richest to the poorest county groupings. Furthermore, the descriptive analysis shows that people with higher education levels are significantly more able to sustain private insurance coverage compared to those with less than high school education, particularly when residing in poorer counties. This further highlights the importance of education in preserving access to healthcare in poorer localities.

Using data from 2015 NVSS files, I conduct a descriptive analysis of payment type precisely while giving birth by education categories across county-groups based on poverty levels. The results are presented in Figure 10 (bottom panel). The first two sub-figures show that the fraction of mothers relying on Medicaid and private health insurance to pay for delivery decreases and increases with education, respectively. The third figure shows the pattern of self-pay when giving birth. The figure suggests that even in 2015, the cases of delivery in absence of affordable cost sharing measure is relatively high among mothers with less than high school education who live in poor localities, whereas such instances of birth are highly reduced among high school graduates residing in similar localities. This figure depicts stark disparity in access to medical care by education category among pregnant women living in poor localities even in recent years.

6 Estimates by Race

Several studies have documented that health return to education is mostly focused among whites by using self-reported own health outcomes or children's health outcomes (See Currie and Moretti (2003); Lleras-Muney (2005); Cutler and Lleras-Muney (2010)).[29] Gage et al. (2013) explores whether maternal education-infant health relationship differs across race by using 2001 natality data file. The authors find that disparity in infant health outcomes between whites and blacks increases with educational attainment. Similarly, using the 1998-2002 National Vital Statistics Birth Cohort Linked files, Green and Hamilton (2019) find that the negative relationship between infant mortality and mother's education is concentrated among non-Hispanic white mothers. In a recent study, Currie and Schwandt (2016) use data from more recent year to find evidence of strong reductions in mortality in poorer county-groups, with large improvements among blacks living in poor localities. Given the significant disparity in health outcomes by race until this day, it is important to separately evaluate mother's education-infant health gradient by race.

The findings from estimating education-birthweight associations by restricting the sample to non-Hispanic black (top panel) and white mothers (bottom panel) are presented in Table 8. The findings show similar improvements in birthweight associated with completion of high school level education and above across both race groups. These findings together with improvements in education outcomes among African-Americans over the past decades may partially explain the results from Currie and Schwandt (2016).[30] Next, to evaluate whether the gradient is still more concentrated in relatively low-income geographic areas, I replicate estimation similar to that presented in Table 3, but by restricting the sample to white and black mothers. The results from these estimations are shown in Appendix Tables A5 and A6 for white and black mothers, respectively. The results suggest that the differential mother's education-infant health gradient across geographic areas defined by poverty levels is present even when restricting the sample by race, within both races. This indicates that the results in Table 3 is not driven by systematic groupings of race correlated with poverty levels.

Some potential factors creating differences in findings between this study and that of Gage et al. (2013) and Green and Hamilton (2019) are: i) this study excludes mothers who are younger than 25 mainly to avoid concerns of reverse causality and restricts the sample to first born, whereas the previous studies include mothers of all ages; and ii) the analysis includes more recent natality file (year 2015).

An important question is how the sample restriction by mother's age and birth order might affect the generalization of the results. This depends on disparity in important aspects such as socio-economic status and risk aversion between mothers who concede their first born before and after 25. Excluding mothers who are below 25 suppresses the proportion

[29] The reason behind this is because of the instruments of education affecting whites more compared to blacks; hence, having more explanatory power for education outcomes among whites.

[30] School dropout rates have decreased among African-Americans and black-white high school completion gap has substantially narrowed over the past decades. See https://nces.ed.gov/pubs2012/2012006.pdf.

of mothers with less than college level educational attainment in the sample, who are more likely to be from lower SES background. This is even more prevalent among blacks compared to whites given the higher teen pregnancy among blacks.[31] If mothers who concede their first born before 25 are in disadvantaged situation compared to mothers who concede the first born when 25 or later, then the coefficients on education attainment (for higher levels of education) will be understated by using the sample restriction by mother's age applied in the study. However, only including the first-born children overestimates the results on higher education categories if disparity in infant health by education shrinks with increases in birth order. Hence, the results presented in this paper are conditional on first born children from mothers who are 25 and above.

7 Discussion

The past studies have analyzed the impact of education on both health behaviors (e.g., smoking, drinking, seat belt use, exercise) and health outcomes (birthweight, obesity, mortality) by using data from various sources. A direct one-to-one comparison across the existing studies is not possible mainly due to the choice of dependent variables and the study-question.[32] The purpose of this section is to provide a general perspective regarding where this study fits in relation to the findings from the previous studies.

Kenkel (1991) investigates the relationship between schooling and health behaviors such as consumption of cigarettes, alcohol, and exercise after accounting for direct measures of health knowledge. The author finds that much of the relationship between education and health outcomes used remain even after controlling for differences in health knowledge across different levels of education. Focusing on education-health relationship over the generation, Gage et al. (2013) explores the association between mother's education and infant health across ethnic sub-groups by using low birthweight and mortality measures from 2001 NVSS file. The authors show that mother's education-infant birth outcomes are weaker among Mexican Americans compared to white and blacks, however, increases in education is associated with disparity in birth outcomes between whites and blacks, favoring whites. In a more recent study, Green and Hamilton (2019) investigate mother's education-infant health gradient across racial ethnicity by focusing on foreign-born versus U.S.-born mothers. The study finds that education-health association is the strongest among Non-Hispanic whites, whereas Non-Hispanic blacks have the lowest gradient.

[31] Teen pregnancy rate among black and white race was 29.3 and 14.3 per 1,000 females aged 15-19 in 2016, respectively. https://www.cdc.gov/teenpregnancy/about/index.htm

[32] A branch of studies investigate the relationship between one's education and health, whereas other studies analyze the relationship between parents' education and infants' or children's health outcomes.

A relatively new branch of studies explore the importance of neighborhood and localities in explaining health disparity in America by allowing for differential income-health relationship at the local level. Aizer and Currie (2014) find that infant health from mothers belonging to the most disadvantaged background has improved over time. Mothers from disadvantaged backgrounds (based on race, marital status, and education) are more likely to live in poorer localities. The Chetty et al. (2016) study focuses on income-health gradient and finds that although improvements in life expectancy have disproportionately favored the rich in recent years, it varies substantially across geographic localities based on income. Particularly, low-income people live longer if they reside in richer commuting zones with more educated individuals and higher government expenditure. While Chetty et al. (2016) focus on relatively older individuals (40 years and above) and is unable to identify an individual's race due to data limitation, Currie and Schwandt (2016) show trends in mortality across localities based on income by focusing on younger sub-groups and conducting analysis to explore racial disparity in mortality over the years. Their findings highlight improvements in mortality outcomes, particularly in poorer localities and among blacks.

A gap in the literature remains as prior studies explore education-health and income health-gradient mainly in isolation, which tend to ignore potential interactive effects of education and income. This study explores the possibility of differential mother's education-infant health gradient across localities based on income by using data from the National Center for Health Statistics. The study highlights four main findings. First, mother's education–infant health relationship is stronger in relatively poorer geographic areas and it increases with higher educational attainment. For instance, a mother with college completion and living in the poorest county-group gives birth to an infant that on average weighs 165 grams more than a mother with less than high school. The disparity in birthweight across these educational categories among mothers living in the richest county-group is only 70 grams. Second, although the magnitude of mother's education-infant health gradient has declined in recent years, the pattern of the relationship across localities based on income is consistent. Third, improvements in access to health care denoted by the utilization of prenatal care (both initiation and adequacy) has improved disproportionately among less educated mothers living in poor neighborhoods in recent years. However, smoking rate during pregnancy has decreased dramatically among less educated sub-group across all county-groups. These results can help explain evolution in differential education-health gradient across localities over time. Fourth, mother's education–infant health relationship is well-evident among blacks.

I provide caution that the relationship between mother's education and infant health should not be interpreted as causal effects because unobserved measures correlated with mother's education and health may be unaccounted for in model specifications. Although the purpose of the study is to conduct correlational analysis, the findings of the study provide a deeper understanding of education-health gradient by performing the analysis across geographic areas defined by poverty rate. The upcoming studies can benefit from simultaneously accounting for differential returns to education on health outcomes across geographic areas by accounting for endogeneity when exploring mother's education–infant health relationship.

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8 Tables and Figures

Table 1. **Summary Statistics**

	(1) less than H.S. b/se	(2) High School b/se	(3) Some College b/se	(4) College or More b/se
Birthweight (in grams)	3159.340	3266.538	3297.603	3326.511
	(3.249)	(1.258)	(1.021)	(0.655)
Low birthweight (below 2500 g)	0.117	0.089	0.078	0.067
	(0.002)	(0.001)	(0.000)	(0.000)
Income from wage (yearly coverted to 2015 D)	18950.920	30733.278	40769.593	71460.450
	(89.464)	(29.600)	(25.700)	(24.113)
County Unemployment Rate	5.238	4.993	4.889	4.622
	(0.009)	(0.004)	(0.003)	(0.002)
Real beer tax (yearly coverted to 2015 D)	0.306	0.327	0.320	0.305
	(0.002)	(0.001)	(0.001)	(0.000)
Real cigarette tax (yearly coverted to 2015 D)	1.207	0.838	1.019	1.117
	(0.005)	(0.002)	(0.002)	(0.001)
Mother's age	29.357	29.035	29.253	30.543
	(0.021)	(0.008)	(0.006)	(0.004)
Age squared	878.901	856.885	869.773	947.207
	(1.339)	(0.470)	(0.397)	(0.280)
White	0.761	0.843	0.838	0.849
	(0.002)	(0.001)	(0.001)	(0.000)
Black	0.151	0.116	0.109	0.059
	(0.002)	(0.001)	(0.001)	(0.000)
Others	0.088	0.041	0.053	0.092
	(0.001)	(0.000)	(0.000)	(0.000)
Child's gender	0.512	0.513	0.513	0.513
	(0.003)	(0.001)	(0.001)	(0.001)
Married	0.477	0.706	0.755	0.919
	(0.003)	(0.001)	(0.001)	(0.000)
Not married	0.523	0.294	0.245	0.081
	(0.003)	(0.001)	(0.001)	(0.000)
1-5 cigarettes per day	0.033	0.029	0.020	0.005
	(0.001)	(0.000)	(0.000)	(0.000)
6-10 cigarettes per day	0.058	0.044	0.024	0.005
	(0.001)	(0.000)	(0.000)	(0.000)
11-20 cigarettes per day	0.049	0.033	0.015	0.002
	(0.001)	(0.000)	(0.000)	(0.000)
21-40 cigarettes per day	0.008	0.004	0.002	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
41 or more cigarettes per day	0.001	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
cigarettes not stated	0.110	0.141	0.114	0.092
	(0.002)	(0.001)	(0.001)	(0.000)
Total Number of Prenatal Visits	11.713	12.992	13.115	13.214
	(0.055)	(0.021)	(0.016)	(0.011)
Observations	38527	244990	349382	760712

	(1) Without controls	(2) Without Controls	(3) Control Earnings	(4) Column3+Other Controls	(5) Column4+risk factors
High School Graduate	70.498***		38.287***	46.573***	38.462***
	(11.690)		(10.278)	(7.302)	(5.918)
Some College	117.007***		64.795***	82.222***	67.333***
	(14.414)		(12.918)	(9.125)	(7.013)
College or More	155.710***		87.413***	114.910***	93.992***
	(17.270)		(15.005)	(9.641)	(7.459)
Between 200 and 300 percent poverty		86.131***	72.337***	25.315***	18.497***
		(5.183)	(4.919)	(2.810)	(2.757)
Between 300 and 400 percent poverty		116.433***	89.917***	29.265***	19.560***
		(8.414)	(7.418)	(3.630)	(3.657)
Between 400 and 500 percent poverty		141.160***	98.540***	32.086***	21.564***
		(10.401)	(9.892)	(4.932)	(4.634)
Above 500 percent poverty		155.982***	98.891***	25.383***	16.686***
		(12.068)	(12.167)	(5.685)	(5.693)
Observations	1393611	1393611	1393611	1393611	1393611
R^2	0.019	0.019	0.020	0.043	0.049

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: **Mother's Education and Birthweight (Basic Results).** All specifications control for county and year fixed effects. Columns (1) and (2) separately include education and income indicators based on per capita income and poverty thresholds, respectively. Column (3) includes both education and per capita income variables, whereas Column (4) adds controls for personal characteristics (age, age square, race, marital status, child's gender), county unemployment rate, state level beer and cigarette taxes. Additionally, Column (5) excludes beer and cigarette taxes and directly controls for risk factors such as smoking behavior and the number of prenatal care visits. Standard errors clustered at the state level are presented in parenthesis.

	(1) Group 1	(2) Group 2	(3) Group 3	(4) Group 4	(5) Group 5	(6) Group 6	(7) Group 7	(8) Group 8	(9) Group 9	(10) Group 10
High School Graduate	31.801***	34.613	32.373***	61.623***	41.560***	62.781***	57.246***	58.953***	16.019	60.281***
	(9.680)	(22.722)	(9.591)	(11.727)	(10.514)	(7.455)	(16.045)	(10.305)	(25.878)	(8.943)
Some College	58.818***	69.006***	75.666***	96.548***	72.447***	102.999***	101.641***	103.519***	44.119	103.152***
	(9.491)	(25.345)	(12.705)	(15.520)	(12.205)	(11.883)	(19.892)	(13.266)	(32.345)	(10.116)
College or More	69.919***	83.993***	110.699***	126.112***	119.757***	167.390***	146.815***	126.700***	82.337**	165.085***
	(11.119)	(30.661)	(14.941)	(23.436)	(17.366)	(16.641)	(20.722)	(21.620)	(31.463)	(13.277)
Between 200 and 300 percent poverty	43.410***	51.692***	27.147***	18.910**	20.851**	14.605	48.267***	28.398***	33.459***	-8.109
	(12.308)	(11.520)	(9.097)	(7.612)	(8.443)	(8.688)	(11.259)	(9.894)	(8.544)	(5.491)
Between 300 and 400 percent poverty	71.880***	53.705***	23.580**	14.678	23.990**	4.353	40.686***	41.056***	37.477***	-18.514*
	(13.704)	(15.056)	(9.831)	(13.997)	(11.333)	(11.174)	(11.446)	(14.013)	(11.259)	(9.692)
Between 400 and 500 percent poverty	63.825***	62.877***	23.726*	25.157	20.555	-10.814	40.210***	39.927**	41.202***	-29.634**
	(14.743)	(16.831)	(12.541)	(18.381)	(15.840)	(15.773)	(11.897)	(19.364)	(15.076)	(12.434)
Above 500 percent poverty	71.399***	73.463***	16.619	21.865	-3.428	-28.276	25.799*	48.054*	28.514	-44.001***
	(16.810)	(22.814)	(14.463)	(22.267)	(20.956)	(20.844)	(14.740)	(23.879)	(22.244)	(15.518)
Observations	143127	142483	134782	140806	136123	156144	138352	126109	142058	129056
R^2	0.046	0.049	0.038	0.040	0.038	0.040	0.038	0.040	0.044	0.049

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: **Mother's Education and Birthweight Based on Poverty Ranking.** The counties are first ranked according to the poverty rate and each county-group consists of about 10 percent of the total number of births in the sample. As such, Group 1 in Column (1) represents the richest county-group (based on poverty rate) and Group 10 include the poorest of counties. All specifications also control for personal characteristics (age, age square, race, marital status, child's gender), county level unemployment rate, and state-level beer and cigarette taxes. Additionally, all specifications include county and year fixed effects. Robust standard errors clustered at the state level are presented in parenthesis.

	(1) Group 1	(2) Group 2	(3) Group 3	(4) Group 4	(5) Group 5	(6) Group 6	(7) Group 7	(8) Group 8	(9) Group 9	(10) Group 10
High School Graduate	31.846***	29.914	32.015***	50.059***	31.404**	53.799***	51.362***	48.878***	4.861	50.193***
	(8.238)	(21.876)	(8.242)	(10.002)	(11.988)	(7.558)	(10.226)	(9.256)	(20.540)	(7.903)
Some College	52.996***	58.558**	69.273***	76.728***	54.945***	86.633***	90.032***	89.306***	26.257	86.615***
	(8.797)	(23.769)	(9.957)	(13.447)	(12.971)	(10.339)	(12.096)	(11.458)	(25.692)	(8.913)
College or More	59.232***	71.065**	100.396***	101.209***	93.307***	144.967***	125.583***	110.007***	54.242**	138.710***
	(10.927)	(28.670)	(12.068)	(20.196)	(19.344)	(16.224)	(12.586)	(17.572)	(24.934)	(12.045)
Between 200 and 300 percent poverty	27.855**	41.010***	16.421*	7.107	11.300	7.325	32.697***	20.132**	26.184***	-8.997
	(11.838)	(12.484)	(8.926)	(6.743)	(7.991)	(7.489)	(9.844)	(9.479)	(7.674)	(5.447)
Between 300 and 400 percent poverty	50.526***	38.864**	7.697	-4.722	12.653	-6.675	22.097**	28.684**	30.613**	-17.102*
	(14.498)	(17.225)	(9.773)	(11.753)	(11.446)	(10.104)	(9.271)	(10.757)	(11.836)	(9.555)
Between 400 and 500 percent poverty	38.160**	44.265**	6.559	2.935	10.113	-22.652	20.578*	26.358*	33.484**	-28.277**
	(15.237)	(19.238)	(12.104)	(15.670)	(15.589)	(14.609)	(10.485)	(14.346)	(14.328)	(13.477)
Above 500 percent poverty	45.389**	54.009**	-1.252	-0.337	-9.481	-37.646*	11.269	32.947*	27.105	-34.218**
	(18.289)	(25.807)	(15.261)	(18.808)	(21.283)	(19.610)	(13.306)	(17.109)	(20.642)	(16.196)
Observations	143127	142483	134782	140806	136123	156144	138352	126109	142058	129056
R^2	0.051	0.054	0.045	0.049	0.045	0.045	0.044	0.044	0.050	0.055

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: **Mother's Education and Birthweight Based on Poverty Ranking (Controling for Risk Factors).** The table is structured similar to Table 3. The specification includes all controls as mentioned in the bottom of Table 3 except for beer and cigarette taxes. Additionally, specification controls for risk factors (smoking status) and the number of prenatal care visits. Robust standard errors clustered at the state level are presented in parenthesis.

	(1) Group 1	(2) Group 2	(3) Group 3	(4) Group 4	(5) Group 5	(6) Group 6	(7) Group 7	(8) Group 8	(9) Group 9	(10) Group 10
High School Graduate	105.701***	84.021**	60.551***	78.451***	97.439***	96.922***	141.064***	78.492***	113.863***	104.152***
	(14.320)	(31.475)	(21.942)	(26.710)	(23.407)	(11.258)	(25.289)	(9.895)	(12.661)	(19.141)
Some College	129.370***	123.711***	101.926***	115.762***	126.920***	140.707***	195.911***	124.770***	159.820***	151.378***
	(15.051)	(32.550)	(27.766)	(31.260)	(24.464)	(13.511)	(30.088)	(9.715)	(18.625)	(21.787)
College or More	152.293***	140.021***	142.166***	151.290***	176.215***	205.904***	239.403***	147.603***	190.484***	210.337***
	(16.177)	(38.703)	(29.787)	(38.322)	(28.644)	(19.557)	(27.565)	(14.346)	(19.225)	(24.173)
High School Graduate*2015	-104.610***	-75.259**	-50.078*	-23.792	-88.672***	-49.156**	-113.454***	-40.171*	-130.071***	-69.709***
	(20.732)	(28.285)	(26.225)	(31.451)	(26.766)	(19.908)	(29.868)	(23.006)	(28.031)	(23.913)
Some College*2015	-100.309***	-88.095***	-48.824	-31.502	-87.097***	-57.083***	-138.632***	-43.268*	-167.255***	-78.884***
	(22.919)	(25.670)	(29.560)	(33.247)	(25.605)	(20.995)	(33.378)	(22.692)	(39.468)	(23.084)
College or More*2015	-126.432***	-89.427***	-64.576**	-42.526	-97.740***	-60.012**	-142.128***	-40.060*	-145.318***	-77.417***
	(22.159)	(26.511)	(29.359)	(32.355)	(28.806)	(23.622)	(32.772)	(23.354)	(38.493)	(25.596)
Observations	143127	142483	134782	140806	136123	156144	138352	126109	142058	129056
R^2	0.046	0.049	0.038	0.040	0.038	0.040	0.039	0.040	0.044	0.049

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: **Mother's Education and Birthweight Based on Poverty Ranking (Did the Relationship Change?)** The table is structured similar to Table 3. The specification includes all controls as mentioned in the bottom of Table 3. Additionally, the specifications include the interactions of educational attainment of high school, some college, and college or more with the 2015 year indicator, respectively. Robust standard errors clustered at the state level are presented in parenthesis.

	(1) Group 1	(2) Group 2	(3) Group 3	(4) Group 4	(5) Group 5	(6) Group 6	(7) Group 7	(8) Group 8	(9) Group 9	(10) Group 10
High School Graduate	0.118***	0.069***	0.083**	0.074***	0.083***	0.074***	0.027	0.087***	0.053*	0.055***
	(0.014)	(0.012)	(0.035)	(0.022)	(0.011)	(0.012)	(0.021)	(0.011)	(0.029)	(0.008)
Some College	0.138***	0.102***	0.112***	0.105***	0.114***	0.110***	0.054**	0.116***	0.067*	0.098***
	(0.018)	(0.010)	(0.032)	(0.018)	(0.014)	(0.013)	(0.020)	(0.014)	(0.039)	(0.008)
College or More	0.156***	0.138***	0.140***	0.135***	0.151***	0.156***	0.087***	0.147***	0.107**	0.150***
	(0.023)	(0.012)	(0.033)	(0.015)	(0.021)	(0.020)	(0.019)	(0.015)	(0.040)	(0.011)
Between 200 and 300 percent poverty	0.031***	0.035***	0.011	0.020***	0.028**	0.012	0.068***	0.049***	0.029	-0.001
	(0.008)	(0.012)	(0.018)	(0.007)	(0.012)	(0.009)	(0.015)	(0.013)	(0.020)	(0.013)
Between 300 and 400 percent poverty	0.040***	0.036**	0.016	0.011	0.028*	0.007	0.069***	0.058***	0.021	-0.029*
	(0.014)	(0.014)	(0.018)	(0.009)	(0.014)	(0.013)	(0.019)	(0.014)	(0.026)	(0.015)
Between 400 and 500 percent poverty	0.035*	0.037**	0.006	0.001	0.021	-0.006	0.065**	0.057***	0.020	-0.034*
	(0.017)	(0.014)	(0.017)	(0.013)	(0.018)	(0.020)	(0.026)	(0.015)	(0.028)	(0.020)
Above 500 percent poverty	0.042*	0.023	-0.002	-0.010	0.008	-0.029	0.048	0.051***	-0.012	-0.077***
	(0.021)	(0.015)	(0.020)	(0.016)	(0.022)	(0.024)	(0.028)	(0.015)	(0.032)	(0.026)
Observations	143127	142483	134782	140806	136123	156144	138352	126109	142058	129056
R^2	0.146	0.118	0.127	0.111	0.136	0.125	0.115	0.125	0.148	0.129

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: **Mother's Education and Prenatal Visits Based on Poverty Ranking.** The dependent variable is an indicator representing whether the first prenatal visit was initiated within the first two months of pregnancy. All specifications control for personal characteristics (age, age square, race, marital status, child's gender), county specific unemployment rate, and state-level beer and cigarette taxes. Additionally, all specifications include county and year fixed effects. Standard errors are clustered at the state level.

	(1) Group 1	(2) Group 2	(3) Group 3	(4) Group 4	(5) Group 5	(6) Group 6	(7) Group 7	(8) Group 8	(9) Group 9	(10) Group 10
High School Graduate	-0.008	-0.016	-0.008	0.026	0.030	0.028	0.028	0.043**	0.037	0.045***
	(0.022)	(0.033)	(0.019)	(0.026)	(0.018)	(0.018)	(0.033)	(0.016)	(0.026)	(0.013)
Some College	0.021	0.013	0.019	0.062*	0.062***	0.059**	0.053	0.059***	0.070**	0.091***
	(0.025)	(0.035)	(0.029)	(0.033)	(0.023)	(0.027)	(0.045)	(0.021)	(0.032)	(0.012)
College or More	0.050*	0.022	0.049	0.087**	0.109**	0.076**	0.108**	0.071**	0.139***	0.201***
	(0.027)	(0.044)	(0.038)	(0.040)	(0.041)	(0.033)	(0.052)	(0.028)	(0.042)	(0.022)
Between 200 and 300 percent poverty	0.077***	0.074***	0.047***	0.062***	0.051***	0.050***	0.068***	0.054***	0.021	-0.016
	(0.016)	(0.016)	(0.012)	(0.010)	(0.019)	(0.012)	(0.019)	(0.018)	(0.017)	(0.016)
Between 300 and 400 percent poverty	0.111***	0.094***	0.077***	0.099***	0.046	0.080***	0.084***	0.075***	0.005	-0.068**
	(0.016)	(0.014)	(0.014)	(0.014)	(0.031)	(0.015)	(0.021)	(0.025)	(0.030)	(0.031)
Between 400 and 500 percent poverty	0.135***	0.130***	0.073***	0.114***	0.050	0.089***	0.091***	0.080**	0.006	-0.091**
	(0.019)	(0.017)	(0.015)	(0.017)	(0.039)	(0.015)	(0.024)	(0.032)	(0.036)	(0.039)
Above 500 percent poverty	0.137***	0.150***	0.081***	0.116***	0.022	0.095***	0.063*	0.096**	-0.041	-0.197***
	(0.020)	(0.019)	(0.024)	(0.023)	(0.056)	(0.020)	(0.031)	(0.037)	(0.055)	(0.069)
Observations	143127	142483	134782	140806	136123	156144	138352	126109	142058	129056
R^2	0.187	0.506	0.613	0.442	0.672	0.586	0.456	0.736	0.625	0.384

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

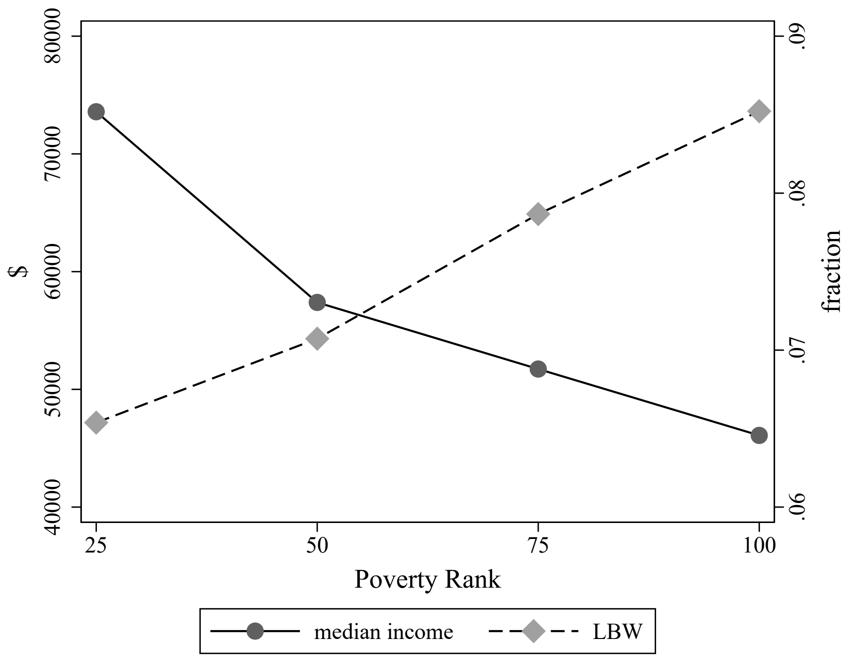
Table 7: **Mother's Education and Non-Smoker Status Based on Poverty Ranking.** The dependent variable is an indicator that takes a value 1 if a mother did not smoke during pregnancy, otherwise the value given is 0. All specifications control for personal characteristics (age, age square, race, marital status, child's gender) and aggregate measures including county level unemployment rate, state-level beer and cigarette taxes. Additionally, all specifications include county and year fixed effects. Robust standard errors clustered at the state level are presented in parenthesis.

Panel A. Black Mothers	(1) Without controls	(2) Without Controls	(3) Control Earnings	(4) Column3+Other Controls	(5) Column4+risk factors
High School Graduate	67.258***		58.555***	54.950***	34.660***
	(12.178)		(11.962)	(11.667)	(10.453)
Some College	116.149***		97.282***	93.541***	66.710***
	(13.521)		(14.852)	(13.885)	(12.324)
College or More	161.306***		133.546***	142.032***	109.968***
	(14.725)		(19.831)	(17.853)	(16.622)
Between 200 and 300 percent poverty		60.214***	34.601***	15.584*	12.041
		(7.090)	(8.884)	(8.761)	(8.889)
Between 300 and 400 percent poverty		79.543***	36.776***	10.156	6.786
		(8.573)	(12.103)	(12.378)	(12.333)
Observations	115629	115629	115629	115629	115629

Panel B. White Mothers	(1) Without controls	(2) Without Controls	(3) Control Earnings	(4) Column3+Other Controls	(5) Column4+risk factors
High School Graduate	74.790***		57.430***	53.134***	45.774***
	(9.447)		(7.522)	(8.526)	(6.673)
Some College	118.800***		93.848***	89.551***	75.038***
	(11.742)		(9.344)	(10.267)	(7.752)
College or More	152.652***		134.270***	125.655***	104.157***
	(12.791)		(9.748)	(10.340)	(8.237)
Between 200 and 300 percent poverty		62.369***	41.259***	24.217***	15.795***
		(3.932)	(3.975)	(3.077)	(2.636)
Between 300 and 400 percent poverty		87.589***	46.393***	28.142***	16.690***
		(6.539)	(6.034)	(4.432)	(3.796)
Observations	1171326	1171326	1171326	1171326	1171326

Table 8: **Mother's Education and Birthweight by Race.** Sample is restricted to black and white mothers in the top and bottom panels, respectively. The table is structured similar to Table 2. Standard errors clustered at state level are presented in parenthesis.

Figure 1: Median Income and Low Birthweight across Poverty Ranking



Note: Data for county-specific median income is extracted from the Bureau of Labor Statistics (1990, 2000, 2015) and birthweight is from the National Vital Statistics System (1990, 2000, 2015), National Center of Health Statistics. The sample is conditional on the first born children from mothers who are 25 years and over. County-specific median income is converted to 2015 dollars by using the CPI. Low birthweight refers to birthweight lower than 2,500 grams.

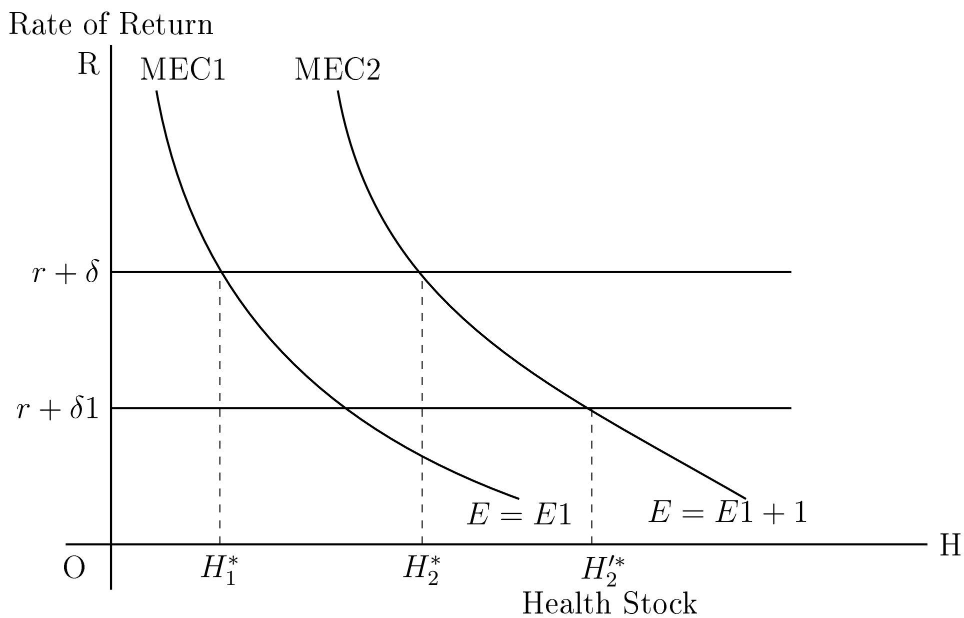
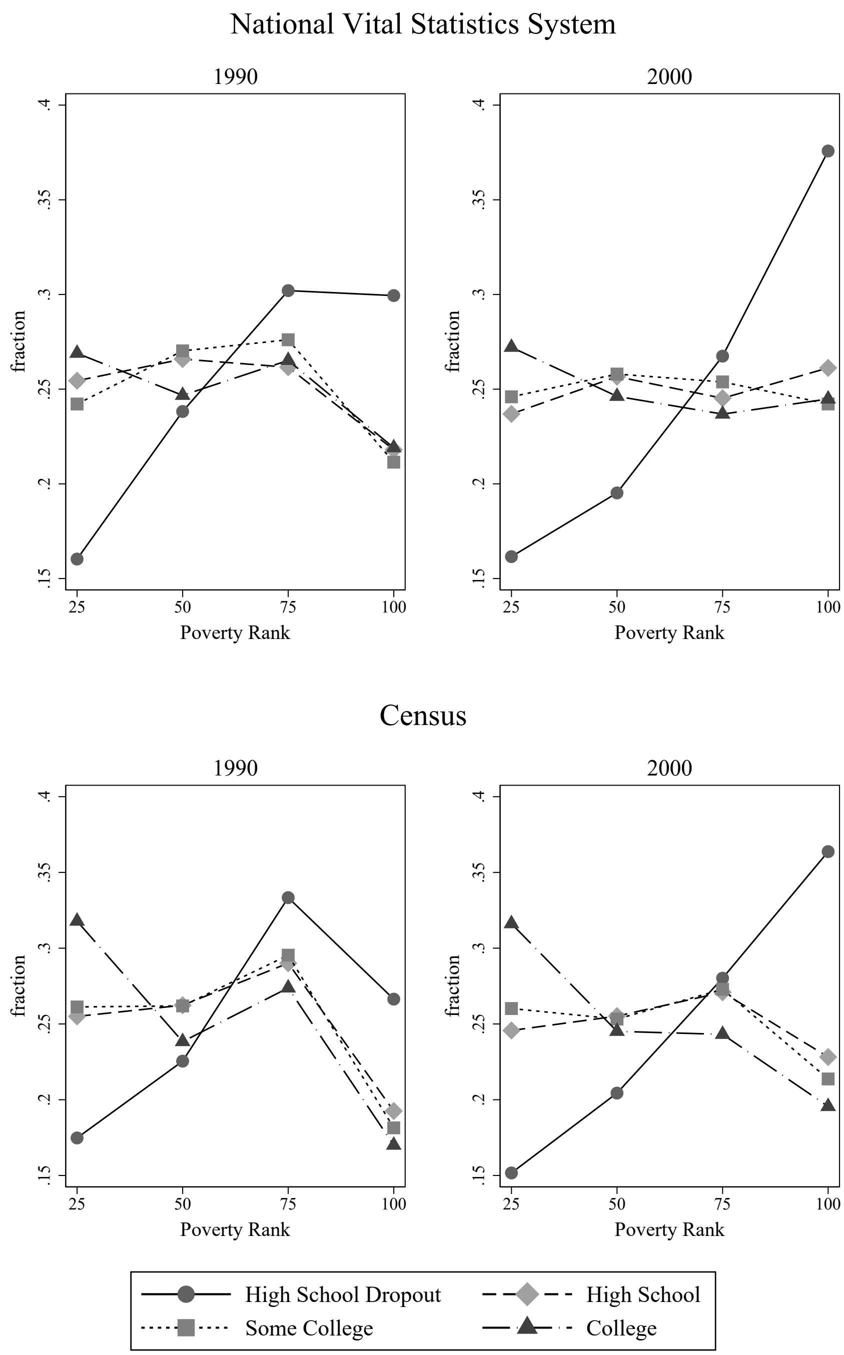


Figure 2: Marginal Efficiency of Capital by Education following Grossman (1972)

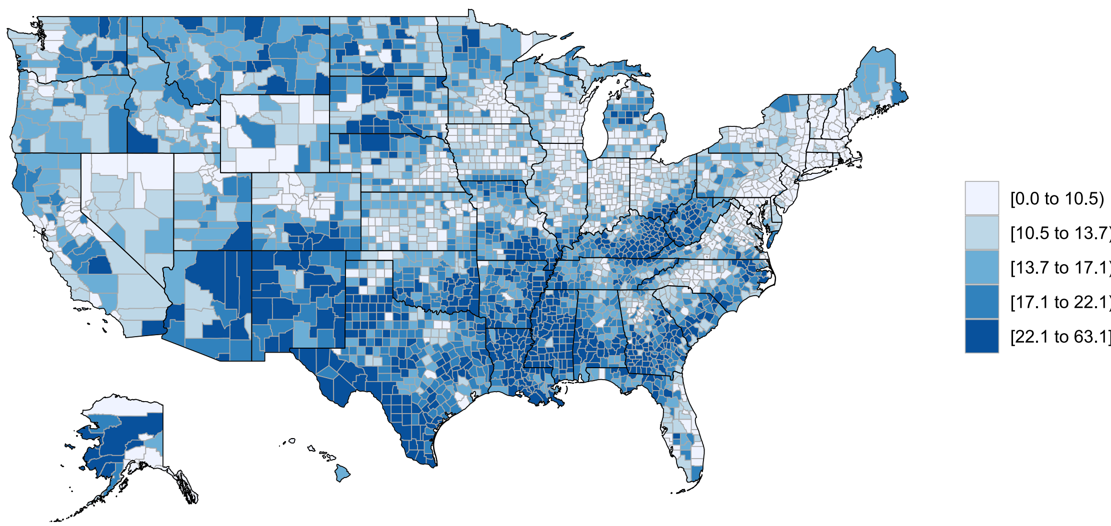
Figure 3: Residence Across Poverty Ranking by Education



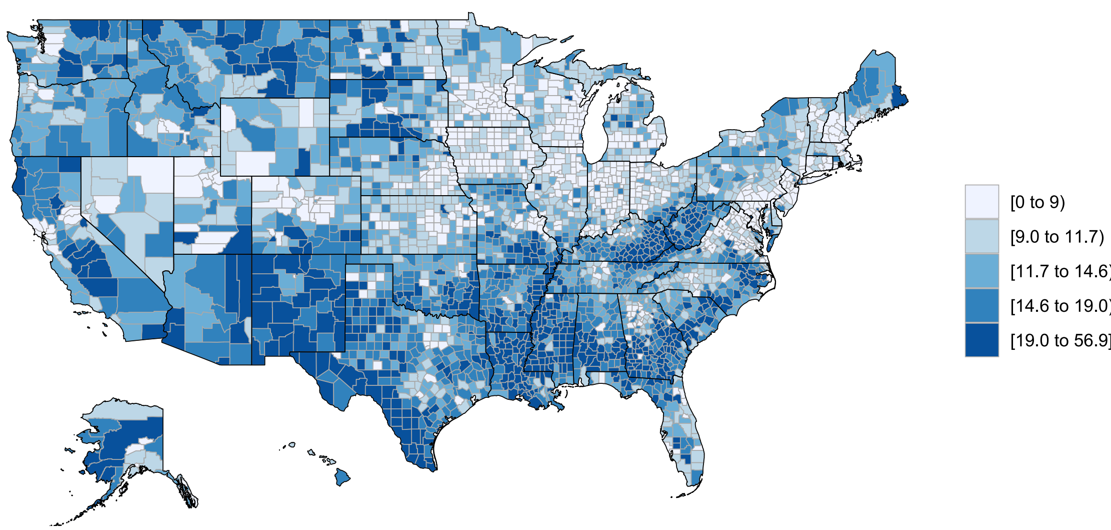
Data Source: Data for the top and bottom panels are extracted from the the National Vital Statistics System and Census years 1990 and 2000, respectively. Note: The figure shows the fraction of people residing across poverty quartiles by education levels. Based on author's calculation.

Figure 4: **Poverty Rate Across Counties**

1990

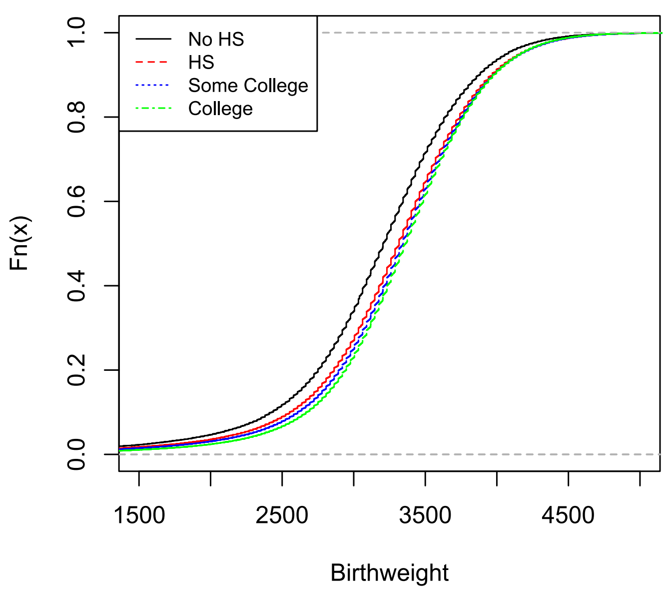


2000



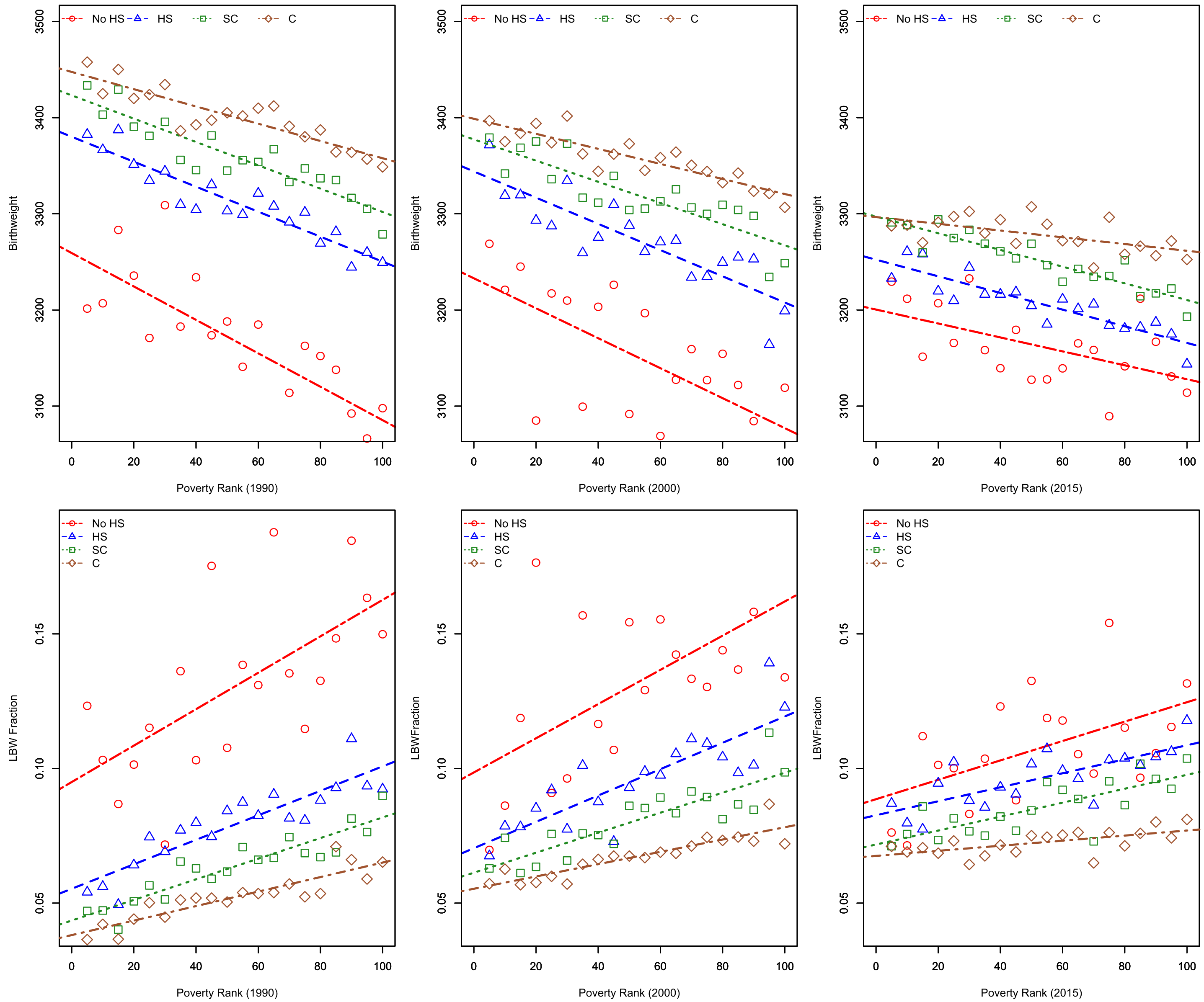
Data Source: 1990 and 2000 U.S. Census.

Figure 5: **CDF-Birthweight by Education**



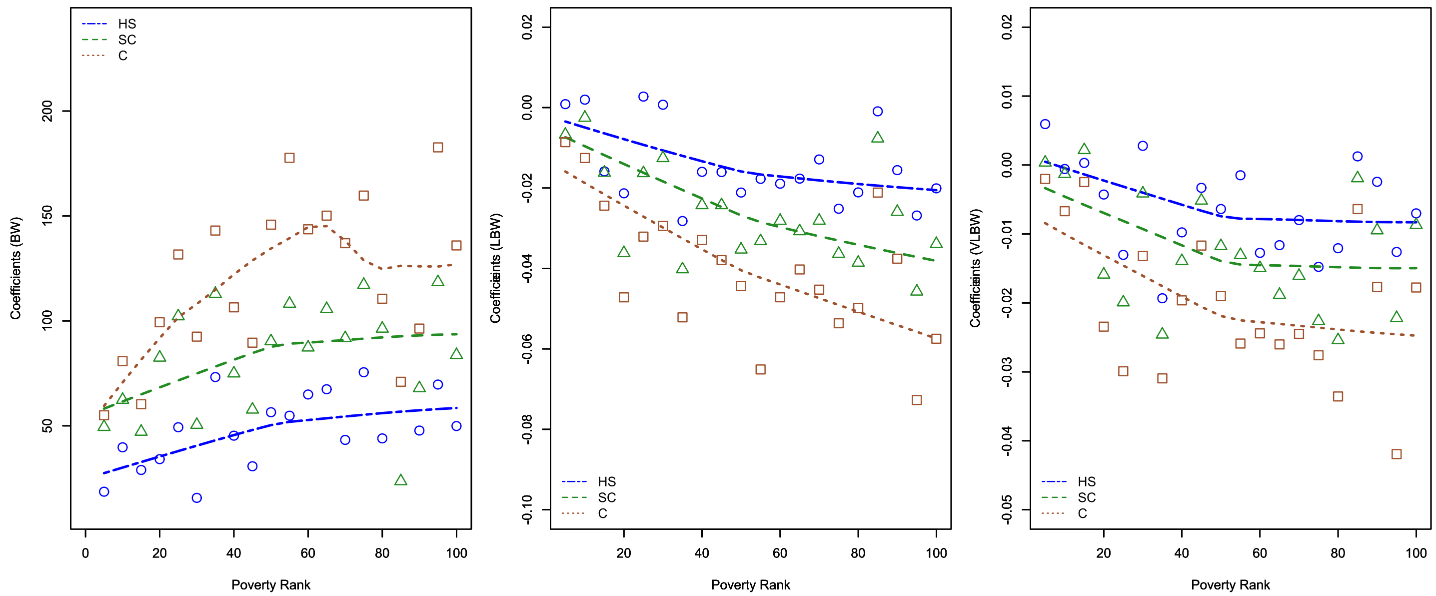
Data Source: National Vital Statistics System, National Center of Health Statistics (1990, 2000 and 2015). Based on author's calculation. No HC = no high school, HS = high school, SC = some college, and C = college and more.

Figure 6: **Birthweight and Low Birthweight Across Poverty Ranking by Education**



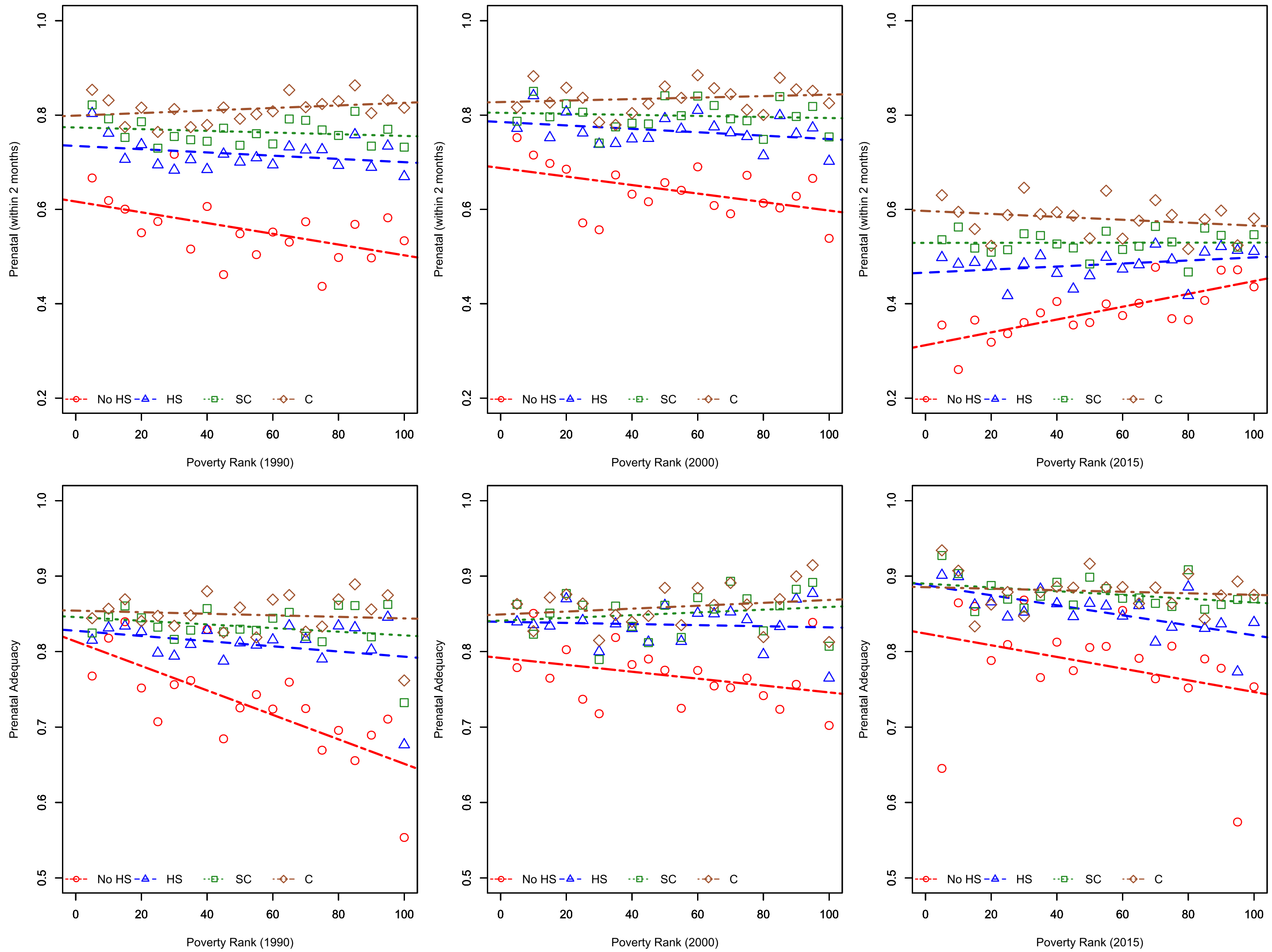
Source: National Vital Statistics System, National Center of Health Statistics (1990, 2000, 2015). No HC = no high school, HS = high school, SC = some college, and C = college and more.
Note: Counties are ranked using the poverty rates from the Census 1990, 2000, and 2015. Then counties are grouped into 20 groups, with each county-group representing about 5 percent of the total births in the sample. Lines are fitted using the OLS for each education category.

Figure 7: **Coefficients Conditional on Poverty Ranking by Education**



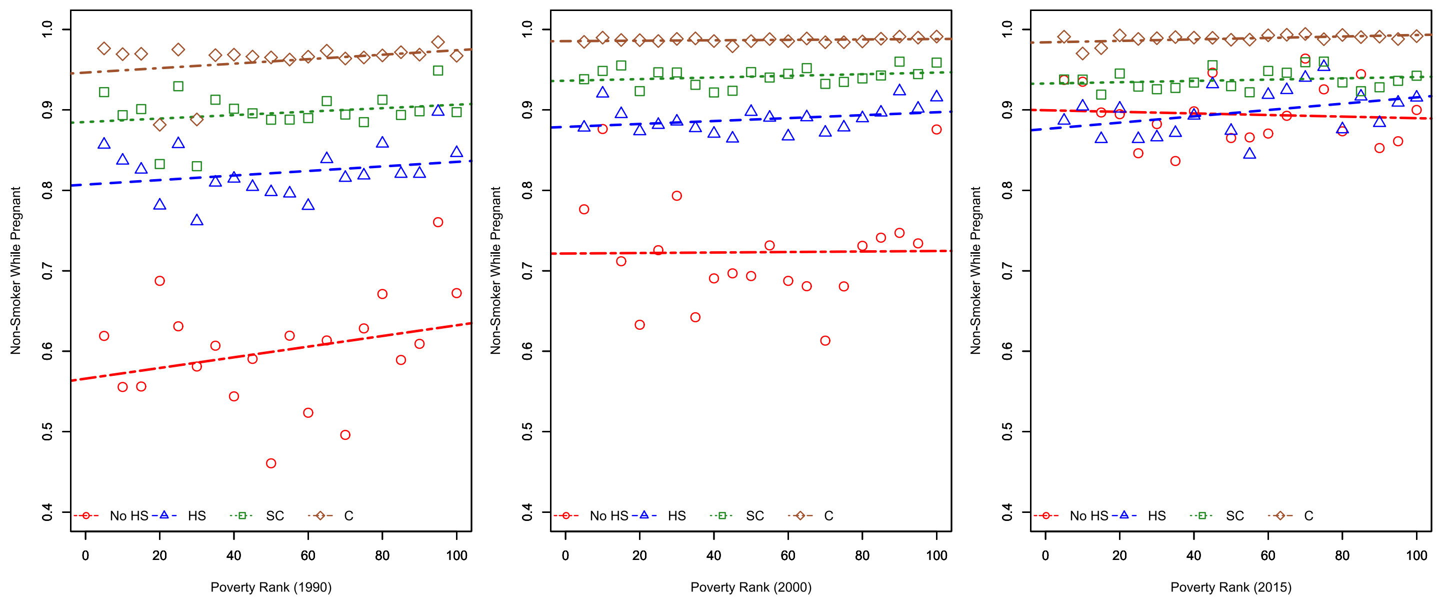
Source: National Vital Statistics System, National Center of Health Statistics (1990, 2000, 2015). HS = high school, SC = some college, and C = college.
Note: Counties are ranked according to their poverty rates and twenty county-groups are created, with each group consisting of about 5 percent of the total births in the sample. Using observations in each county-grouping, I evaluate mother's education and infant health (birthweight, prevalence of low birthweight ($< 2,500\, grams$) and very low birthweight ($< 2,000\, grams$) relationship by accounting for control variables as described in the bottom of Table 3. The education category included in the specification are high school completion, some college, and college or more, where less than high school is left as the omitted group. Each marker represents the magnitude of the coefficient specific to a county-group and education category. Curves are fitted using the local linear regressions and smoothing parameters are chosen by using the leave one out cross-validation method to minimize the root mean squared error for each education criteria.

Figure 8: **Prenatal Care by Poverty Ranking**



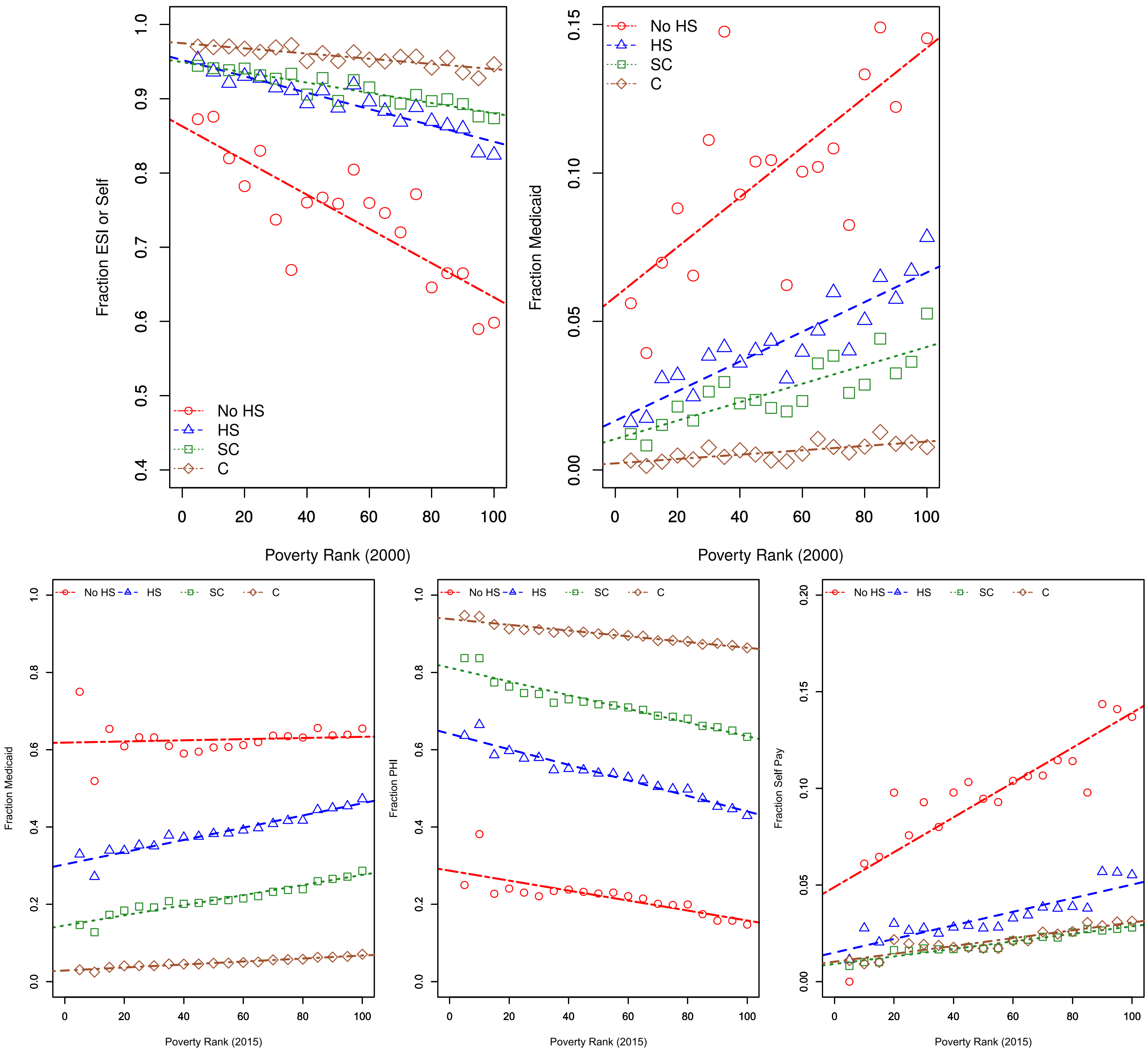
Source: National Vital Statistics System, National Center of Health Statistics (1990, 2000, 2015). HS = high school, SC = some college, and C = college.
Note: Counties are ranked using the poverty rates from Census 1990, 2000 and 2015 similar to Figure 6. The top panel shows the percentage of females with any prenatal visits within the first two months of pregnancy by education attainment and the bottom panel shows the fraction with adequacy measure of prenatal visits throughout pregnancy. Lines are fitted using the OLS regression.

Figure 9: **Percent of Non-Smokers by Poverty Ranking**



Source: National Vital Statistics System, National Center of Health Statistics (1990, 2000, 2015). HS = high school, SC = some college, and C = college.
Note: Counties are ranked using the poverty rates from Census 1990, 2000 and 2015, respectively. The counties are grouped into 20 groups, with each county-group representing about 5 percent of the total births in the sample. The markers represent the fraction of non-smokers during pregnancy within a specific county-group and education category. Lines are fitted using the OLS regression.

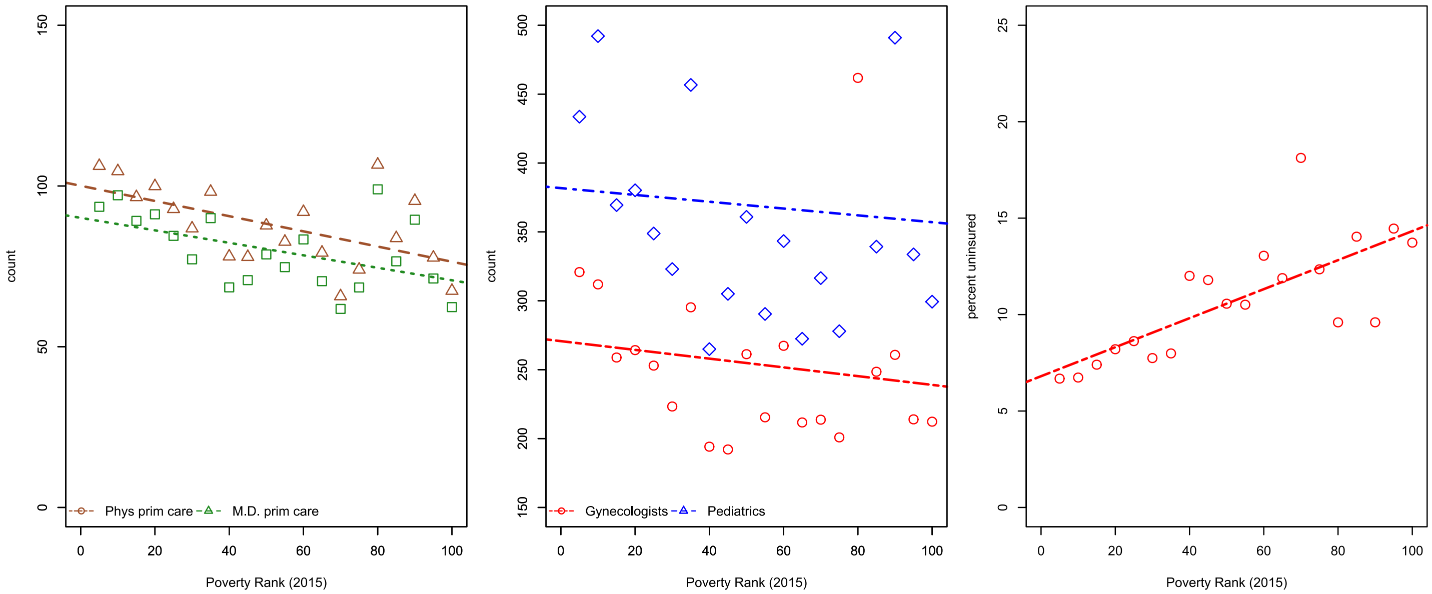
Figure 10: **Insurance Pattern by Poverty Ranking**



Source: Behavioral Risk Factor Surveillance System (1996 to 2000) for the top panel. Sample is restricted to 25 years or older but less than 65 years. National Vital Statistics System, National Center of Health Statistics (2015) for the bottom panel. HS = high school, SC = some college, and C = college. Lines are fitted using OLS regression.
Note: Counties are ranked using the poverty rates from Census 2000 (top panel) and Census 2015 (bottom panel). Then counties are grouped into 20 groups, with each county-group representing about 5 percent of the total people in BRFSS 2000 sample (top panel) and total births in 2015 (bottom panel). The markers represent the fraction of respondents with either employer sponsored or self insured (on top left) and the fraction of respondents with Medicaid (top right). The bottom panel represents the type of payment used while giving birth as reported in 2015 natality files, including Medicaid, personal health insurance, and self-pay, respectively. Lines are fitted using OLS regression.

9 Online Appendix

Figure A1: **Access to Health Care by Poverty Ranking**



Source: Area Health Resource File and National Vital Statistics System (year 2015).
Note: Variables in Area Health Resource File are merged with the NVSS file of year 2015 by county. Counties are ranked using the poverty rates from Census 2015. Then counties are grouped into 20 groups, with each county-group representing about 5 percent of the total births in the sample. The counts for primary physician care and M.D. primary care are per 100,000 people, the count for obstetrician-gynecologists and pediatrics are per 20,000 births in 2015 and 100,000 children below 5 years of age, respectively. Lines are fitted using OLS regression.

A10.1 Adjusting Per capita Income by Education, Age and Race

One challenge is that NVSS files do not provide income information for mothers who gave birth. Proper controls for income is necessary as education and income are positively associated and income tend to rise sharply following the completion of educational landmarks such as high school and college completion. To properly control for income, I choose a different approach rather than directly using county level income from publicly available data sets or performing aggregation at finer cells defined by race, age group, and education category by using publicly available individual level data. The former approach does not capture variation in income across important demographic characteristics across counties such as race, whereas the latter comes with technical difficulties as many of the county identifiers are reported missing in large data files such as micro level Census data (that is publicly available) and CPS Merged Outgoing Rotation Groups (MORG). The approach I take is to adjust per capita personal income in county c based on important characteristics such as education attainment, race, and age groups by using the micro level data from CPS Merged Outgoing

Rotation Groups (MORG) and CPER along with several county level aggregate files that are publicly available and discussed in the steps below. Next, I describe this approach in detail using four steps.

1. Use the CPS MORG files of 1990, 2000 and CPER Uniform Extracts file of 2015 to run the regression as defined below for every state for each year (1990, 2000, and 2015):

$$Y_i = \delta + \sum_{j=2}^{4} \gamma_j I(E_i = j) + \sum_{j=2}^{3} \alpha_j I(R_i = j) + \sum_{j=2}^{8} \beta_j I(A_i = j) + \kappa G_i + \eta M_i + \epsilon_i \quad (3)$$

   where, Y_i is yearly earning of an individual i, E is education level ($j = \{2, 3, 4\}$ refers to high school, some college, and college or more, respectively) and I_i is an indicator representing whether an individual i has the highest education attainment of level j, R refers to race (black and other race, white used as the omitted group), and A pertains to age group of an individual i ($age\, group\, categories\, are\, 30-34$, $35-39$, $40-44$, $45-49$, $50-54.\, 55-59$, $60-64\,, where\, 25-29\, is\, the\, omitted\, group$). G and M represents gender and marital status of an individual i, respectively. Specification 3 is estimated for each state and year and these estimates are stored in a matrix.

2. Get the county-level per capita personal income file from the U.S. Bureau of Labor Statistics and county level age-race specific population files for years 1990, 2000, and 2015 (available in the NBER website sourced through Census Bureau's Population Estimates Program). For each county (c) in a year (y) per capita county-level personal income (I_c) can be written as:

$$I_c = P_{w1} * I_{w1} + \sum_{j=2}^{8} P_{wj} * (I_{wj}) + P_{b1} * I_{b1} + \sum_{j=2}^{8} P_{bj} * (I_{bj}) + P_{o1} * I_{o1} + \sum_{j=2}^{8} P_{oj} * (I_{oj})$$
$$I_c = P_{w1} * I_{w1} + \sum_{j=2}^{8} P_{wj} * (I_{w1} + \hat{\beta}_j) + P_{b1} * I_{b1} + \sum_{j=2}^{8} P_{bj} * (I_{b1} + \hat{\beta}_j)$$
$$+ P_{o1} * I_{o1} + \sum_{j=2}^{8} P_{oj} * (I_{o1} + \hat{\beta}_j)$$
$$I_c = P_{w1} * I_{w1} + \sum_{j=2}^{8} P_{wj} * (I_{w1} + \hat{\beta}_j) + P_{b1} * (I_{w1} + \hat{\alpha}_2) + \sum_{j=2}^{8} P_{bj} * (I_{w1} + \hat{\beta}_j + \hat{\alpha}_2)$$
$$+ P_{o1} * (I_{w1} + \hat{\alpha}_3) + \sum_{j=2}^{8} P_{oj} * (I_{w1} + \hat{\beta}_j + \hat{\alpha}_3) \quad (4)$$

where, I_c is the county-level per capita personal income obtained from BLSS, and P_{RA} refers to the probability of an individual being from a given race ($w = white$, $b = black$, $o = other$) and age group ($1 = 25-29\,yrs$, $2 = 30-34\,yrs$, $3 = 35-39\,yrs$, $4 = 40-44\,yrs$, $5 = 45-49\,yrs$, $6 = 50-54\,yrs$, $7 = 55-59\,yrs$, $and\,8 = 60-64$). For instance, P_{w1} is the probability of an individual being white and of age group $25-29\,yrs$ in a county c. Now, $\hat{\beta}_j$ are the estimates on age-specific indicators from specification 3 such that $\hat{\beta}_j$ refers to the estimate of change in yearly earnings for an individual of age group j compared to group $25-29\,yrs$; $\hat{\alpha}_2$ and $\hat{\alpha}_3$ are coefficients on the race indicators. $\hat{\alpha}_2$ and $\hat{\alpha}_3$ pertain to average yearly earning differences among blacks and other races compared to whites, respectively. $\hat{\beta}_j$,$\hat{\alpha}_2$, and $\hat{\alpha}_3$ are state and year specific estimates.[33] In fact, Equation 4 is the weighted average of personal income, where weights are defined as race-age specific fraction of population in the county (P_{RA}). The goal in equation 4 is to solve for I_{w1}–county specific personal income of whites who are of the age group $25-29\,yrs$. Then using the values of I_{w1}, one can estimate the personal income specific to each race and age group. For instance, personal income for blacks who are of age group $35-39$ can be estimated as $I_{b3} = I_{w1} + \hat{\beta}_3 + \hat{\alpha}_2$.

3. The next step is to adjust for education differences in personal income within a county by race specific educational attainment in each year (1990, 2000, and 2015). I acquire county-level race specific educational attainment files from the U.S. Census Bureau (years 1990 and 2000) and the American Community Survey (year 2015) pertaining to individuals who are 25 years and over. Next, I formulate the following equation:

$$
\begin{aligned}
I_{RA} &= P(E=1|R) * I_{RAE=1} + \sum_{j=2}^{4} P(E=j|R) * (I_{RAE=j}) \\
I_{RA} &= P(E=1|R) * I_{RAE=1} + \sum_{j=2}^{4} P(E=j|R) * (I_{RAE=1} + \hat{\gamma}_j)
\end{aligned} \tag{5}
$$

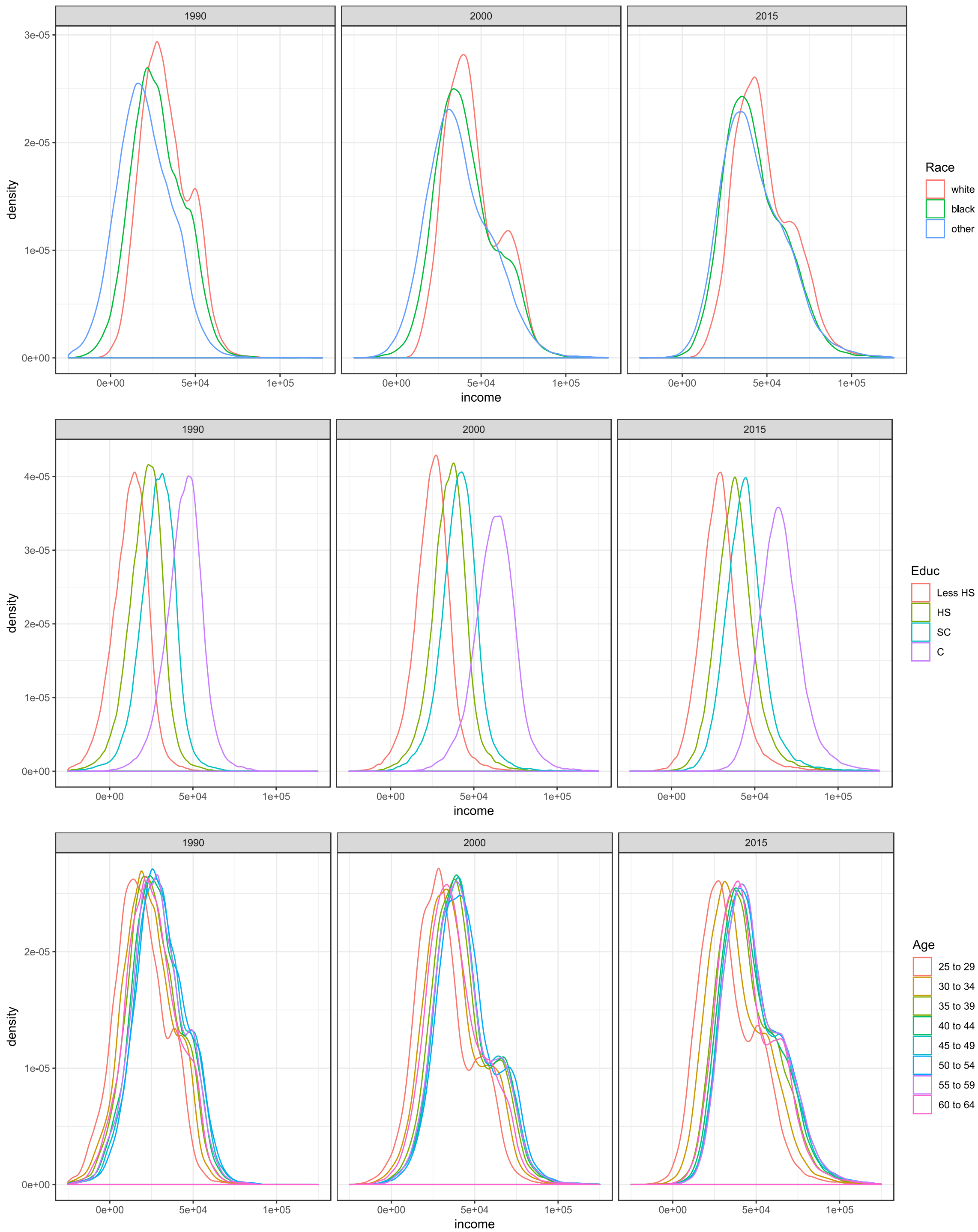
Here, R, A and E stands for race, age group and education attainment ($\{E = 1,2,3,4\}$; less than high school, high school completion, some college, and college or more). I_{RA}

[33] The assumption here is that earnings differences by race and age group is similar across all counties within a state.

is the estimate of per capita income for race group R and age group A computed from step 2. $P(E = j|R)$ represents the probability that a person of race R has the highest education attainment of j. Ideally we would want to use $P(E = j|R, A)$, the probability that a person of a certain race and a specific age group having an education attainment of j, however, county level data for education attainment by both race and age groups are not available to my knowledge. Hence, I assume that the probability of education attainment is similar across all age groups within a race in a given county. $\hat{\gamma}_j\,; j = \{2, 3, 4\}$ in equation 5 are the coefficient estimates pertaining to high school completion, some college, and college or more from specification 3.

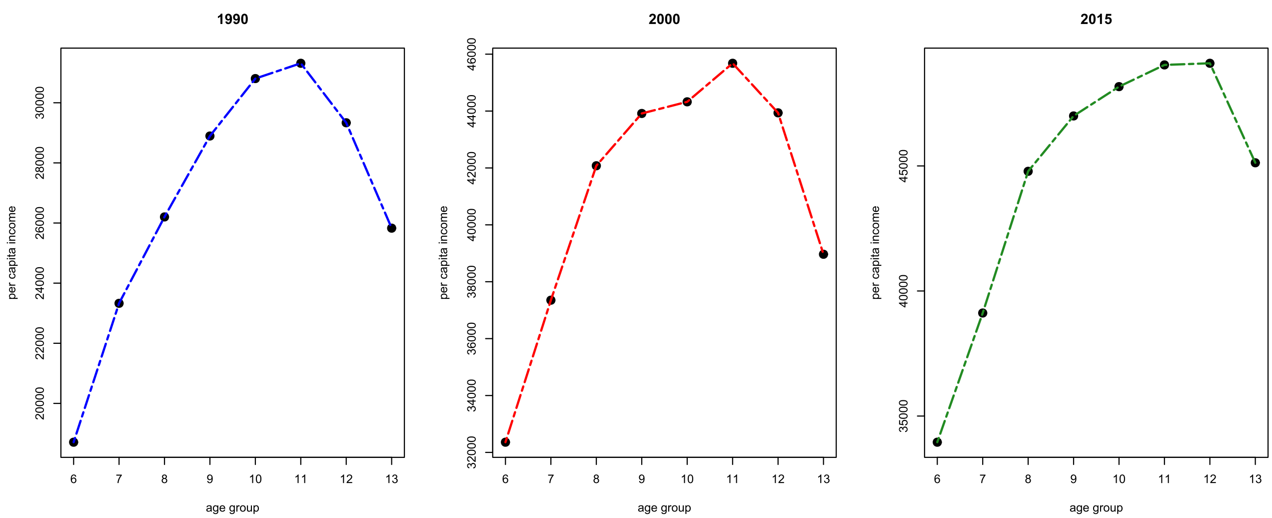
4. Next, I solve for $I_{RAE=1}$ in equation 5 and adjust income for each race, age group and education attainment by using the coefficient estimates from specification 3. This will give per capita income for sub-groups in a county adjusted by education, race, and age.

Figure A2: Income Plots by Demographic Characteristics



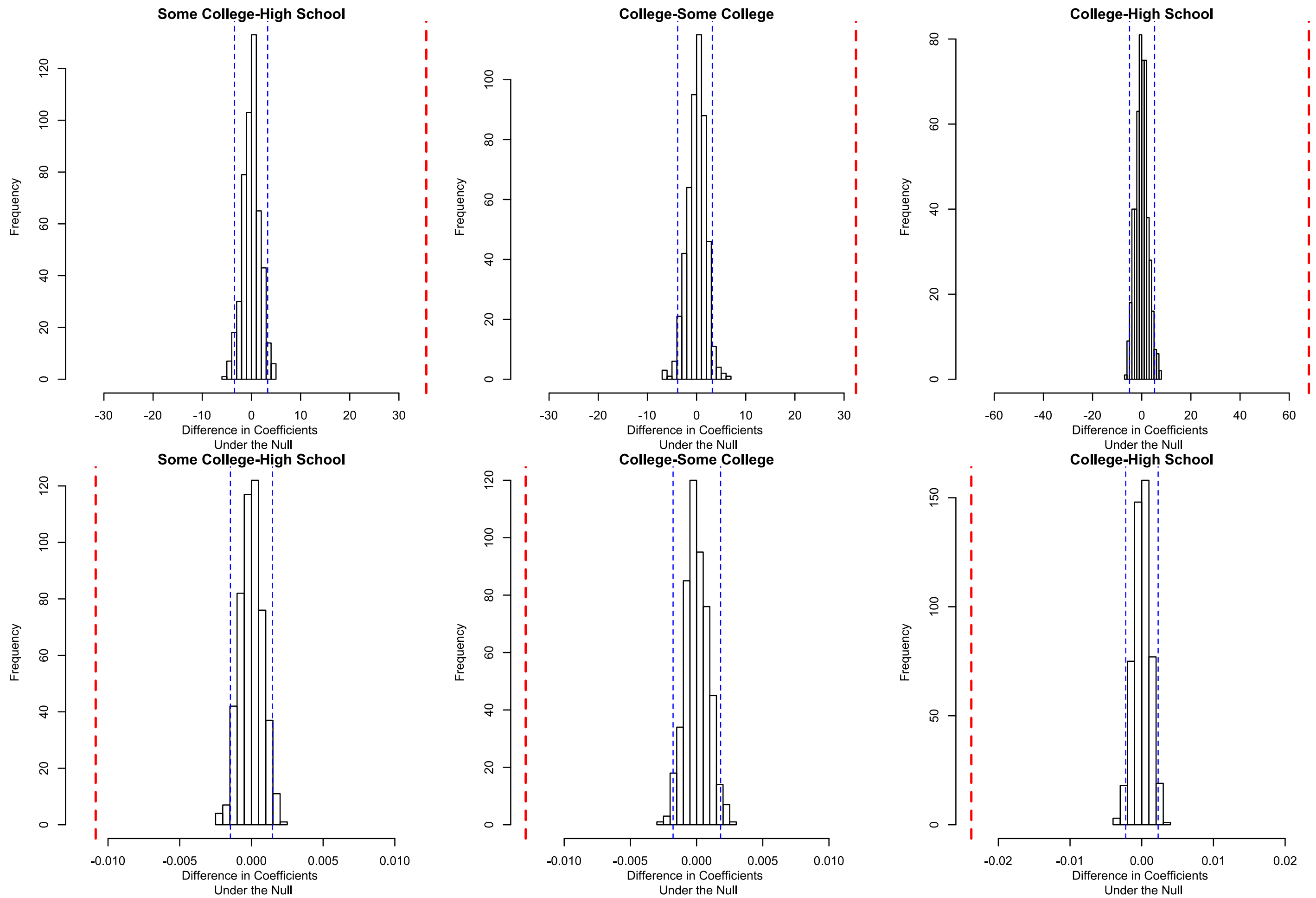
Note: The figure shows the distribution of per capita personal income by race (top panel), education (middle panel), and age groups (bottom panel) using the computation method described in section A10.1.

Figure A3: Income by Age Group



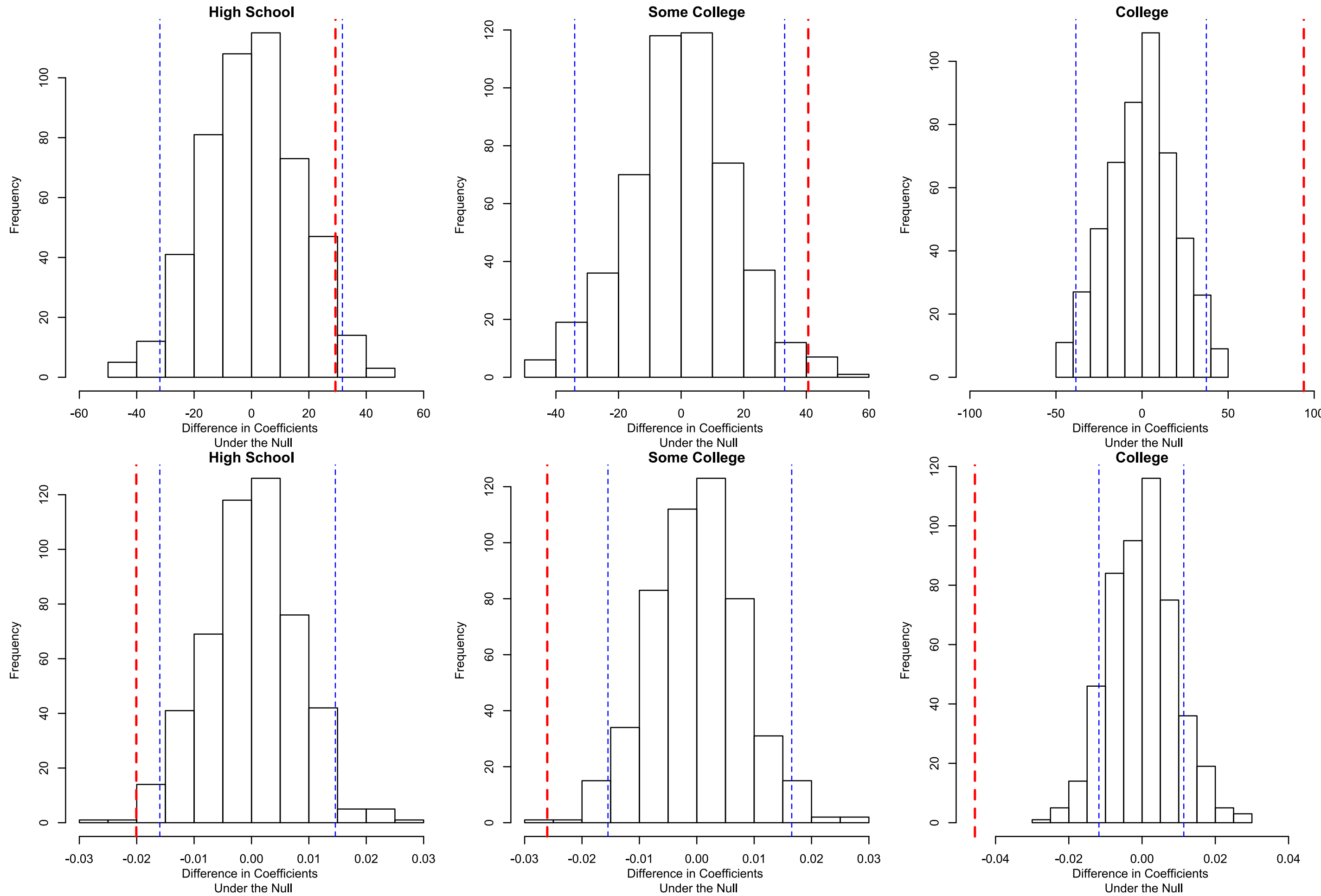
Note: The figure shows per capita personal income by age group using the computation method described in section A10.1. Age group reported on the x-axis at the ascending order corresponds to 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, and 60-64 years, respectively.

Figure A4: **Bootstrap Testing of Differences in Education Coefficients**



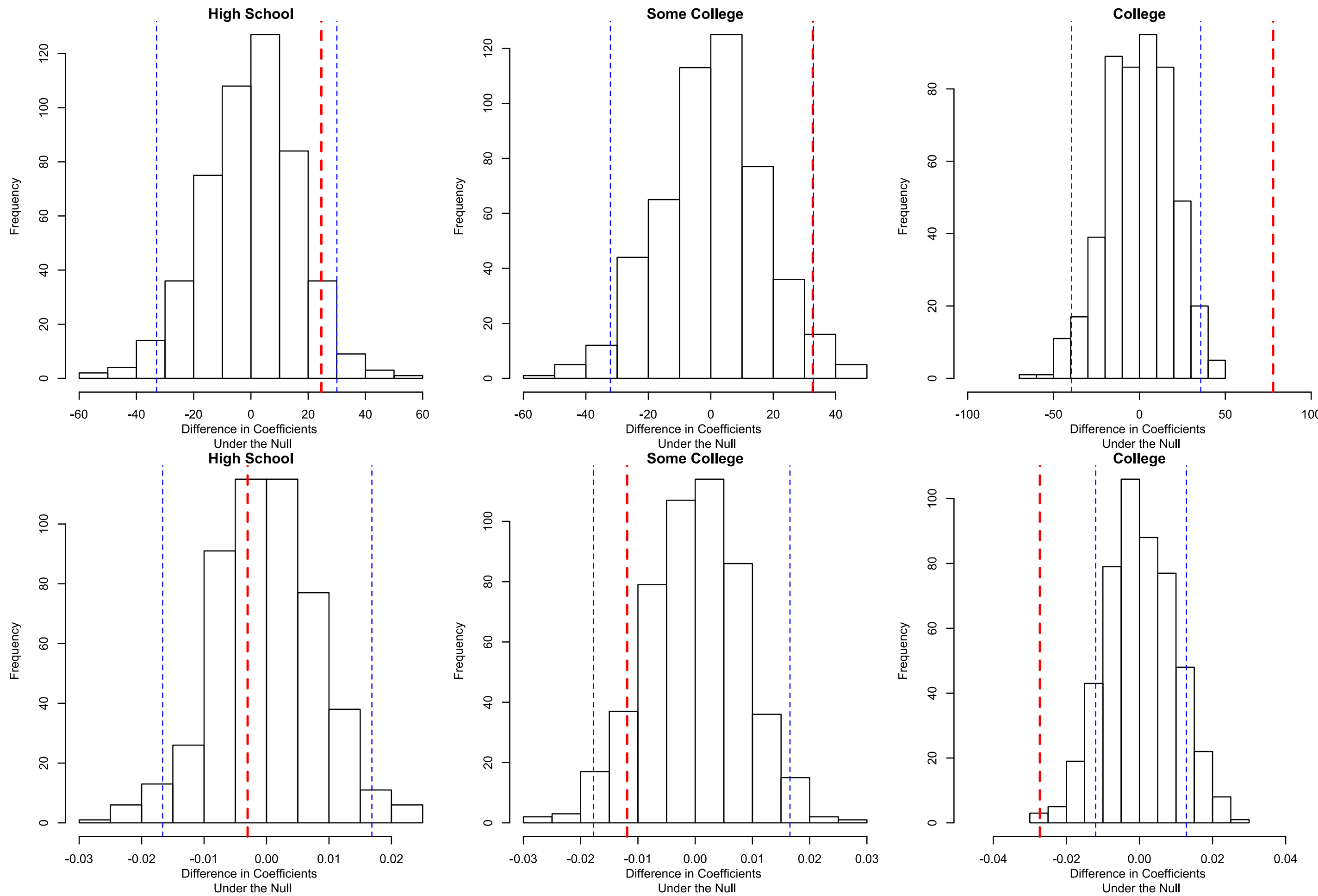
Source: National Vital Statistics System, National Center of Health Statistics (1990, 2000, 2015).
Note: The figure shows the bootstrap distribution of difference in education specific coefficients on birthweight (top panel) and low birthweight (bottom panel) between the coefficient on education categories using specification given by Column (4) of Table 2 and under the null hypothesis that there is no difference between the coefficients across two education categories. The number of bootstrap replications used is 499. The blue lines represent the 2.5^{th} and 97.5^{th} percentiles of the distribution and the red line represents the actual difference between the education coefficeints.

Figure A5: **Bootstrap Testing of Differences in Coefficients between County-Groups**



Source: National Vital Statistics System, National Center of Health Statistics (1990, 2000, 2015).
Note: The figure shows the bootstrap distribution of difference in education specific coefficients on birthweight (top panel) and low birthweight (bottom panel) between the county-groups at the $50-60^{th}$ (Group 6) and $0-10^{th}$ (Group 1) percentile of poverty rate using specification given in Table 3 and under the null hypothesis that there is no difference between the coefficients across the two county-groups. The number of bootstrap replications used is 499. The blue lines represent the 2.5^{th} and 97.5^{th} percentiles of the distribution and the red line represents the actual difference between the coefficeints.

Figure A6: **Bootstrap Testing of Differences in Coefficients between County-Groups**



Source: National Vital Statistics System, National Center of Health Statistics (1990, 2000, 2015).
Note: The figure shows the bootstrap distribution of difference in education specific coefficients on birthweight (top panel) and low birthweight (bottom panel) between the county-groups at the $90-100^{th}$ (Group 10) and $10-20^{th}$ (Group 2) percentile of poverty rate using specification given in Table 3 and under the null hypothesis that there is no difference between the coefficients across the two county-groups. The number of bootstrap replications used is 499. The blue lines represent the 2.5^{th} and 97.5^{th} percentiles of the distribution and the red line represents the actual difference between the coefficeints.

	(1) Without controls	(2) Without Controls	(3) Control Earnings	(4) Column3+Other Controls	(5) Column4+risk factors
High School Graduate	-0.023***		-0.014***	-0.015***	-0.013***
	(0.004)		(0.003)	(0.003)	(0.003)
Some College	-0.036***		-0.023***	-0.026***	-0.022***
	(0.005)		(0.005)	(0.004)	(0.003)
College or More	-0.051***		-0.036***	-0.040***	-0.034***
	(0.006)		(0.005)	(0.004)	(0.004)
Between 200 and 300 percent poverty		-0.026***	-0.021***	-0.008***	-0.006***
		(0.002)	(0.002)	(0.001)	(0.001)
Between 300 and 400 percent poverty		-0.033***	-0.023***	-0.008***	-0.005***
		(0.003)	(0.002)	(0.002)	(0.002)
Between 400 and 500 percent poverty		-0.042***	-0.023***	-0.008***	-0.005**
		(0.003)	(0.003)	(0.002)	(0.002)
Above 500 percent poverty		-0.049***	-0.023***	-0.008***	-0.005*
		(0.004)	(0.004)	(0.003)	(0.003)
Observations	1393611	1393611	1393611	1393611	1393611
R^2	0.008	0.008	0.009	0.016	0.019

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A1: **Mother's Education and Low Birthweight.** Results are from the linear probability model. The dependent variable is an indicator for low birthweight. The table is structured similar to Table 2 and controls used are similar to those mentioned in the bottom of Table 2. Standard errors are clustered at state level and presented in parenthesis.

	(1) Group 1	(2) Group 2	(3) Group 3	(4) Group 4	(5) Group 5	(6) Group 6	(7) Group 7	(8) Group 8	(9) Group 9	(10) Group 10
High School Graduate	0.001	-0.020**	0.002	-0.023***	-0.017***	-0.019***	-0.016**	-0.023***	-0.007	-0.024***
	(0.006)	(0.009)	(0.006)	(0.006)	(0.006)	(0.005)	(0.007)	(0.005)	(0.008)	(0.005)
Some College	-0.005	-0.028***	-0.014**	-0.033***	-0.028***	-0.033***	-0.030***	-0.037***	-0.016	-0.041***
	(0.006)	(0.009)	(0.006)	(0.008)	(0.006)	(0.006)	(0.007)	(0.006)	(0.012)	(0.006)
College or More	-0.011*	-0.038***	-0.029***	-0.043***	-0.040***	-0.059***	-0.044***	-0.052***	-0.028**	-0.067***
	(0.006)	(0.011)	(0.007)	(0.010)	(0.008)	(0.008)	(0.007)	(0.004)	(0.014)	(0.008)
Between 200 and 300 percent poverty	-0.008	-0.011**	-0.012**	-0.007	-0.007*	-0.002	-0.014***	-0.006	-0.014***	0.007**
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Between 300 and 400 percent poverty	-0.010	-0.013**	-0.008	-0.008	-0.006	0.003	-0.008*	-0.010***	-0.014***	0.014**
	(0.008)	(0.005)	(0.006)	(0.006)	(0.004)	(0.006)	(0.005)	(0.004)	(0.005)	(0.006)
Between 400 and 500 percent poverty	-0.009	-0.015**	-0.004	-0.010	-0.008	0.008	-0.010*	-0.006	-0.016**	0.018**
	(0.009)	(0.006)	(0.006)	(0.008)	(0.006)	(0.008)	(0.005)	(0.004)	(0.007)	(0.008)
Above 500 percent poverty	-0.010	-0.016**	-0.004	-0.011	-0.002	0.013	-0.011	-0.010*	-0.020*	0.018*
	(0.008)	(0.007)	(0.007)	(0.009)	(0.009)	(0.010)	(0.007)	(0.005)	(0.010)	(0.010)
Observations	143127	142483	134782	140806	136123	156144	138352	126109	142058	129056
R^2	0.015	0.016	0.013	0.015	0.014	0.016	0.013	0.016	0.018	0.026

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: **Mother's Education and Low Birthweight.** The table is stuctured similar to Table 3, except that the dependent variable used is an indicator for low birthweight. The results are obtained from a linear probability model and controls used are similar to those mentioned in the bottom of Table 3. Robust standard errors clustered at the state level are presented in parenthesis.

	(1) Group 1	(2) Group 2	(3) Group 3	(4) Group 4	(5) Group 5	(6) Group 6	(7) Group 7	(8) Group 8	(9) Group 9	(10) Group 10
High School Graduate	0.002	-0.003	-0.005	-0.015***	-0.004	-0.008**	-0.011***	-0.014***	-0.001	-0.010**
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Some College	-0.001	-0.008	-0.012**	-0.020***	-0.007**	-0.016***	-0.019***	-0.025***	-0.006	-0.016***
	(0.003)	(0.005)	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
College or More	-0.005	-0.014**	-0.020***	-0.026***	-0.015***	-0.027***	-0.027***	-0.033***	-0.012**	-0.032***
	(0.004)	(0.006)	(0.005)	(0.006)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.006)
Between 200 and 300 percent poverty	-0.003	0.001	-0.001	0.002	-0.005**	-0.000	-0.004	0.006***	-0.001	0.005***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Between 300 and 400 percent poverty	-0.004	0.002	0.003	0.004	-0.006*	0.001	0.003	0.003	-0.001	0.009***
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)
Between 400 and 500 percent poverty	-0.000	0.003	0.006*	0.006	-0.004	0.004	0.001	0.007	-0.004	0.013***
	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)	(0.005)	(0.003)	(0.004)	(0.003)	(0.005)
Above 500 percent poverty	-0.001	0.002	0.005	0.002	-0.004	0.003	0.001	0.004	-0.005	0.009*
	(0.005)	(0.006)	(0.004)	(0.005)	(0.006)	(0.007)	(0.004)	(0.005)	(0.005)	(0.005)
Observations	143127	142483	134782	140806	136123	156144	138352	126109	142058	129056
R^2	0.009	0.010	0.009	0.010	0.010	0.011	0.008	0.012	0.012	0.020

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: **Mother's Education and Birthweight under 2,000 grams.** The table is structured similar to Table 3 except that the dependent variable used is an indicator of an infant having a birthweight less than 2,000 grams. Robust standard errors clustered at the state level are presented in parenthesis.

Panel A. Year 1990	(1) Without controls	(2) Without Controls	(3) Control Earnings	(4) Column 3+Other Controls	(5) Column 4 + risk factors
High School Graduate	146.747***		94.285***	102.922***	78.867***
	(18.956)		(16.195)	(12.654)	(9.047)
Some College	192.899***		112.128***	148.902***	115.198***
	(22.452)		(19.415)	(15.091)	(10.856)
College or More	236.243***		130.920***	194.232***	153.389***
	(23.553)		(21.202)	(13.803)	(12.219)
Between 200 and 300 percent poverty		114.440***	95.914***	2.443	0.334
		(9.401)	(8.417)	(5.360)	(5.277)
Observations	361436	361436	361436	361436	361436
R^2	0.011	0.012	0.013	0.040	0.049

Panel B. Year 2000	(1) Without controls	(2) Without Controls	(3) Control Earnings	(4) Column 3+Other Controls	(5) Column 4 + risk factors
High School Graduate	123.235***		76.262***	87.886***	64.738***
	(12.997)		(11.431)	(10.253)	(7.888)
Some College	169.932***		105.812***	122.777***	93.189***
	(15.362)		(13.547)	(12.478)	(9.327)
College or More	207.531***		124.983***	144.792***	110.884***
	(17.691)		(15.434)	(14.183)	(11.592)
Between 200 and 300 percent poverty		74.710***	59.565***	16.269***	11.483**
		(9.075)	(9.770)	(5.415)	(5.676)
Observations	375549	375549	375549	375549	375549
R^2	0.008	0.008	0.009	0.030	0.033

Panel C. Year 2015	(1) Without controls	(2) Without Controls	(3) Control Earnings	(4) Column 3+Other Controls	(5) Column 4 + risk factors
High School Graduate	37.880***		21.515**	22.539**	22.522**
	(10.386)		(10.276)	(9.028)	(9.174)
Some College	82.253***		54.160***	54.445***	49.801***
	(13.278)		(13.281)	(11.360)	(11.515)
College or More	110.609***		85.131***	87.168***	78.314***
	(15.994)		(18.023)	(14.622)	(14.524)
Between 200 and 300 percent poverty		57.771***	44.671***	17.628***	8.352
		(6.077)	(6.262)	(5.206)	(5.712)
Observations	656626	656626	656626	656626	656626
R^2	0.005	0.005	0.006	0.033	0.039

Table A4: **Mother's Education and Birthweight Based on Poverty Ranking: By Separate Years.** The table is structured similar to Table 2 except that the estimation is conducted for each year 1990, 2000, and 2015 separately. Standard errors are clustered at the state level.

	(1) Group 1	(2) Group 2	(3) Group 3	(4) Group 4	(5) Group 5	(6) Group 6	(7) Group 7	(8) Group 8	(9) Group 9	(10) Group 10
High School Graduate	42.188***	52.868**	47.331***	75.591***	42.858***	66.065***	49.107***	78.959***	14.364	59.710***
	(9.781)	(26.075)	(11.423)	(13.509)	(12.808)	(13.416)	(15.847)	(11.283)	(25.091)	(10.228)
Some College	67.093***	91.485***	87.900***	112.140***	73.272***	109.980***	92.441***	124.740***	43.405	100.828***
	(10.350)	(28.889)	(15.503)	(16.036)	(13.779)	(17.873)	(21.049)	(13.833)	(31.242)	(11.752)
College or More	83.939***	121.379***	127.960***	140.913***	114.402***	175.761***	132.698***	155.074***	85.939**	167.447***
	(11.150)	(33.123)	(17.469)	(24.533)	(18.754)	(17.624)	(20.872)	(18.446)	(32.158)	(17.699)
Between 200 and 300 percent poverty	51.423***	48.147***	28.153***	16.998**	19.940**	21.892***	47.848***	25.519***	41.798***	-13.051**
	(18.319)	(12.785)	(9.463)	(7.367)	(9.076)	(7.892)	(11.136)	(8.700)	(8.440)	(5.614)
Between 300 and 400 percent poverty	81.958***	47.435***	25.852**	11.025	27.037**	11.981	43.985***	38.274***	48.774***	-24.408**
	(20.354)	(16.074)	(10.729)	(14.203)	(10.656)	(10.494)	(12.256)	(11.202)	(11.378)	(9.772)
Between 400 and 500 percent poverty	73.917***	50.928***	24.926*	22.566	25.587	-3.847	45.677***	32.524**	49.302***	-41.792***
	(20.958)	(17.547)	(13.883)	(19.291)	(15.505)	(12.337)	(12.591)	(15.424)	(14.563)	(12.542)
Above 500 percent poverty	80.212***	49.942**	20.016	18.819	10.135	-19.947	39.384**	34.926*	38.243*	-49.324***
	(22.911)	(21.691)	(15.587)	(22.986)	(18.805)	(18.937)	(16.380)	(18.967)	(19.159)	(15.764)
Observations	125236	117964	120330	121945	117530	133438	112618	104759	116528	100978
R^2	0.033	0.032	0.030	0.028	0.025	0.027	0.027	0.028	0.028	0.028

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: **Mother's Education and Birthweight Based on Poverty Ranking: White Mothers.** The table is structured similar to Table 3 except that the sample is restricted to white mothers. Robust standard errors clustered at the state level are presented in parenthesis.

	(1) Group 1	(2) Group 2	(3) Group 3	(4) Group 4	(5) Group 5	(6) Group 6	(7) Group 7	(8) Group 8	(9) Group 9	(10) Group 10
High School Graduate	-3.456	11.565	-14.161	15.800	80.747	37.898	140.206***	44.217	31.257	76.911***
	(47.929)	(75.275)	(54.812)	(34.653)	(52.496)	(31.988)	(32.511)	(29.635)	(40.630)	(22.858)
Some College	60.766	46.305	50.972	42.019	108.483*	53.164	189.614***	81.630***	64.345	135.348***
	(44.405)	(72.154)	(52.079)	(39.817)	(54.112)	(38.089)	(31.621)	(27.721)	(49.567)	(14.788)
College or More	57.941	21.001	71.373	131.723*	193.568**	114.082**	249.365***	153.962***	111.440*	208.249***
	(56.259)	(89.218)	(70.299)	(69.482)	(80.703)	(47.374)	(34.911)	(27.743)	(64.125)	(31.016)
Between 200 and 300 percent poverty	14.064	62.730*	22.354	-20.590	34.822	8.827	15.667	17.803	14.376	-11.575
	(33.101)	(32.138)	(34.040)	(26.453)	(30.866)	(25.424)	(21.425)	(17.938)	(28.887)	(15.883)
Between 300 and 400 percent poverty	-7.461	70.324	7.029	-5.235	38.310	1.540	-10.736	-22.313	0.257	-18.850
	(32.267)	(45.793)	(34.708)	(44.105)	(52.104)	(40.217)	(32.709)	(30.316)	(41.109)	(38.437)
Between 400 and 500 percent poverty	-41.550	102.548**	14.304	-59.523	5.172	-0.677	-3.049	-18.192	-4.070	-37.225
	(37.265)	(47.948)	(48.844)	(60.154)	(57.301)	(48.001)	(38.642)	(20.146)	(57.132)	(51.452)
Above 500 percent poverty	-42.028	155.543**	34.765	-48.047	-45.398	-22.124	-35.988	-17.590	-20.354	-34.292
	(34.979)	(61.525)	(68.924)	(69.824)	(74.312)	(60.296)	(46.987)	(30.729)	(78.485)	(66.401)
Observations	8615	7452	5802	7945	9747	12265	12463	12634	17679	21027
R^2	0.035	0.039	0.051	0.044	0.037	0.034	0.027	0.036	0.030	0.038

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: **Mother's Education and Birthweight Based on Poverty Ranking: Black Mothers.** The table is structured similar to Table 3 except that the sample is restricted to black mothers. Robust standard errors clustered at the state level are presented in parenthesis.